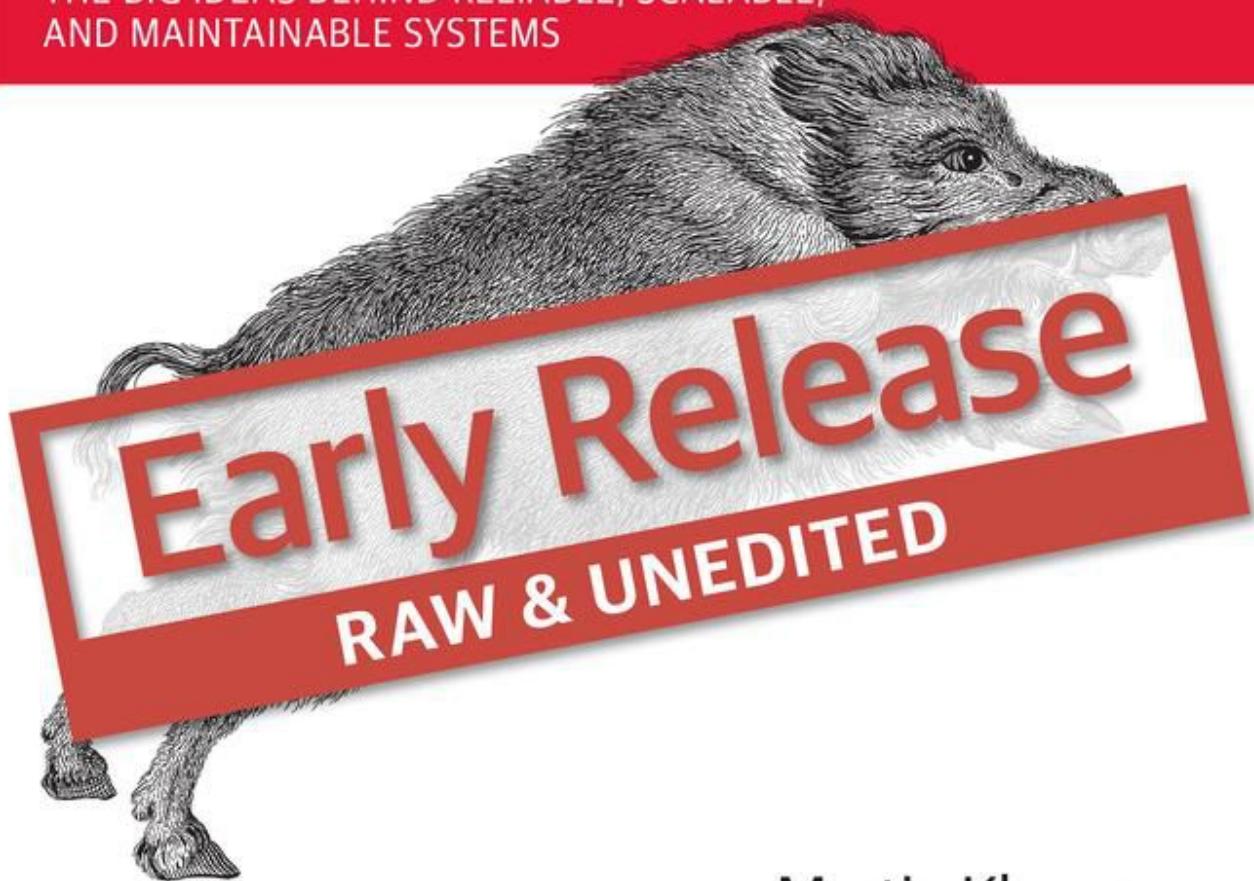


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Designing Data-Intensive Applications

THE BIG IDEAS BEHIND RELIABLE, SCALABLE,
AND MAINTAINABLE SYSTEMS



Martin Kleppmann

Designing Data-Intensive Applications

Martin Kleppmann



Beijing • Cambridge • Farnham • Köln • Sebastopol • Tokyo

Designing Data-Intensive Applications

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Computing is pop culture. [...] Pop culture holds a disdain for history. Pop culture is all about identity and feeling like you're participating. It has nothing to do with cooperation, the past or the future—it's living in the present. I think the same is true of most people who write code for money. They have no idea where [their culture came from]...

And the Internet was done so well that most people think of it as a natural resource like the Pacific Ocean, rather than something that was man-made. When was the last time a technology with a scale like that was so error-free?

— [Alan Kay](#) *Dr Dobb's Journal — July 2012*

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About the Author

Martin Kleppman is a Senior Software Engineer at LinkedIn, a company with highly advanced data systems teams: open source projects including Apache Kafka, Samza, Voldemort, Helix and Databus, contributions to Hadoop and other major projects, and research papers are continuously published by LinkedIn.

Martin joined LinkedIn through the acquisition of Rapportive, a startup that he co-founded, and for which he worked on data processing infrastructure. His in-depth technical blog posts are popular amongst software developers, and several of them have reached #1 on Hacker News . In fact, the idea for this book came from wanting to write an expanded version of his post Rethinking Caching in Web Apps.

About this Book

If you have worked in software engineering in recent years, especially in server-side and backend systems, you have probably been bombarded with a plethora of buzzwords relating to storage and processing of data. NoSQL! Big Data! Web-scale! Sharding! Eventual consistency! ACID! CAP theorem! Cloud services! Map-reduce! Real-time!

In the last decade we have seen many interesting developments in databases, distributed systems and in the ways we build applications on top of them. There are various driving forces for these developments, including:

- Internet companies such as Google, Yahoo!, Amazon, Facebook, LinkedIn and Twitter are handling huge volumes of data and traffic, forcing them to create new tools that enable them to efficiently handle such scale.
- Businesses need to be agile, test hypotheses cheaply, and respond quickly to new market insights, by keeping development cycles short and data models flexible.
- Free and open source software has become very successful, and is now preferred to commercial or bespoke in-house software in many environments.
- CPU clock speeds are barely increasing, but multi-core processors are standard, and networks are getting faster. This means parallelism is only going to increase.

- Even if you work on a small team, you can now build systems that are distributed across many machines and even multiple geographic regions, thanks to infrastructure as a service (IaaS) such as Amazon Web Services.
- Many services are now expected to be highly available; extended downtime due to outages or maintenance is becoming increasingly unacceptable.

Data-intensive applications are pushing the boundaries of what is possible by making use of these technological developments. We call an application *data-intensive* if data is its primary challenge: the quantity of data, the complexity of data, or the speed at which it is changing.

The tools and technologies that help data-intensive applications store and process data have been rapidly adapting to these changes. New types of database system (“NoSQL”) have been getting lots of attention, but message queues, caches, search indexes, frameworks for batch and stream processing, and related technologies are very important too. Many applications use some combination of these.

The buzzwords that fill this space are a sign of enthusiasm for the new possibilities, which is a great thing. However, as software engineers and architects, we also need to have a technically accurate and precise understanding of the various technologies and their trade-offs if we want to build good applications. For that understanding, we have to dig deeper than buzzwords.

Fortunately, behind the rapid changes in technology, there are enduring principles that remain true, no matter which version of a particular tool you are using. If you understand those principles, you’re in a position to see where each tool fits in, how to make good use of it, and how to avoid its pitfalls. That’s where this book comes in.

The goal of this book is to help you navigate the diverse and fast-changing landscape of technologies for **processing and storing data**. This book is not a tutorial for one particular tool, nor is it a textbook full of dry theory. Instead, we will look at examples of successful data systems: technologies that form the foundation of many popular applications, and that have to meet scalability, performance and reliability requirements every day.

We will **dig into** the internals of those systems, tease apart their key algorithms, discuss their principles and the **trade-offs** they have to make. On this journey, we will try to find useful ways of *thinking about* data systems—not just *how* they work, but also *why* they work that way, and what questions we need to ask.

After reading this book, you will be in a great position to decide which kind of technology is appropriate for which purpose, and understand how tools can be combined to form the foundation of a good application architecture. You won’t be ready to **build your own database**

storage engine **from scratch**, but fortunately that is rarely necessary. You will, however, develop a good intuition for what your systems are doing under the hood, so that you can reason about their behavior, make good design decisions, and track down any problems that may arise.

Who Should Read this Book?

This book is for software engineers, software architects and technical managers who love to code. It is especially relevant if you need to make decisions about the architecture of the systems you work on—for example, if you need to choose tools for solving a given problem, and figure out how best to apply them.

You should have some experience building web-based applications or network services, and you should be familiar with relational databases and SQL. Any non-relational databases and other data-related tools you know are a bonus. A general understanding of common network protocols like TCP and HTTP is helpful. Your choice of programming languages or frameworks makes no difference for this book.

If you have a natural curiosity for the way things work, you're in for a treat. This book breaks down the internals of various software tools, and it's great fun to explore the bright thinking that went into their design.

Some people are interested in data systems from a scalability point of view, for example to support web or mobile apps with millions of users. That's a good reason to be interested, but not the only reason. As outlined in [Chapter 1](#), there is also plenty of interest in designing systems to be more reliable and easier to maintain in the long run, even as they grow, and as requirements and technologies change. This kind of application can also be data-intensive: small amounts of data can also be challenging to deal with if they are particularly complex or variable.

Sometimes, when discussing scalable data systems, people make comments along the lines of *“you’re not Google or Amazon, stop worrying about scale and just use a relational database”*. There is truth in that statement: building for scale that you don’t need is wasted effort, and may lock you into an inflexible design. In effect, it is a form of premature optimization. However, it’s also important to choose the right tool for the job, and different technologies each have their own strengths and weaknesses. As we shall see, relational databases are important, but not the final word on dealing with data.

Scope of this Book

This book does not attempt to give detailed instructions on how to install or use specific software packages or APIs, since there is already plenty of documentation for those things. Instead we discuss the various principles and trade-offs that are fundamental to data systems, and we explore the different design decisions taken by different products.

Most of what we discuss in this book has already been said elsewhere in some form or another—in conference presentations, research papers, blog posts, code, bug trackers, and engineering folklore. This book summarizes the most important ideas from many different sources, and it includes pointers to the original literature throughout the text. The references at the end of each chapter are a great resource if you want to explore an area in more depth.

We look primarily at the *architecture* of data systems and the ways how they are integrated into data-intensive applications. This book doesn't have space to cover deployment, operations, security, management and other areas—those are complex and important topics, and we wouldn't do them justice by making them superficial side-notes in this book. They deserve books of their own.

Many of the technologies described in this book fall within the realm of the *Big Data* buzzword. However, the term *Big Data* is so over-used and under-defined that it is not useful in a serious engineering discussion. This book uses less ambiguous terms, such as single-node vs. distributed systems, or online/interactive vs. offline/batch processing systems.

This book has a bias towards free and open source software (FOSS), because reading, modifying and executing source code is a great way to understand how something works in detail. Open platforms also reduce the risk of vendor lock-in. However, where appropriate, we also discuss proprietary software (closed-source software, software as a service, or companies' in-house software that is only described in literature but not released publicly).

Early Release Status and Feedback

This is an early release copy of *Designing Data-Intensive Applications*. The text, figures and examples are a work in progress, and several chapters are yet to be written. We are releasing the book before it is finished because we hope that it is already useful in its current form, and because we would love your feedback in order to create the best possible finished product.

If you find any errors or glaring omissions, if you find anything confusing, or if you have any ideas for improving the book, please email the author and editors

Part I. The Big Picture

Chapter 1. Reliable, Scalable and Maintainable Applications

Many applications today are *data-intensive*, as opposed to *compute-intensive*. Raw CPU power is rarely a limiting factor for these applications—bigger problems are usually the amount of data, the complexity of data, and the speed at which it is changing.

A data-intensive application is typically built from standard building blocks which provide commonly needed functionality. For example, many applications need to:

- Store data so that they, or another application, can find it again later (*databases*),
- Remember the result of an expensive operation, to speed up reads (*caches*),
- Allow users to search data by keyword or filter it in various ways (*search indexes*),
- Send a message to another process, to be handled asynchronously (*message queues*),
- Observe what is happening, and act on events as they occur (*stream processing*),
- Periodically crunch a large amount of accumulated data (*batch processing*).

If that sounds painfully obvious, that's just because these *data systems* are such a successful abstraction: we use them all the time without thinking too much. When building an application, most engineers wouldn't dream of writing a new data storage engine from scratch, because databases are a perfectly good tool for the job.

But reality is not that simple. There are many database systems with different characteristics, because different applications have different requirements. There are various approaches to caching, several ways of building search indexes, and so on. When building an application, we still need to figure out which tools and which approaches are the most appropriate for the task at hand. Sometimes it can be hard to combine several tools when you need to do something that a single tool cannot do alone.

This book is a journey through both the principles and the practicalities of data systems, and how you can use them to build data-intensive applications. We will explore what different tools have in common, what distinguishes them, and how they achieve their characteristics.

Thinking About Data Systems

We typically think of databases, queues, caches etc. as being very different categories of tools. Although a database and a message queue have some superficial similarity—both store data for some time—they have very different access patterns, which means different performance characteristics, and thus very different implementations.

So why should we lump them all together under an umbrella term like *data systems*?

Many new tools for data storage and processing have emerged in recent years. They are optimized for a variety of different use cases, and they no longer neatly fit into these categories. [1] For example, there are data stores that are also used as message queues (Redis), and there are message queues with database-like durability guarantees (Kafka), so the boundaries between the categories are becoming blurred.

Secondly, increasingly many applications now have such demanding or wide-ranging requirements that a single tool can no longer meet all of its data processing and storage needs. Instead, the work is broken down into tasks that *can* be performed efficiently on a single tool, and those different tools are stitched together using application code.

For example, if you have an application-managed caching layer (using memcached or similar), or a full-text search server separate from your main database (such as Elasticsearch or Solr), it is normally the application code's responsibility to keep those caches and indexes in sync with the main database. [Figure 1-1](#) gives a glimpse of what this may look like (we will go into detail in later chapters).

When you combine several tools in order to provide a service, the service's interface or API usually hides those implementation details from clients. Now you have essentially created a new, special-purpose data system from smaller, general-purpose components. Your composite data system may provide certain guarantees, e.g. that the cache will be correctly invalidated or updated on writes, so that outside clients see consistent results. You are now not only an application developer, but also a data system designer.

If you are designing a data system or service, a lot of tricky questions arise. How do you ensure that the data remains correct and complete, even when things go wrong internally? How do you provide consistently good performance to clients, even when parts of your system are degraded? How do you scale to handle an increase in load? What does a good API for the service look like?

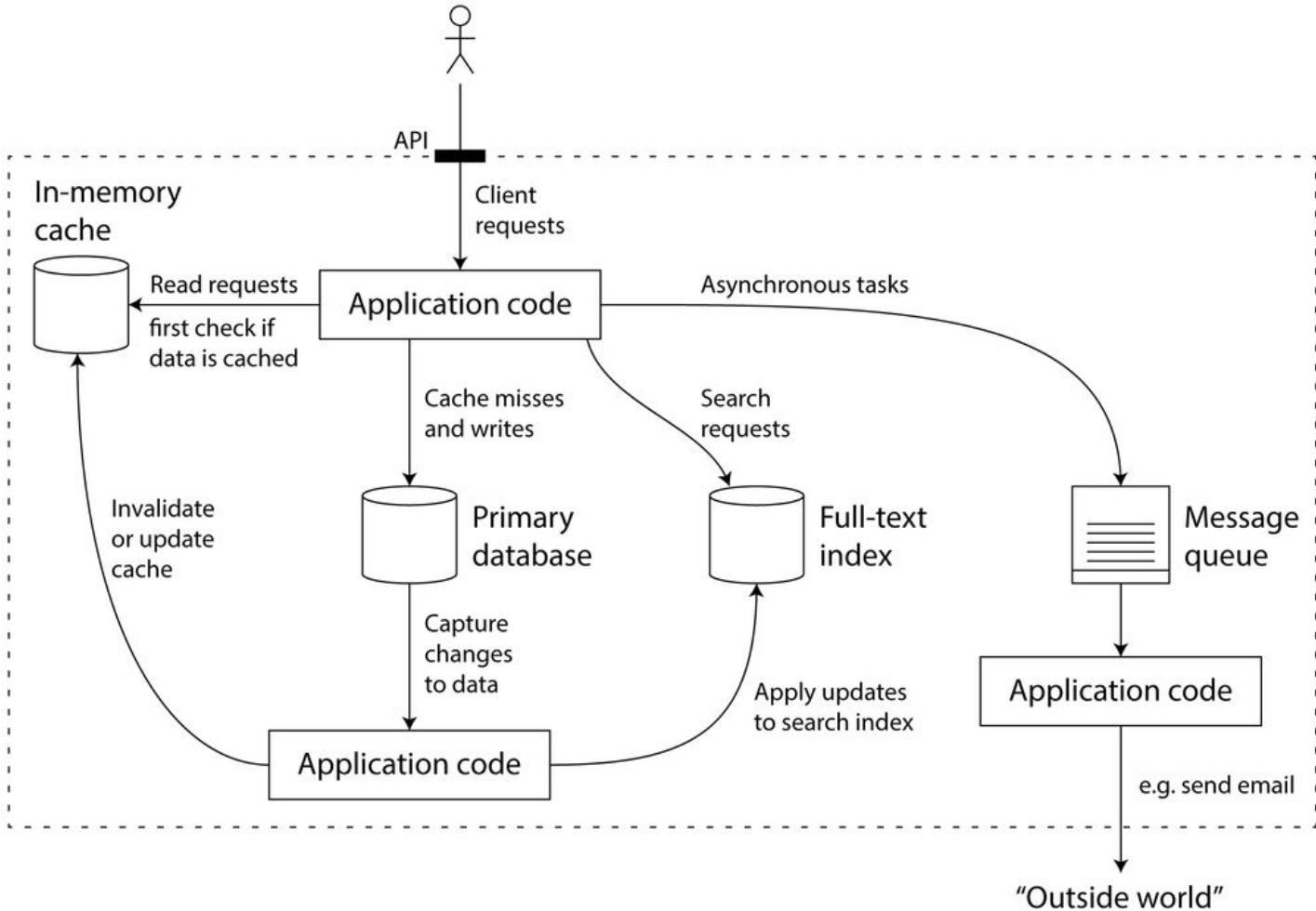


Figure 1-1. One possible architecture for a data system that combines several components.

There are many factors that may influence the design of a data system, including the skills and experience of the people involved, legacy system dependencies, the timescale for delivery, your organization's tolerance of different kinds of risk, regulatory constraints, etc. Those factors depend very much on the situation.

In this book, we focus on three concerns that are important in most software systems:

Reliability

The system should continue to work *correctly* (performing the correct function at the desired performance) even in the face of *adversity* (hardware or software faults, and even human error). See [Reliability](#).

Scalability

As the system *grows* (in data volume, traffic volume or complexity), there should be reasonable ways of dealing with that growth. See [Scalability](#).

Maintainability

Over time, many different people will work on the system (engineering and operations, both maintaining current behavior and adapting the system to new use cases), and they should all be able

to work on it *productively*. See [Maintainability](#).

These words are often cast around without a clear understanding of what they mean. In the interest of thoughtful engineering, we will spend the rest of this chapter exploring ways of thinking about reliability, scalability and maintainability. Then, in the following chapters, we will look at various techniques, architectures and algorithms that are used in order to achieve those goals.

Reliability

Everybody has an intuitive idea of what it means for software to be reliable or unreliable. For software, typical expectations include:

- The application performs the function that the user expected.
- It can tolerate the user making mistakes, or using the software in unexpected ways.
- Its performance is good enough for the required use case, under expected load and data volume.
- The system prevents any unauthorized access and abuse.

If all those things together mean “working correctly”, then we can understand *reliability* as meaning, roughly, “[continuing to work correctly, even when things go wrong](#)”.

The things that can go wrong are called *faults*, and systems that anticipate faults and can cope with them are called *fault-tolerant*. The term is slightly misleading: it suggests that we could make a system tolerant of every possible kind of fault, which in reality is not feasible (if the entire planet Earth, and all servers on Earth, is sucked into a black hole, tolerance of that fault would require web hosting in space—good luck getting that budget item approved). So it only makes sense to talk about tolerance of certain *types of fault*.

Note that a fault is not the same as a failure—see [\[2\]](#) for an overview of the [terminology](#). A fault is usually defined as one component of the system deviating from its spec, whereas a failure is when the system as a whole stops providing the required service to the user. It is impossible to reduce the probability of a fault to zero; therefore it is usually best to design fault tolerance mechanisms that [prevent faults from causing failures](#). In this book we cover several techniques for building reliable systems from unreliable parts.

Counter-intuitively, in such fault-tolerant systems, it can make sense to deliberately *increase* the rate of faults by triggering them deliberately. Software that deliberately causes faults—for example, randomly killing individual processes without warning—is known as a [chaos monkey](#) [\[3\]](#). It ensures that the [fault-tolerance machinery](#) is continually exercised and tested, so that we can be confident that faults will be handled correctly when they occur naturally.

Although we generally prefer tolerating faults over preventing faults, there are cases where prevention is better than cure (e.g. because no cure exists). This is the case with security matters, for example: if an attacker has compromised a system and gained access to sensitive data, that event cannot be undone. However, this book mostly deals with the kinds of fault that can be cured, as described in the following sections.

Hardware faults

When we think of causes of system failure, hardware faults quickly come to mind. Hard disks crash, RAM becomes faulty, the power grid has a blackout, someone unplugs the wrong network cable. Anyone who has worked with large data centers can tell you that these things happen *all the time* when you have a lot of machines.

Hard disks are reported as having a mean time to failure (MTTF) of about 10 to 50 years [4]. Thus, on a storage cluster with 10,000 disks, we should expect on average one disk to die per day.

Our first response is usually to add redundancy to the individual hardware components in order to reduce the failure rate of the system. Disks may be set up in a RAID configuration, servers may have dual power supplies and hot-swappable CPUs, and data centers may have batteries and diesel generators for backup power. When one component dies, the redundant component can take its place while the broken component is replaced. This approach cannot completely prevent hardware problems from causing failures, but it is well understood, and can often keep a machine running uninterrupted for years.

Until recently, redundancy of hardware components was sufficient for most applications, since it makes total failure of a single machine fairly rare. As long as you can restore a backup onto a new machine fairly quickly, the downtime in case of failure is not catastrophic in most applications. Thus, multi-machine redundancy was only required by a small number of applications for which high availability was absolutely essential.

However, as data volumes and applications' computing demands increase, more applications are using larger numbers of machines, which proportionally increases the rate of hardware faults. Moreover, in some "cloud" platforms such as Amazon Web Services it is fairly common for virtual machine instances to become unavailable without warning [5], as the platform is designed for flexibility and elasticity in favor of single-machine reliability.

Hence there is a move towards systems that can tolerate the loss of entire machines, by using software fault-tolerance techniques in preference to hardware redundancy. Such systems also have operational advantages: a single-server system requires planned downtime if you need to

reboot the machine (to apply security patches, for example), whereas a system that can tolerate machine failure can be patched one node at a time, without downtime of the entire system.

Software errors

We usually think of hardware faults as being random and independent from each other: one machine's disk failing does not imply that another machine's disk is going to fail. There may be weak correlations (for example due to a common cause, such as the temperature in the server rack), but otherwise it is unlikely that a large number of hardware components will fail at the same time.

Another class of fault is a systematic error within the system. Such faults are harder to anticipate, and because they are correlated across nodes, they tend to cause many more system failures than uncorrelated hardware faults [4]. Examples include:

- A software bug that causes every instance of an application server to crash when given a particular bad input. For example, consider the leap second on June 30, 2012 that caused many applications to hang simultaneously, due to a bug in the Linux kernel. [6]
- A runaway process uses up some shared resource—CPU time, memory, disk space or network bandwidth.
- A service that the system depends on slows down, becomes unresponsive or starts returning corrupted responses.
- Cascading failures, where a small fault in one component triggers a fault in another component, which in turn triggers further faults (see [7] for example).

The bugs that cause these kinds of software fault often lie dormant for a long time until they are triggered by an unusual set of circumstances. In those circumstances, it is revealed that the software is making some kind of assumption about its environment—and whilst that assumption is usually true, it eventually stops being true for some reason.

There is no quick solution to the problem of systematic faults in software. Lots of small things can help: carefully thinking about assumptions and interactions in the system, thorough testing, measuring, monitoring and analyzing system behavior in production. If a system is expected to provide some guarantee (for example, in a message queue, that the number of incoming messages equals the number of outgoing messages), it can constantly check itself while it is running, and raise an alert if a discrepancy is found [8].

Human errors

Humans design and build software systems, and the operators who keep the system running are also human. Even when they have the best intentions, humans are known to be unreliable. How do we make our system reliable, in spite of unreliable humans?

The best systems combine several approaches:

- Design systems in a way that minimizes opportunities for error. For example, well-designed abstractions, APIs and admin interfaces make it easy to do “the right thing”, and discourage “the wrong thing”. However, if the interfaces are too restrictive, people will work around them, negating their benefit, so this is a tricky balance to get right.
- Decouple the places where people make the most mistakes from the places where they can cause failures. In particular, provide fully-featured non-production *sandbox* environments where people can explore and experiment safely, using real data, without affecting real users.
- Test thoroughly at all levels, from unit tests to whole-system integration tests and manual tests. **Automated testing** is widely used, well understood, and especially valuable for covering corner cases that rarely arise in normal operation.
- Allow quick and **easy recovery** from human errors, to minimize the impact in the case of a failure. For example, make it fast to roll back configuration changes, roll out new code gradually (so that any unexpected bugs affect only a small subset of users), and provide tools to recompute data (in case it turns out that the old computation was incorrect).
- Set up detailed and clear monitoring and **telemetry**, such as performance metrics and error rates. (The term *telemetry* is not often applied to software, but it is very apt. We can learn about good telemetry from other engineering disciplines, such as aerospace [9].) Monitoring can show us early warning signals, and allow us to check whether any assumptions or constraints are being violated. When a problem occurs, metrics can be invaluable in diagnosing the issue.
- Good management practices, training etc—a complex and important aspect, and beyond the scope of this book.

How important is reliability?

Reliability is not just for nuclear power stations and air traffic control software—more mundane applications are also expected to work reliably. Bugs in business applications cause lost productivity (and legal risks if figures are reported incorrectly), and outages of e-commerce sites can have huge costs in terms of lost revenue and reputation.

Even in “non-critical” applications we have a responsibility to our users. Consider a parent who stores all pictures and videos of their children in your photo application [10]. How would they feel if that database was suddenly corrupted? Would they know how to restore it from a backup?

There are situations in which we may choose to sacrifice reliability in order to reduce development cost (e.g. when developing a prototype product for an unproven market) or operational cost (e.g. for a service with a very narrow profit margin)—but we should be very conscious of when we are cutting corners.

Scalability

Even if a system is working reliably today, that doesn't mean it will necessarily work reliably in future. One common reason for degradation is increased load: perhaps it has grown from 10,000 concurrent users to 100,000 concurrent users, or from 1 million to 10 million. Perhaps it is processing much larger volumes of data than it did before.

Scalability is the term we use to describe a system's ability to adapt to increased load. Note, however, that it is not a one-dimensional label that we can attach to a system: it is meaningless to say “X is scalable” or “Y doesn't scale”. Rather, discussing scalability means to discuss the question: if the system grows in a particular way, what are our options for coping with the growth?

Describing load

First, we need to succinctly describe the current load on the system; only then can we discuss growth questions (what happens if our load doubles?). Load can be described with a few numbers which we call *load parameters*. The best choice of parameters depends on the architecture of your system: perhaps it's requests per second, ratio of reads to writes, the number of simultaneously active users, or something else. Perhaps the average case is what matters for you, or perhaps your bottleneck is dominated by a small number of extreme cases.

To make this idea more concrete, let's consider Twitter as an example, using data published in November 2012 [[11](#)]. Two of Twitter's main operations are:

Post tweet

A user can publish a new message to their followers (4.6 k requests/sec on average, over 12 k requests/sec at peak).

Home timeline

A user can view tweets recently published by the people they follow (300 k requests/sec).

Simply handling 12,000 writes per second (the peak rate for posting tweets) would be fairly easy. However, Twitter's scaling challenge is not primarily due to tweet volume, but due to *fan-out*^[12]—each user follows many people, and each user is followed by many people. There are broadly two approaches to implementing these two operations:

1. Posting a tweet simply inserts the new tweet into a global collection of tweets. When a user requests *home timeline*, look up all the people they follow, find all recent tweets for each of those users, and merge them (sorted by time). In a relational database like the one in [Figure 1-2](#), this would be a query along the lines of:
2. SELECT tweets.* , users.* FROM tweets
3. JOIN users ON tweets.sender_id = users.id
4. JOIN follows ON follows.followee_id = users.id
WHERE follows.follower_id = current_user
5. Maintain a cache for each user's home timeline—like a mailbox of tweets for each recipient user (see [Figure 1-3](#)). When a user *posts a tweet*, look up all the people who follow that user, and insert the new tweet into each of their home timeline caches. The request to read the home timeline is then cheap, because its result has been computed ahead of time.

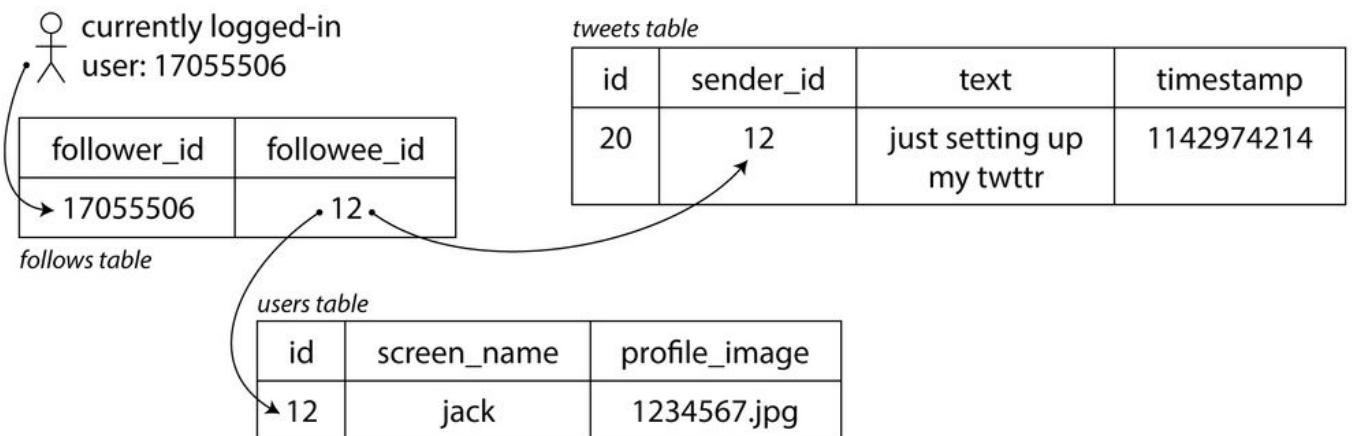


Figure 1-2. Simple relational schema for implementing a Twitter home timeline

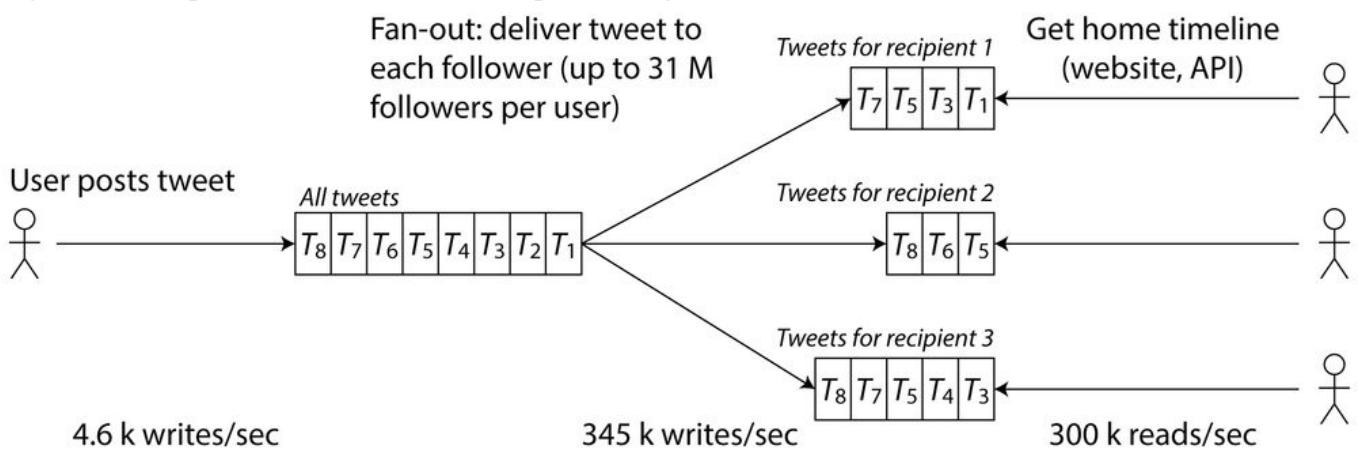


Figure 1-3. Twitter's data pipeline for delivering tweets to followers, with load parameters as of November 2012 [[11](#)]

The first version of Twitter used approach 1, but the systems struggled to keep up with the load of home timeline queries, so the company switched to approach 2. This works better because the average rate of published tweets is almost two orders of magnitude lower than the rate of home

timeline reads, and so in this case it's preferable to do more work at write time and less at read time.

However, the downside of approach 2 is that posting a tweet now requires a lot of extra work. On average, a tweet is delivered to about 75 followers, so 4.6 k tweets per second become 345 k writes per second to the home timeline caches. But this average hides the fact that the number of followers per user varies wildly, and some users have over 30 million followers. This means that a single tweet may result in over 30 million writes to home timelines! Doing this in a timely manner—Twitter tries to deliver tweets to followers within 5 seconds—is a significant challenge.

In the example of Twitter, the distribution of followers per user (maybe weighted by how often those users tweet), is a key load parameter for discussing scalability, since it determines the fan-out load. Your application may have very different characteristics, but you can apply similar principles to reasoning about its load.

The final twist of the Twitter anecdote: now that approach 2 is robustly implemented, Twitter is moving to a hybrid of both approaches. Most users' tweets continue to be fanned out to home timelines at the time when they are posted, but a small number of users with a very large number of followers are excepted from this fan-out. Instead, when the home timeline is read, the tweets from celebrities followed by the user are fetched separately and merged with the home timeline when the timeline is read, like in approach 1. This hybrid approach is able to deliver consistently good performance.

Describing performance

Once you have described the load on our system, you can investigate what happens when the load increases. You can look at it in two ways:

- When you increase a load parameter, and keep the system resources (CPU, memory, network bandwidth, etc.) unchanged, how is performance of your system affected?
- When you increase a load parameter, how much do you need to increase the resources if you want to keep performance unchanged?

Both questions require performance numbers, so let's look briefly at describing the performance of a system.

In a batch-processing system such as Hadoop, we usually care about *throughput*—the number of records we can process per second, or the total time it takes to run a job on a dataset of a certain size.^[13] In online systems, *latency* is usually more important—the time it takes to serve a request, also known as *response time*.

Even if you only make the same request over and over again, you'll get a slightly different latency every time. In practice, in a system handling a variety of requests, the latency per request can vary a lot. We therefore need to think of latency not as a single number, but as a *probability distribution*.

In [Figure 1-4](#), each gray bar represents a request to a service, and its height shows how long that request took. Most requests are reasonably fast, but there are occasional *outliers* that take much longer. Perhaps the slow requests are intrinsically more expensive, e.g. because they process more data. But even in a scenario where you'd think all requests should take the same time, you get variation: random additional latency could be introduced by a context switch to a background process, the loss of a network packet and TCP retransmission, a garbage collection pause, a page fault forcing a read from disk, or many other things.

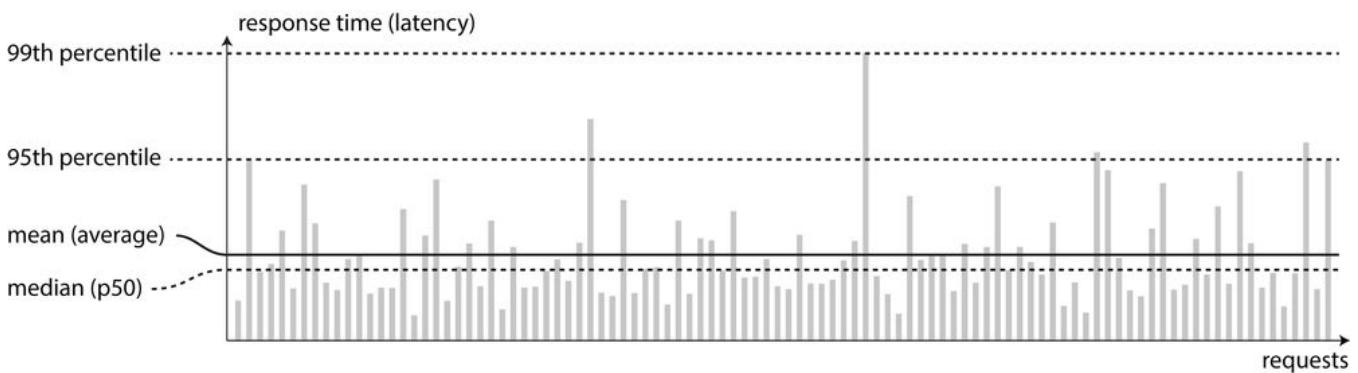


Figure 1-4. Illustrating mean and percentiles: response times for a sample of 100 requests to a service

It's common to see the *average* response time of a service reported. (Strictly speaking, the term *average* doesn't refer to any particular formula, but in practice it is usually understood as the *arithmetic mean*: given a set of n values, add up all the values, and divide by n .) However, the mean is not a very good metric if you want to know your "typical" response time, because it is easily biased by outliers.

Usually it is better to use *percentiles*. If you take your list of response times and sort it, from fastest to slowest, then the *median* is the half-way point: for example, if your median response time is 200 ms, that means half your requests return in less than 200 ms, and half your requests take longer than that. This makes the median a good metric if you want to know how long users typically have to wait. The median is also known as *50th percentile*, and sometimes abbreviated as *p50*.

In order to figure out how bad your outliers are, you can look at higher percentiles: the *95th*, *99th* and *99.9th* percentile are common (abbreviated *p95*, *p99* and *p999*). They are the response time thresholds at which 95%, 99% or 99.9% of requests are faster than that particular threshold. For example, if the 95th percentile response time is 1.5 seconds, that means 95 out of 100

requests take less than 1.5 seconds, and 5 out of 100 requests take 1.5 seconds or more. This is illustrated in [Figure 1-4](#).

Now, when testing a system at various levels of load, you can track the median and higher percentiles of response times in order to get a quick measure of the performance.

Percentiles in Practice

You may wonder whether the high percentiles are worth worrying about—if just 1 in 1,000 requests is unacceptably slow for the end user, and the other 999 are fast enough, you may still consider the overall level of service to be acceptable.

High percentiles become especially important in backend services that are called multiple times as part of serving a single end-user request. Even if you make the calls in parallel, the end-user request still needs to wait for the slowest of the parallel calls to complete. As it takes just one slow call to make the entire end-user request slow, rare slow calls to the backend become much more frequent at the end-user request level ([Figure 1-5](#)). See [\[14\]](#) for a discussion of approaches to solving this problem.

If you want to add response time percentiles to the monitoring dashboards for your services, you need to efficiently calculate them on an ongoing basis. For example, you may want to keep a rolling window of response times of requests in the last ten minutes. Every minute, you calculate the median and various percentiles over the values in that window, and plot those metrics on a graph.

The naïve implementation is to keep a list of response times for all requests within the time window, and to sort that list every minute. If that is too inefficient for you, there are algorithms which give a good approximation of percentiles at minimal CPU and memory cost, such as forward decay [\[15\]](#), which has been implemented in Java [\[16\]](#) and Ruby [\[17\]](#).

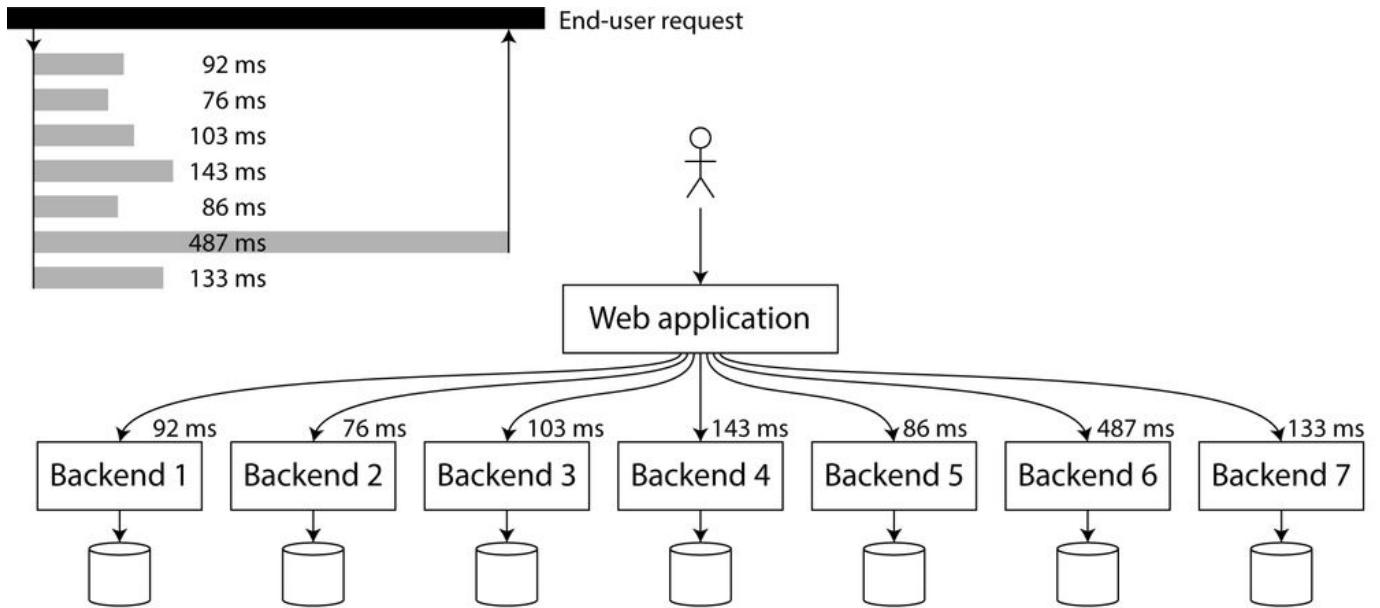


Figure 1-5. When several backend calls are needed to serve a request, it takes just a single slow backend request to slow down the entire end-user request.

Approaches for coping with load

Now that we have discussed the parameters for describing load, and metrics for measuring performance, we can start discussing scalability in earnest: how do we maintain good performance, even when our load parameters increase by some amount?

An architecture that is appropriate for one level of load is unlikely to cope with ten times that load. If you are working on a fast-growing service, it is therefore likely that you will need to re-think your architecture on every order of magnitude load increase—perhaps even more often than that.

People often talk of a dichotomy between *scaling up* (*vertical scaling*, using a single, powerful machine) and *scaling out* (*horizontal scaling*, distributing the load across multiple smaller machines). In reality, good architectures usually involve a pragmatic mixture of approaches.

While distributing stateless services across multiple machines is fairly straightforward, taking stateful data systems from a single node to a distributed setup can introduce a lot of additional complexity. For this reason, common wisdom until recently was to keep your database on a single node (scale up) until scaling cost or high-availability requirements forced you to make it distributed.

As the tools and abstractions for distributed systems get better, this common wisdom may change, at least for some kinds of application. It is conceivable that distributed data systems will become the default in future, even for use cases that don't handle large volumes of data or traffic.

Over the course of the rest of this book we will cover many kinds of distributed data system, and discuss how they fare not just in terms of scalability, but also ease of use and maintainability.

The architecture of systems that operate at large scale is usually highly specific to the application—there is no such thing as a generic, one-size-fits-all scalable architecture (informally known as *magic scaling sauce*). The problem may be the volume of reads, the volume of writes, the volume of data to store, the complexity of the data, the latency requirements, the access patterns, or (usually) some mixture of all of these plus many more issues.

For example, a system that is designed to handle 100,000 requests per second, each 1 kB in size, looks very different from a system that is designed for three requests per minute, each 2 GB in size—even though the two systems have the same data throughput.

An architecture that scales well for a particular application is built around assumptions of which operations will be common, and which will be rare—the load parameters. If those assumptions turn out to be wrong, the engineering effort for scaling is at best wasted, and at worst counter-productive. In an early-stage startup or an unproven product it's usually more important to be able to iterate quickly on product features, than it is to scale to some hypothetical future load.

However, whilst being specific to a particular application, scalable architectures are usually built from general-purpose building blocks, arranged in familiar patterns. In this book we discuss those building blocks and patterns.

Maintainability

It is well-known that the majority of the cost of software is not in its initial development, but in its ongoing maintenance—fixing bugs, keeping its systems operational, investigating failures, adapting it to new platforms, modifying it for new use cases, repaying technical debt, and adding new features.

Yet, unfortunately, many people working on software systems dislike maintenance of so-called *legacy* systems—perhaps it involves fixing other people's mistakes, or working with platforms that are now outdated, or systems that were forced to do things they were never intended for. Every legacy system is unpleasant in its own way, and so it is difficult to give general recommendations for dealing with them.

However, we can and should design software in such a way that it will hopefully minimize pain during maintenance, and thus avoid creating legacy software ourselves. To this end, we will pay particular attention to three design principles for software systems:

Operability

Make it easy for operations teams to keep the system running smoothly.

Simplicity

Make it easy for new engineers to understand the system, by removing as much complexity as possible from the system. (Note this is not the same as simplicity of the user interface.)

Plasticity

Make it easy for engineers in future to make changes to the system, adapting it for unanticipated use cases as requirements change. Also known as *extensibility*, *modifiability* or *malleability*.

As previously with reliability and scalability, there are no quick answers to achieving these goals. Rather, we will try to think about systems with operability, simplicity and plasticity in mind.

Operability: making life easy for operations

It has been suggested that “*good operations can often work around the limitations of bad (or incomplete) software, but good software cannot run reliably with bad operations*”. [[\[8\]](#)] While some aspects of operations can and should be automated, it is still up to humans to set up that automation in the first place, and to make sure it’s working correctly.

Operations teams are vital to keeping a software system running smoothly. A good operations team typically does the following, and more:

- monitoring the health of the system, and quickly restoring service if it goes into a bad state;
- tracking down the cause of problems, such as system failures or degraded performance;
- keeping software and platforms up-to-date, including security patches;
- keeping tabs on how different systems affect each other, so that a problematic change can be avoided before it causes damage;
- anticipating future problems and solving them before they occur, e.g. capacity planning;
- establishing good practices and tools for deployment, configuration management and more;
- performing complex maintenance tasks, such as moving an application from one platform to another;
- maintaining security of the system as configuration changes are made;
- defining processes that make operations predictable and help keep the production environment stable;
- preserving the organization’s knowledge about the system, even as individual people come and go.

Good operability means making routine tasks easy, allowing the operations team to focus their effort on high-value activities. Data systems can do various things to make routine tasks easy, including:

- provide visibility into the runtime behavior and internals of the system, with good monitoring and telemetry;
- good support for automation and integration with standard tools;
- good documentation and an easy-to-understand operational model (“if I do X, Y will happen”);
- good default behavior, but also giving administrators the freedom to override defaults when needed;
- self-healing where appropriate, but also giving administrators manual control over the system state when needed;
- predictable behavior, minimizing surprises.

Simplicity: managing complexity

Small software projects can have delightfully simple and expressive code, but as projects get larger, they often become very complex and difficult to understand. This complexity slows down everyone who needs to work on the system, further increasing the cost of maintenance.

There are many possible symptoms of complexity: explosion of the state space, tight coupling of modules, tangled dependencies, inconsistent naming and terminology, hacks aimed at solving performance problems, special-casing to work around issues elsewhere, and many more.

Much has been written on this topic already—to mention just two articles, *No Silver Bullet* [[18](#)] is a classic, and its ideas are further developed in *Out of the Tar Pit* [[19](#)].

When complexity makes maintenance hard, budgets and schedules are often overrun. In complex software, there is also a greater risk of introducing bugs when making a change: when the system is harder for developers to understand and reason about, hidden assumptions, unintended consequences and unexpected interactions are more easily overlooked. Conversely, reducing complexity greatly improves the maintainability of software, and thus simplicity should be a key goal for the systems we build.

Making a system simpler does not necessarily mean reducing its functionality; it can also mean removing *accidental* complexity. Moseley and Marks [[19](#)] define complexity as *accidental* if it is not inherent in the problem that the software solves (as seen by the users), but arises only from the implementation.

One of the best tools we have for removing accidental complexity is *abstraction*. A good abstraction can hide a great deal of implementation detail behind a clean, simple-to-understand façade. A good abstraction can also be used for a wide range of different applications. Not only is

this reuse more efficient than re-implementing a similar thing multiple times, but it also leads to higher-quality software, as quality improvements in the abstracted component benefit all applications that use it.

For example, high-level programming languages are abstractions that hide machine code, CPU registers and syscalls. SQL is an abstraction that hides complex on-disk and in-memory data structures, concurrent requests from other clients, and inconsistencies after crashes. Of course, when programming in a high-level language, we are still using machine code; we are just not using it *directly*, because the programming language abstraction saves us from having to think about it.

However, finding good abstractions is very hard. In the field of distributed systems, although there are many good algorithms, it is much less clear how we should be packaging them into abstractions that help us keep the complexity of the system at a manageable level.

Throughout this book, we will keep our eyes open for good abstractions that allow us to extract parts of a large system into well-defined, reusable components.

Plasticity: making change easy

It's extremely unlikely that your system's requirements will remain unchanged forever. Much more likely, it is in constant flux: you learn new facts, previously unanticipated use cases emerge, business priorities change, users request new features, new platforms replace old platforms, legal or regulatory requirements change, growth of the system forces architectural changes, etc.

In terms of organizational processes, *agile* working patterns provide a framework for adapting to change. The agile community has also developed technical tools and patterns that are helpful when developing software in a frequently-changing environment, such as test-driven development (TDD) and refactoring.

Most discussions of these agile techniques focus on a fairly small, local scale (a couple of source code files within the same application). In this book, we search for ways of increasing agility on the level of a larger data system, perhaps consisting of several different applications or services with different characteristics. For example, how would you “refactor” Twitter’s architecture for assembling home timelines ([Describing load](#)) from approach 1 to approach 2?

The ease with which you can modify a data system, and adapt it to changing requirements, is closely linked to its simplicity and its abstractions: simple and easy-to-understand systems are usually easier to modify than complex ones. But since this is such an important idea, we will use a different word to refer to agility on a data system level: *plasticity*.^[20]

Summary

In this chapter, we have explored some fundamental ways of thinking about data-intensive applications. These principles will guide us through the rest of the book, when we dive into deep technical detail.

An application has to meet various requirements in order to be useful. There are *functional requirements* (what it should do, e.g. allow data to be stored, retrieved, searched and processed in various ways), and some *non-functional requirements* (general properties like security, reliability, compliance, scalability, compatibility and maintainability). In this chapter we discussed reliability, scalability and maintainability in detail.

Reliability means making systems work correctly, even when faults occur. Faults can be in hardware (typically random and uncorrelated), software (bugs are typically systematic and hard to deal with), and humans (who inevitably make mistakes from time to time). Fault tolerance techniques can hide certain types of fault from the end user.

Scalability means having strategies for keeping performance good, even when load increases. In order to discuss scalability, we first need ways of describing load and performance quantitatively. We briefly looked at Twitter's home timelines as an example of describing load, and latency percentiles as a way of measuring performance.

Maintainability has many facets, but in essence it's about making life better for the engineering and operations teams who need to work with the system. Good abstractions can help reduce complexity and make the system easier to modify and adapt for new use cases. Good operability means having good visibility into the system's health, and having effective ways of managing it.

There is unfortunately no quick answer to making applications reliable, scalable or maintainable. However, there are certain patterns and techniques which keep re-appearing in various different kinds of application. In the next few chapters we will take a look at some examples of data systems, and analyze how they work towards those goals.

Later in the book, in (to come), we will look at patterns for systems that consist of several components working together, such as the one in [Figure 1-1](#).

^[1] Michael Stonebraker and Uğur Çetintemel: "[One Size Fits All: An Idea Whose Time Has Come and Gone](#)," at *21st International Conference on Data Engineering* (ICDE), April 2005.

- [2] Walter L Heimerdinger and Charles B Weinstock: “[A Conceptual Framework for System Fault Tolerance](#),” Technical Report CMU/SEI-92-TR-033, Software Engineering Institute, Carnegie Mellon University, October 1992.
- [3] Yury Izrailevsky and Ariel Tseitlin: “[The Netflix Simian Army](#),” techblog.netflix.com, 19 July 2011.
- [4] Daniel Ford, François Labelle, Florentina I Popovici, et al.: “[Availability in Globally Distributed Storage Systems](#),” at *9th USENIX conference on Operating Systems Design and Implementation* (OSDI), October 2010.
- [5] Laurie Voss: “[AWS: The Good, the Bad and the Ugly](#),” blog.awe.sm, 18 December 2012.
- [6] Nelson Minar: “[Leap Second crashes half the internet](#),” somebits.com, 3 July 2012.
- [7] Amazon Web Services: “[Summary of the Amazon EC2 and Amazon RDS Service Disruption in the US East Region](#),” aws.amazon.com, 29 April 2011.
- [8] Jay Kreps: “[Getting Real About Distributed System Reliability](#),” blog.empathybox.com, 19 March 2012.
- [9] Nathan Marz: “[Principles of Software Engineering, Part 1](#),” nathanmarz.com, 2 April 2013.
- [10] Michael Jurewitz: “[The Human Impact of Bugs](#),” jury.me, 15 March 2013.
- [11] Raffi Krikorian: “[Timelines at Scale](#),” at *QCon San Francisco*, November 2012.
- [12] A term borrowed from electronic engineering, where it describes the number of logic gate inputs that are attached to another gate’s output. The output needs to supply enough current to drive all the attached inputs. In transaction processing systems, we use it to describe the number of requests to other services that we need to make in order to serve one incoming request.
- [13] In an ideal world, the running time of a batch job is the size of the dataset divided by throughput. In practice, the running time is often longer, due to skew (data not being spread evenly across worker processes) or waiting for the slowest task to complete.
- [14] Jeffrey Dean and Luiz André Barroso: “[The Tail at Scale](#),” *Communications of the ACM*, volume 56, number 2, pages 74–80, February 2013. [doi:10.1145/2408776.2408794](https://doi.org/10.1145/2408776.2408794)

[15] Graham Cormode, Vladislav Shkapenyuk, Divesh Srivastava, and Bojian Xu: “[Forward Decay: A Practical Time Decay Model for Streaming Systems](#),” at *25th IEEE International Conference on Data Engineering* (ICDE), pages 138–149, March 2009.

[16] Coda Hale: “Metrics,” Apache License Version 2.0. <http://metrics.codahale.com>

[17] Eric Lindvall: “Metriks Client,” MIT License. <https://github.com/eric/metriks>

[18] Frederick P Brooks: “No Silver Bullet – Essence and Accident in Software Engineering,” in *The Mythical Man-Month*, Anniversary edition, Addison-Wesley, 1995. ISBN: 9780201835953

[19] Ben Moseley and Peter Marks: “[Out of the Tar Pit](#),” at *BCS Software Practice Advancement* (SPA), 2006.

[20] A term borrowed from materials science, where it refers to the ease with which an object’s shape can be changed by pushing or pulling forces, without fracture. It is also used in neuroscience, referring to the brain’s ability to adapt to environmental changes.

Chapter 2. The Battle of the Data Models

The limits of my language mean the limits of my world.

— Ludwig Wittgenstein *Tractatus Logico-Philosophicus* (1922)

Data models are perhaps the most important part of developing software, because they have such a profound effect: not only on how the software is written, but also how we *think about the problem* that we are solving.

Most applications are built by layering one data model on top of another. For each layer, the key question is: how is it *represented* in terms of the next-lower layer? For example:

1. As an application developer, you look at the real world (in which there are people, organizations, goods, actions, money flows, sensors, etc.) and model it in terms of objects or data structures, and APIs which manipulate those data structures. Those structures are often specific to your application.
2. When you want to store those data structures, you express them in terms of a general-purpose data model, such as JSON or XML documents, tables in a relational database, or a graph model.
3. The engineers who built your database software decided on a way of representing that JSON/XML/relational/graph data in terms of bytes in memory, on disk, or on a network. The representation may allow the data to be queried, searched, manipulated and processed in various ways.
4. On yet lower levels, hardware engineers have figured out how to represent bytes in terms of electrical currents, pulses of light, magnetic fields, and more.

In a complex application there may be more intermediary levels, such as APIs built upon APIs, but the basic idea is still the same: **each layer hides the complexity of the layers below it** by providing a clean data model. These abstractions allow different groups of people—for example, the engineers at the database vendor and the application developers using their database—to work together effectively.

There are many different kinds of data model, and every data model embodies assumptions about how it is going to be used. Some kinds of usage are easy and some are not supported; some operations are fast and some perform badly; some data transformations feel natural and some are awkward.

It can take a lot of effort to master just one data model (think how many books there are on relational data modeling). Building software is hard enough, even when working with just one data model, and without worrying about its inner workings. But since the data model has such a profound effect on what the software above it can and can't do, it's important to choose one that is appropriate to the application.

In this chapter, we will look at a range of general-purpose data models for data storage and querying (point 2 in the list of layers above). In [Chapter 3](#) we will discuss how they are implemented (point 3).

Rivals of the Relational Model

The best-known data model today is probably that of SQL, based on the relational model proposed by Edgar Codd in 1970 [[21](#)]: data is organized into *relations* (in SQL: tables), where each relation is an unordered collection of *tuples* (rows).

The relational model was a theoretical proposal, and many people at the time doubted whether it could be implemented efficiently. However, by the mid-1980s, relational database management systems (RDBMS) and SQL had become the tool of choice for most people who needed to store and query data with some kind of regular structure. The dominance of relational databases has lasted around 25–30 years—an eternity in computing history.

The roots of relational databases lie in *business data processing*, which was performed on mainframe computers in the 1960s and 70s. The use cases appear mundane from today's perspective: typically *transaction processing* (entering sales or bank transactions, airline reservations, stock-keeping in warehouses) and *batch processing* (customer invoicing, payroll, reporting).

Other databases at that time forced application developers to think a lot about the internal representation of the data in the database. The goal of the relational model was to hide that implementation detail behind a cleaner interface.

Over the years, there have been many competing approaches to data storage and querying. In the 1970s and early 1980s, CODASYL (the network model) and IMS (the hierarchical model) were the main alternatives, but the relational model came to dominate them. Object databases came and went again in the late 1980s and early 1990s. XML databases appeared in the early 2000s, but have only seen niche adoption. Each competitor to the relational model generated a lot of hype in its time, but it never lasted. [[22](#)]

As computers became vastly more powerful and networked, they started being used for increasingly diverse purposes. And remarkably, relational databases turned out to generalize very well, beyond their original scope of business data processing, to a broad variety of use cases. Much of what you see on the web today is still powered by relational databases—be it online publishing, discussion, social networking, e-commerce, games, software-as-a-service productivity applications, or much more.

Now, in the 2010s, *NoSQL* is the latest attempt to overthrow the relational model’s dominance. The term *NoSQL* is unfortunate, since it doesn’t actually refer to any particular technology—it was intended simply as a catchy Twitter hashtag for a meetup on open source, distributed, non-relational databases in 2009. [\[23\]](#) Nevertheless, the term struck a nerve, and quickly spread through the web startup community and beyond. A number of interesting database systems are now associated with the #*NoSQL* hashtag.

There are several **driving forces** behind the adoption of NoSQL databases, including:

- A need for greater scalability than relational databases can easily achieve, including very large datasets or very high write throughput;
- Specialized query operations that are not well supported by the relational model;
- Frustration with the restrictiveness of relational schemas, and a desire for a more dynamic and expressive data model. [\[24\]](#)

Different applications have different requirements, and the best choice of technology for one use case may well be different from the best choice for another use case. It therefore seems likely that in the foreseeable future, relational databases will continue to be used alongside a broad variety of non-relational data stores—an idea that is sometimes called *polyglot persistence* [\[23\]](#).

The object-relational mismatch

Most application development today is done in object-oriented programming languages, which leads to a common criticism of the SQL data model: if data is stored in relational tables, an awkward translation layer is required between the objects in the application code and the database model of tables, rows and columns. The disconnect between the models is sometimes called an *impedance mismatch*[\[25\]](#).

Object-relational mapping (ORM) frameworks like ActiveRecord and Hibernate reduce the amount of boilerplate code required for this translation layer, but they can’t completely hide the differences between the two models.

For example, [Figure 2-1](#) illustrates how a résumé (a LinkedIn profile) could be expressed in a relational schema. The profile as a whole can be identified by a unique identifier, **user_id**. Fields

like `first_name` and `last_name` appear exactly once per user, so they can be modeled as columns on the `users` table.

However, most people have had more than one job in their career (`positions`), varying numbers of periods of education, and any number of pieces of contact information. There is a one-to-many relationship from the `user` to these items, which can be represented in various ways:

- In the traditional SQL model (prior to SQL:1999), the most common normalized representation is to put `positions`, `education` and `contact_info` in separate tables, with a **foreign key** reference to the `users` table, as in [Figure 2-1](#).
- Later versions of the SQL standard added support for structured datatypes and XML data, which allow **multi-valued data to be stored within a single row**, with support for querying and indexing inside those documents. These features are supported to varying degrees by Oracle, IBM DB2, MS SQL Server and PostgreSQL. [\[26\]](#), [\[27\]](#) PostgreSQL also has vendor-specific extensions for JSON, array datatypes, and more. [\[28\]](#)
- Serialize `jobs`, `education` and `contact info` into a JSON or XML document, store it on a text column in the database, and let the application interpret its structure and content. In this setup, you typically cannot use the database to query for values inside that serialized column.

For a data structure like a résumé, which is mostly a self-contained *document*, a JSON representation can be quite appropriate: see [Example 2-1](#). JSON has the appeal of being much simpler than XML. Document-oriented databases like **MongoDB** [\[29\]](#), RethinkDB [\[30\]](#), CouchDB [\[31\]](#) and Espresso [\[32\]](#) support this data model, and many developers feel that the JSON model reduces the impedance mismatch between the application code and the storage layer.

The JSON representation also has **better locality**: in the relational model of [Figure 2-1](#), if you want to fetch a profile, you need to either perform multiple queries (query each table by `user_id`) or perform a messy multi-way join between the `users` table and its subordinate tables. In the JSON representation, all the relevant information is in once place, and one simple query is sufficient.

The one-to-many relationships from the user profile to its positions, educational history and contact information imply a tree structure in the data, and the JSON representation makes this tree structure explicit (see [Figure 2-2](#)).

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Bill Gates
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Summary
Co-chair of the Bill & Melinda Gates Foundation. Chairman, Microsoft Corporation. Voracious reader. Avid traveler. Active blogger.

Experience
Co-chair • Bill & Melinda Gates Foundation
2000 – Present
Co-founder, Chairman • Microsoft
1975 – Present

Education
Harvard University
1973 – 1975
Lakeside School, Seattle

Contact Info
Blog: thegatesnotes.com
Twitter: @BillGates

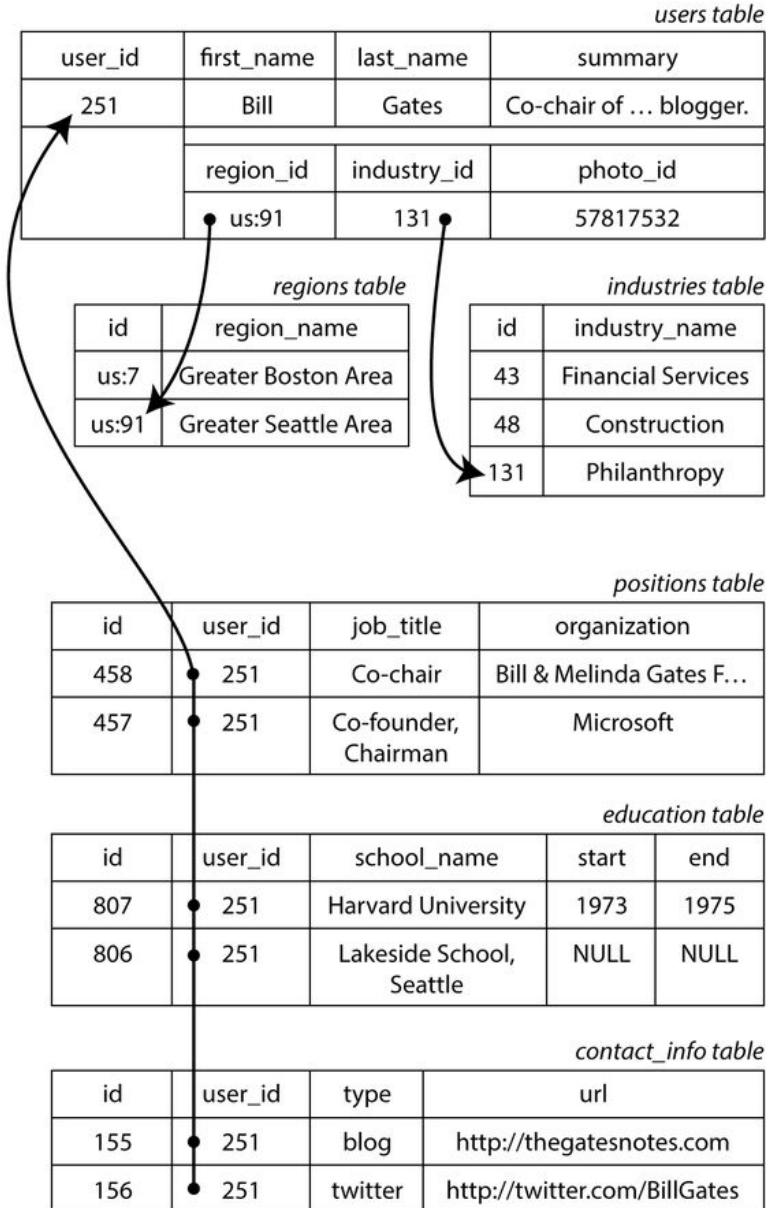


Figure 2-1. Representing a LinkedIn profile using a relational schema.

Example 2-1. Representing a LinkedIn profile as a JSON document.

```
{
  "user_id": 251,
  "first_name": "Bill",
  "last_name": "Gates",
  "summary": "Co-chair of the Bill & Melinda Gates... Active blogger.",
  "region_id": "us:91",
  "industry_id": 131,
  "photo_url": "/p/7/ooo/253/05b/308dd6e.jpg",
  "positions": [
    {"job_title": "Co-chair", "organization": "Bill & Melinda Gates Foundation"},
    {"job_title": "Co-founder, Chairman", "organization": "Microsoft"}
  ],
}
```

```

"education": [
    {"school_name": "Harvard University",      "start": 1973, "end": 1975},
    {"school_name": "Lakeside School, Seattle", "start": null, "end": null}
],
"contact_info": {
    "blog":     "http://thegatesnotes.com",
    "twitter": "http://twitter.com/BillGates"
}
}

```

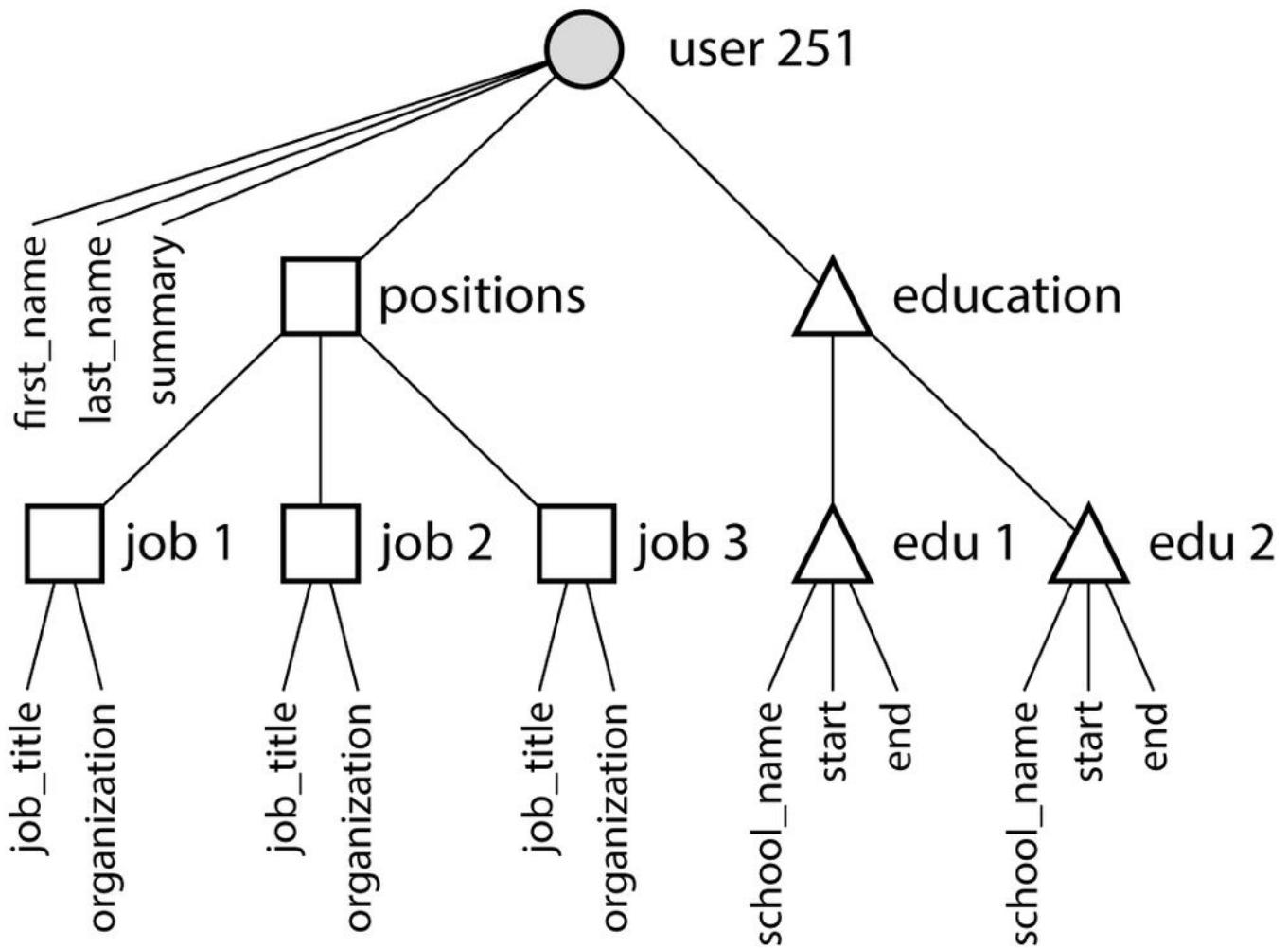


Figure 2-2. One-to-many relationships forming a tree structure.

Many-to-one and many-to-many relationships

In [Example 2-1](#) above, `region_id` and `industry_id` are given as IDs, not as plain-text strings "Greater Seattle Area" and "Philanthropy". Why?

If the user interface has free-text fields for entering the region and the industry, it makes sense to store them as plain strings. But there are advantages to having standardized lists of

geographic regions and industries, and letting users choose from a drop-down list or autocomplete:

- Consistent style and spelling across profiles,
- Avoiding ambiguity, e.g. if there are several cities with the same name,
- The name is stored only in one place, so it is easy to update across the board if it ever needs to be changed (for example, change of a city name due to political events),
- When the site is translated into other languages, the standardized lists can be localized, and so the region and industry can be displayed in the viewer's language,
- Better search—for example, a search for philanthropists in the state of Washington can match this profile, because the list of regions can include the fact that Seattle is in Washington.

A database in which entities like region and industry are referred to by ID is called *normalized*,^[33] whereas a database that duplicates the names and properties of entities on each document is *denormalized*. Normalization is a popular topic of debate among database administrators.

Note

Duplication of data is appropriate in some situations and inappropriate in others, and it generally needs to be handled carefully. We discuss caching, denormalization and derived data in (to come) of this book.

Unfortunately, normalizing this data requires many-to-one relationships (many people live in one particular region), which don't fit nicely into the document model. In relational databases, it's normal to refer to rows in other tables by ID, because joins are easy. In document databases, joins are not needed for one-to-many tree structures, and support for joins is often weak.^[34]

If the database itself does not support joins, you have to emulate a join in application code by making multiple queries to the database. (In this case, the lists of regions and industries are probably small and slow-changing enough that the application can simply keep them in memory. But nevertheless, the work of making the join is shifted from the database to the application code.)

Moreover, even if the initial version of an application fits well in a join-free document model, data has a tendency of becoming more interconnected as features are added to applications. For example, consider some changes we could make to the résumé example:

Organizations and schools as entities

In the description above, organization (the company where the user worked) and school_name (where they studied) are just strings. Perhaps they should be references to entities instead? Then each

organization, school or university could have its own web page (with logo, news feed, etc); each résumé can link to the organizations and schools that it mentions, and include their logos and other information (see [Figure 2-3](#) for example).

Recommendations

Say you want to add a new feature: one user can write a recommendation for another user. The recommendation is shown on the résumé of the user who was recommended, together with the name and photo of the user making the recommendation. If the recommender updates their photo, any recommendations they have written need to reflect the new photo. Therefore, the recommendation should have a reference to the author's profile.

[Figure 2-4](#) illustrates how these new features require many-to-many relationships. The data within each dotted rectangle can be grouped into one document, but the references to organizations, schools and other users need to be represented as references, and require joins when queried.

The screenshot shows a resume section for 'Experience'. It includes a 'Co-chair' position at the Bill & Melinda Gates Foundation from 2000 to Present (13 years). Below this is a 'Co-founder Chairman' position at Microsoft from 1975 to Present. A callout box provides more details about Microsoft, including its mission statement, size, website, HQ, industry, and links to follow the company or view careers. The Microsoft logo is also displayed.

Experience

Co-chair
Bill & Melinda Gates Foundation
2000 – Present (13 years)

Co-founder Chairman
Microsoft
1975 – Pres

Ed
Harvard U
1973 – 1975

Microsoft

Come as you are. Do what you love. At Microsoft we help people and businesses throughout the world realize their full potential. We make this simple mission come to life every day through our ... [More »](#)

Co. Size: 10,001+ employees
Website: <http://www.microsoft.com/>
HQ: Greater Seattle Area
Industry: Computer Software

[Follow company](#) | [Careers](#)

Figure 2-3. The company name is not just a string, but a link to a company entity.

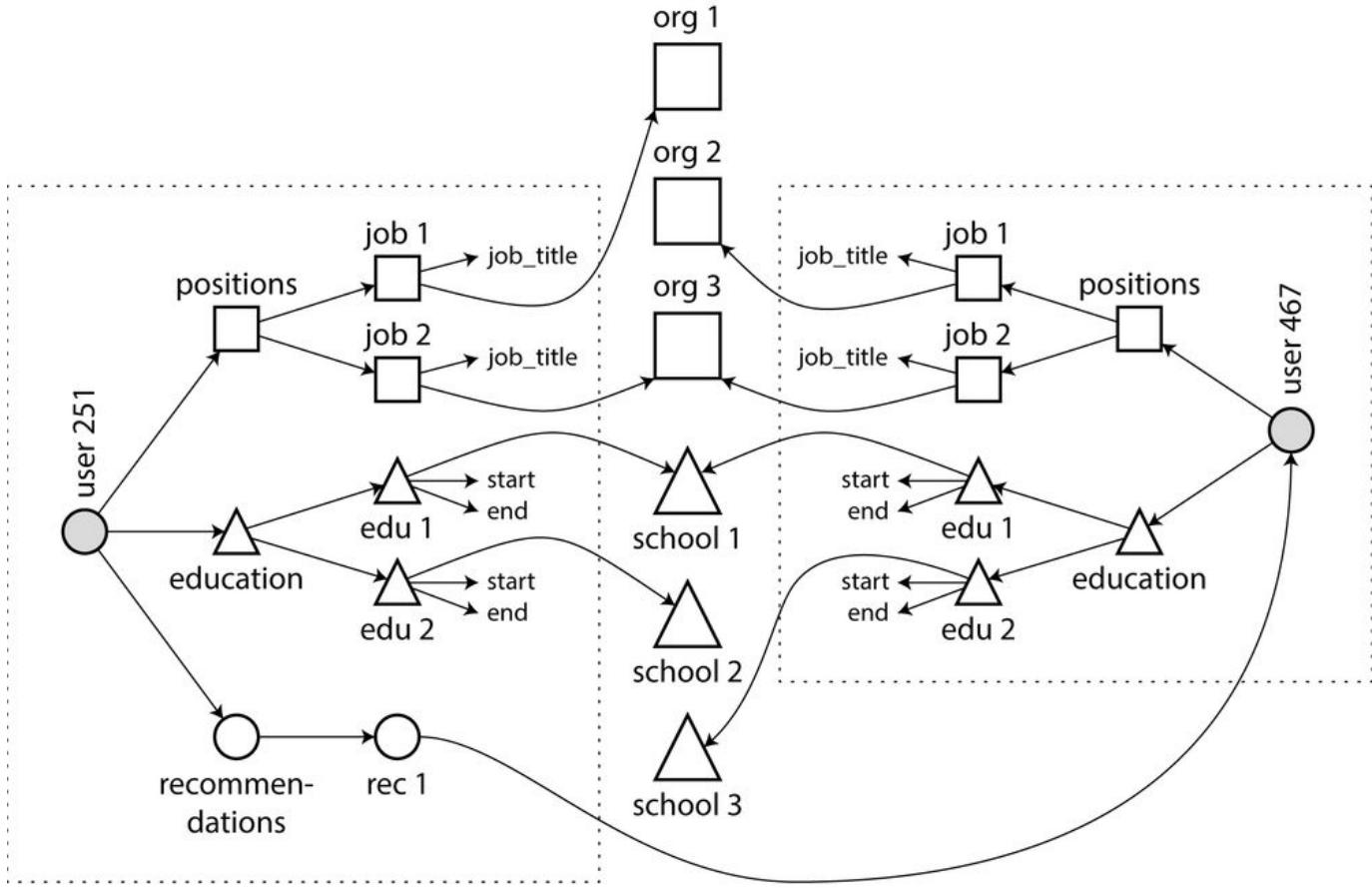


Figure 2-4. Extending résumés with many-to-many relationships.

Historical interlude

While many-to-many relationships and joins are routinely used in relational databases without thinking twice, document databases and NoSQL reopened the debate on how best to represent such relationships in a database. This debate is much older than NoSQL—in fact, it goes back to the very earliest computerized database systems.

The most popular database for business data processing in the 1970s was IBM's *Information Management System* (IMS), a database system originally developed for stock-keeping in the Apollo space program, and first commercially released in 1968. [35] It is still in use and maintained today, running on OS/390 on IBM mainframes. [36]

The design of IMS used a fairly simple data model called the *hierarchical model*, which has some remarkable similarities to the JSON model used by document databases. [22] It represented all data as a tree of records nested within records, much like the JSON structure of [Figure 2-2](#) above.

Like document databases, IMS worked well for one-to-many relationships, but it made many-to-many relationships difficult and it didn't support joins. Developers had to decide whether to duplicate (denormalize) data, or to manually resolve references from one record to

another. These problems of the 1960s were very much like the problems that developers are running into with document databases today. [37]

Various solutions were proposed to solve the limitations of the hierarchical model. The two most prominent were the *relational model* (which became SQL, and took over the world), and the *network model* (which initially had a large following but eventually faded into obscurity). The "great debate" between these two camps lasted for much of the 1970s. [22]

Since the problem that the two models were solving is still so relevant today, it's worth briefly revisiting this debate in today's light.

The network model

The network model was standardized by a committee called *Conference on Data Systems Languages* (CODASYL), and implemented by several different database vendors, so it is also known as the *CODASYL model*. [38]

The CODASYL model is a generalization of the hierarchical model. In the tree structure of the hierarchical model, every record has exactly one parent; in the network model, a record can have multiple parents. For example, there could be one record for the "Greater Seattle Area" region, and every user who lives in that region could be its parent. This allows many-to-one and many-to-many relationships to be modeled.

The links between records in the network model are not foreign keys, but more like pointers in a programming language (while still being stored on disk). The only way of accessing a record was to follow a path from a root record along these chains of links. This was called an *access path*.

In the simplest case, an access path could be like the traversal of a linked list: start at the head of the list, and look at one record at a time, until you find the one you want. But in a world of many-to-many relationships, several different paths can lead to the same record, and a programmer working with the network model had to keep track of these different access paths in their head.

A query in CODASYL was performed by moving a cursor through the database by iterating over lists of records and following access paths. If a record had multiple parents, the application code had to keep track of all the various parent relationships. Even CODASYL committee members admitted that this was like navigating around an n -dimensional data space. [39]

The problem with access paths is that they make the code for querying and updating the database complicated and inflexible. With both the hierarchical and the network model, if you

didn't have a path to the data you wanted, you were in a difficult situation. You could change the access paths, but then you had to go through a lot of hand-written database query code and rewrite it to handle the new access paths. It was difficult to make changes to an application's data model.

The relational model

What the relational model did, by contrast, was to lay out all the data in the open: a relation (table) is simply a collection of tuples (rows), and that's it. There are no labyrinthine nested structures, no complicated access paths to follow if you want to look at the data. You can read any or all of the rows in a table, selecting those that match an arbitrary condition. You can read a particular row by designating some columns as a key, and matching on those. You can insert a new row into any table, without worrying about foreign key relationships to and from other tables.^[40]

In a relational database, the query optimizer automatically decides which parts of the query to execute in which order, and which indexes to use. Those choices are effectively the “access path”, but the big difference is that they are made automatically by the query optimizer, not by the application developer, so we rarely need to think about them.

If you want to query your data in new ways, you can just declare a new index, and queries will automatically use whichever indexes are most appropriate. You don't need to change your queries to take advantage of a new index. (See also [Query Languages for Data](#).) The relational model thus made it much easier to add new features to applications.

Query optimizers for relational databases are complicated beasts, and they have consumed many years of research and development effort. ^[41] But a key insight of the relational model was this: you only need to build a query optimizer once, and then all applications that use the database can benefit from it. If you don't have a query optimizer, it's easier to hand-code the access paths for a particular query than to write a general-purpose optimizer—but the general-purpose solution wins in the long run.

Comparison to document databases

Document databases reverted back to the hierarchical model in one aspect: storing nested records (one-to-many relationships, like positions, education and contact_info in [Figure 2-1](#)) within their parent record rather than in a separate table.

However, when it comes to representing many-to-one and many-to-many relationships, relational and document databases are not fundamentally different: in both cases, the related item is referenced by a unique identifier, which is called a *foreign key* in the relational model, and a *document reference* in the document model. [29] That identifier is resolved at read time, by using a join or follow-up queries. To date, document databases have not followed the path of CODASYL.

Relational vs. document databases today

There are many differences to consider when comparing relational databases to document databases, including their fault-tolerance properties (see [Chapter 4](#)) and handling of concurrency (see [Link to Come]). In this chapter, we will concentrate only on the differences of data model.

The main arguments in favor of the document data model are: simpler application code, schema flexibility, and better performance due to locality.

Documents for simplifying application code

If the data in your application has a document-like structure (i.e. a tree of one-to-many relationships, where typically the entire tree is loaded at once), then it's probably a good idea to use a document model. The relational technique of *shredding*—splitting a document-like structure into multiple tables (like positions, education and contact_info in [Figure 2-1](#))—can lead to cumbersome schemas and unnecessarily complicated application code.

The document model has minor limitations—for example, you cannot refer directly to a nested item within a document, but instead you need to say something like “*the second item in the list of positions for user 251*” (much like an access path in the hierarchical model). However, as long as documents are not too deeply nested, that is not usually a problem.

The poor support for joins in document databases may or may not be a problem, depending on the application. For example, many-to-many relationships may never be needed in an analytics application that uses a document database to record which events occurred at which time. [42]

If your application does use many-to-many relationships, the document model becomes less appealing. It's possible to reduce the need for joins by denormalizing, but then the application code needs to do additional work to keep the denormalized data consistent. Joins can be emulated in application code by making multiple requests to the database, but that also moves complexity into the application. In this case, the problems of managing denormalization and joins may be greater than the problem of object-relational mismatch.

Documents for schema flexibility

Most document databases, and the JSON support in relational databases, do not enforce any schema on the data in documents. XML support in relational databases usually comes with optional schema validation. No schema means that arbitrary keys and values can be added to a document, and when reading, clients have no guarantees as to what fields the documents may contain.

The question of whether databases should have schemas is a contentious issue, very much like the debate between advocates of static and dynamic type-checking in programming languages. [\[43\]](#) Many developers have strong opinions and good arguments for their respective viewpoints, and in general there's no right or wrong answer.

The difference in philosophy is particularly noticeable in situations when an application wants to change the format of its data. For example, say you are currently storing each user's full name in one field, and you want to change it to store first name and last name separately. [\[44\]](#) In a schemaless database, you would just start writing new documents with the new fields, and have code in the application which handles the case when old documents are read, for example:

```
if (user && user.name && !user.first_name) {  
    // Documents written before Dec 8, 2013 don't have first_name  
    user.first_name = user.name.split(" ")[0];  
}
```

On the other hand, in a ‘statically typed’ database schema, you would typically perform a migration along the lines of:

```
ALTER TABLE users ADD COLUMN first_name text DEFAULT NULL;  
UPDATE users SET first_name = split_part(name, ' ', 1);      -- PostgreSQL  
UPDATE users SET first_name = substring_index(name, ' ', 1);  -- MySQL
```

Schema changes have a bad reputation of being slow and requiring downtime. This reputation is not entirely deserved: most relational database systems execute the ALTER TABLE statement in a few milliseconds—with the exception of MySQL, which copies the entire table on ALTER TABLE, which can mean minutes or even hours of downtime when altering a large table. Various tools exist to work around this limitation of MySQL. [\[45\]](#), [\[46\]](#)

Running the UPDATE statement on a large table is likely to be slow on any database, since every row needs to be re-written. If that is not acceptable, the application can leave first_name set to its default of NULL, and fill it in at read time, like it would with a document database.

The schemaless approach is advantageous if the data is heterogeneous, i.e. the items in the collection don't all have the same structure for some reason, for example because:

- there are many different types of objects, and it is not practical to put each type of object in its own table, or
- the structure of the data is determined by external systems, over which you have no control, and which may change at any time.

In situations like these, a schema may hurt more than it helps, and schemaless documents can be a much more natural data model.

Documents for query locality

A document is usually stored as a single continuous string, encoded as JSON, XML or a binary variant thereof (such as MongoDB's BSON). If your application often needs to access the entire document (for example, to render it on a web page), there is a performance advantage to this *storage locality*. If data is split across multiple tables, like in [Figure 2-1](#), multiple index lookups are required to retrieve it all, which may require more disk seeks and take more time.

The locality advantage only applies if you need large parts of the document at the same time. The database typically needs to load the entire document, even if you access only a small portion of it, which can be wasteful on large documents. On updates to a document, the entire document usually needs to be re-written—only modifications that don't change the encoded size of a document can easily be performed in-place. [\[\[42\]\]](#) For these reasons, it is generally recommended that you keep documents fairly small.

It's worth pointing out that the idea of grouping related data together for locality is not limited to the document model. For example, Google's Spanner database offers the same locality properties in a relational data model, by allowing the schema to declare that a table's rows should be interleaved (nested) within a parent table. [\[\[47\]\]](#) Oracle allows the same, using a feature called *multi-table index cluster tables*. [\[\[48\]\]](#) The *column-family* concept in the Bigtable data model (used in Cassandra and HBase) has a similar purpose in managing locality. [\[\[49\]\]](#)

We will also see more on locality in [Chapter 3](#).

Convergence of document and relational databases

Most relational database systems (other than MySQL) have supported XML since the mid-2000s. This includes functions to make local modifications to XML documents, and the

ability to index and query inside XML documents, which allows applications to use data models very similar to what they would do when using a document database.

PostgreSQL since version 9.3 [[28](#)] and IBM DB2 since version 10.5 [[50](#)] also have a similar level of support for JSON documents. Given the popularity of JSON for web APIs, it is likely that other relational databases will follow their footsteps and add JSON support.

On the document database side, RethinkDB supports relational-like joins in its query language, and some MongoDB drivers automatically resolve database references (effectively performing a client-side join).

It seems that relational and document databases are becoming more similar over time, and that is a good thing: the data models complement each other.^[51] If a database is able to handle document-like data and also perform relational queries on it, applications can use the combination of features that best fits their needs.

A hybrid of the relational and document models is a good route for databases to take in future.

Query Languages for Data

When the relational model was introduced, it included a new way of querying data: it used a *declarative* query language, whereas IMS and CODASYL queried the database using *imperative* code. What does that mean?

Many commonly-used programming languages are imperative. For example, if you have a list of animal species, you might write something like this to return only the sharks in the list:

```
function getSharks() {  
    var sharks = [];  
    for (var i = 0; i < animals.length; i++) {  
        if (animals[i].family === "Lamniformes") {  
            sharks.push(animals[i]);  
        }  
    }  
    return sharks;  
}
```

In the relational algebra, you would instead write:

```
sharks = σfamily = "Lamniformes" (animals)
```

where σ (the Greek letter sigma) is the selection operator, returning only those animals that match the condition *family* = “*Lamniformes*”.

When SQL was defined, it followed the structure of the relational algebra fairly closely:

```
SELECT * FROM animals WHERE family = 'Lamniformes';
```

An imperative language tells the computer to perform certain operations in a certain order. You can imagine stepping through the code, line by line, evaluating conditions, updating variables, and deciding whether to go around the loop one more time.

Declarative querying means that you just specify the pattern of the data you want—what conditions the results must meet, and how you want it to be transformed (e.g. sorted, grouped and aggregated), but not *how* to achieve that goal. It is up to the database system’s query optimizer to decide which indexes and which join methods to use, and in which order to execute various parts of the query.

A declarative query language is attractive because it is typically more concise and easier to work with than an imperative API. But more importantly, it also hides implementation details of the database engine, which makes it possible for the database system to introduce performance improvements without requiring any changes to queries.

For example, in the imperative code above, the list of animals appears in a particular order. If the database wants to reclaim unused disk space behind the scenes, it might need to move records around, changing the order in which the animals appear. Can the database do that safely, without breaking queries?

The SQL example doesn’t guarantee any particular ordering, and so it doesn’t mind if the order changes. But if the query is written as imperative code, the database can never be sure whether the code is relying on the ordering or not. The fact that SQL is more limited in functionality gives the database much more room for automatic optimizations.

Finally, declarative languages often lend themselves to parallel execution. Today, CPUs are getting faster by adding more cores, not by running at significantly higher clock speeds than before. Imperative code is very hard to parallelize across multiple cores and multiple machines, but declarative languages have a chance of getting faster. [[\[52\]](#)]

Declarative queries on the web

The advantages of declarative query languages are not limited to just databases. To illustrate the point, let's compare declarative and imperative approaches in a completely different environment: a web browser.

Say you have a website about animals in the ocean. The user is currently viewing the page on sharks, so you mark the navigation item *sharks* as currently selected, like this:

```
<ul>
  <li class="selected"> ❶<p>Sharks</p> ❷<ul>
    <li>Great White Shark</li>
    <li>Tiger Shark</li>
    <li>Hammerhead Shark</li>
  </ul>
</li>
<li>
  <p>Whales</p>
  <ul>
    <li>Blue Whale</li>
    <li>Humpback Whale</li>
    <li>Fin Whale</li>
  </ul>
</li>
</ul>
```

❶

The selected item is marked with the CSS class "selected".

❷

<p>Sharks</p> is the title of the currently selected page.

Now say you want the title of the currently selected page to have a blue background, so that it is visually highlighted. This is easy, using CSS:

```
li.selected > p {
  background-color: blue;
}
```

Here the CSS selector `li.selected > p` declares the pattern of elements to which we want to apply the blue style: namely, all `<p>` elements whose direct parent is a `` element with a CSS class of `selected`. The element `<p>Sharks</p>` in the example matches this pattern, but `<p>Whales</p>` does not match, because its `` parent lacks `class="selected"`.

If you were using XSL instead of CSS, you could do something similar:

```
<xsl:template match="li[@class='selected']/p">
  <fo:block background-color="blue">
    <xsl:apply-templates/>
  </fo:block>
</xsl:template>
```

Here the XPath expression `li[@class='selected']/p` is equivalent to the CSS selector `li.selected > p` above. What CSS and XSL have in common is that they are both *declarative* languages for specifying the styling of a document.

Imagine what life would be like if you had to use an imperative approach. In JavaScript, using the core Document Object Model (DOM) API, the result might look something like this:

```
var liElements = document.getElementsByTagName("li");
for (var i = 0; i < liElements.length; i++) {
  if (liElements[i].className === "selected") {
    var children = liElements[i].childNodes;
    for (var j = 0; j < children.length; j++) {
      var child = children[j];
      if (child.nodeType === Node.ELEMENT_NODE && child.tagName === "P") {
        child.setAttribute("style", "background-color: blue");
      }
    }
  }
}
```

This code imperatively sets the element `<p>Sharks</p>` to have a blue background, but the code is awful. Not only is it much longer and harder to understand than the CSS and XSL equivalents, but it also has some serious problems:

- If the `selected` class is removed (e.g. because the user clicked on a different page), the blue color won't be removed, even if the code is re-run—and so the item will remain highlighted until the page is

reloaded. With CSS, the browser automatically detects when the `li.selected > p` rule no longer applies, and removes the blue background as soon as the selected class is removed.

- If you want to take advantage of a new API, such as `document.getElementsByClassName("selected")` or even `document.evaluate()`—which may improve performance—you have to rewrite the code. On the other hand, browser vendors can improve the performance of CSS and XPath without breaking compatibility.

In a web browser, declarative CSS styling is much better than manipulating styles imperatively in JavaScript. Similarly, in databases, declarative query languages like SQL turned out to be much better than imperative query APIs.^[53]

MapReduce querying

MapReduce is a programming model for processing large amounts of data in bulk across many machines, popularized by Google. ^[54] A limited form of MapReduce is supported by some NoSQL data stores, including MongoDB and CouchDB, as a mechanism for performing read-only queries across many documents.

MapReduce in general is described in more detail in the chapter on batch processing (TODO forward reference). For now, we'll just briefly discuss MongoDB's use of the model.

MapReduce is neither a declarative query language, nor a fully imperative query API, but somewhere in between: the logic of the query is expressed with snippets of code, which are called repeatedly by the processing framework. It is based on the *map* (also known as *collect*) and *reduce* (also known as *fold* or *inject*) functions that exist in many functional programming languages.

The MapReduce model is best explained by example. Imagine you are a marine biologist, and you add an observation record to your database every time you see animals in the ocean. Now you want to generate a report saying how many sharks have been sighted per month.

In PostgreSQL you might express that query like this:

```
SELECT date_trunc('month', observation_timestamp) AS observation_month,  
①sum(num_animals) AS total_animals  
FROM observations  
WHERE family = 'Lamniformes'  
GROUP BY observation_month;
```

①

The `date_trunc('month', timestamp)` function takes a timestamp and rounds it down to the nearest start of calendar month.

This query first filters the observations to only show species in the *Lamniformes* (mackerel sharks) family, then groups the observations by the calendar month in which they occurred, and finally adds up the number of animals seen in all observations in that month.

The same can be expressed with MongoDB's MapReduce feature as follows:

```
db.observations.mapReduce(  
    function map() { ❶var year = this.observationTimestamp.getFullYear();  
        var month = this.observationTimestamp.getMonth() + 1;  
        emit(year + "-" + month, this.numAnimals); ❷},  
    function reduce(key, values) { ❸return Array.sum(values); ❹},  
    {  
        query: { family: "Lamniformes" }, ❺out: "monthlySharkReport" ❻}  
)  
❺
```

The filter to consider only *Lamniformes* species can be specified declaratively (this is a MongoDB-specific extension to MapReduce).

❶

The JavaScript function `map` is called once for every document that matches `query`, with `this` set to the document object.

❷

The `map` function emits a key (a string consisting of year and month, such as "2013-12" or "2014-1") and a value (the number of animals in that observation).

❸

The key-value pairs emitted by `map` are grouped by key. For all key-value pairs with the same key (i.e. the same month and year), the `reduce` function is called once.

❹

The `reduce` function adds up the number of animals from all observations in a particular month.

6

The final output is written to the collection monthlySharkReport.

For example, say the observations collection contains these two documents:

```
{  
  observationTimestamp: Date.parse("Mon, 25 Dec 1995 12:34:56 GMT"),  
  family:      "Lamniformes",  
  species:     "Carcharodon carcharias",  
  numAnimals: 3  
}  
  
{  
  observationTimestamp: Date.parse("Tue, 12 Dec 1995 16:17:18 GMT"),  
  family:      "Lamniformes",  
  species:     "Carcharias taurus",  
  numAnimals: 4  
}
```

The map function would be called once for each document, resulting in emit("1995-12", 3) and emit("1995-12", 4). Subsequently, the reduce function would be called with reduce("1995-12", [3, 4]), returning 7.

The map and reduce function are somewhat restricted in what they are allowed to do. They must be *pure* functions, which means: they only use the data that is passed to them as input, they cannot perform additional database queries and they must not have any side-effects. They are nevertheless powerful: they can parse strings, call library functions, perform calculations and more.

Being able to use JavaScript code in the middle of a query is a great feature for advanced queries, and it's not limited to MapReduce—SQL databases can be extended with JavaScript functions too. [[55](#)] This means that MongoDB's MapReduce and SQL are roughly equivalent in terms of the kinds of queries you can express.

The difference is that with MapReduce, you have to write two carefully coordinated JavaScript functions, even for simple queries. This makes it harder to use than SQL, without significant advantages. So why was MapReduce chosen in the first place? Probably because it is easier to implement than a declarative query language, and perhaps because the term *MapReduce* sounds like high scalability, due to its association with Google.

The MongoDB team realized this too, and added a declarative query language called *aggregation pipeline* to MongoDB 2.2. [29] The kinds of queries you can write with it are very similar to SQL. Because it is declarative, it is able to perform automatic optimizations that are not possible with MapReduce. The same shark-counting query looks like this:

```
db.observations.aggregate([
  { $match: { family: "Lamniformes" } },
  { $group: {
    _id: {
      year: { $year: "$observationTimestamp" },
      month: { $month: "$observationTimestamp" }
    },
    totalAnimals: { $sum: "$numAnimals" }
  } }
]);
```

SQL is often criticized for its cumbersome syntax, but it's debatable whether this is any better.

Graph-like Data Models

We saw earlier that many-to-many relationships are an important distinguishing feature between different data models. If your application has mostly one-to-many relationships (tree-structured data) or no relationships between records, the document model is appropriate.

But what if many-to-many relationships are very common in your data? The relational model can handle simple cases of many-to-many relationships, but as the connections within your data become more complex, it becomes more natural to start modeling your data as a graph ([Figure 2-5](#)).

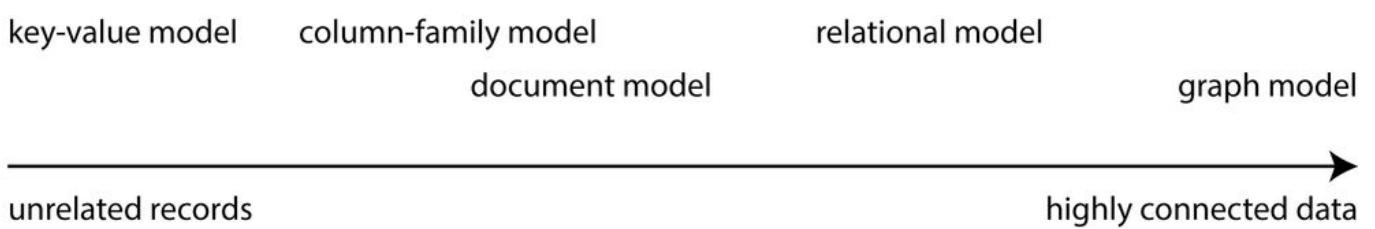


Figure 2-5. Classifying data models by connectedness between items.

A graph consists of two kinds of objects: *vertices* (also known as *nodes* or *entities*) and *edges* (also known as *relationships*). Many kinds of data can be modeled as a graph. Typical examples include:

Social graphs

Vertices are people, edges indicate which people know each other.

The web graph

Vertices are web pages, edges indicate HTML links to other pages.

Road or rail networks

Vertices are junctions, and edges represent the roads or railway lines between them.

Well-known algorithms can operate on these graphs: for example, the shortest path in a road network is useful for routing, and PageRank on the web graph can be used to determine the popularity of a web page, and thus its ranking in search results.

In the examples above, all the vertices in a graph represent the same kind of thing (people, web pages or road junctions, respectively). However, graphs are not limited to such *homogeneous* data: an equally powerful use of graphs is to provide a consistent way of storing completely different types of object in a single data store. For example, Facebook maintains a single graph with many different types of vertex and edge: vertices represent people, locations, events, checkins and comments made by users; edges indicate which people are friends with each other, which checkin happened in which location, who commented on which post, who attended which event, etc. [56]

In this section we will use the example shown in [Figure 2-6](#). It could be taken from a social network or a genealogical database: it shows two people, Lucy from Idaho and Alain from Beaune, France. They are married and living in London.

There are several different, but related, ways of structuring and querying data in graphs. In this section we will discuss the property graph model (implemented by Neo4j, Titan, InfiniteGraph) and the triple-store model (implemented by Datomic, AllegroGraph and others). We will look at three declarative query languages for graphs: Cypher, SPARQL, and Datalog. Imperative graph query languages such as Gremlin [57] are beyond the scope of this discussion, and graph processing frameworks like Pregel are covered in the chapter on batch processing (TODO forward reference).

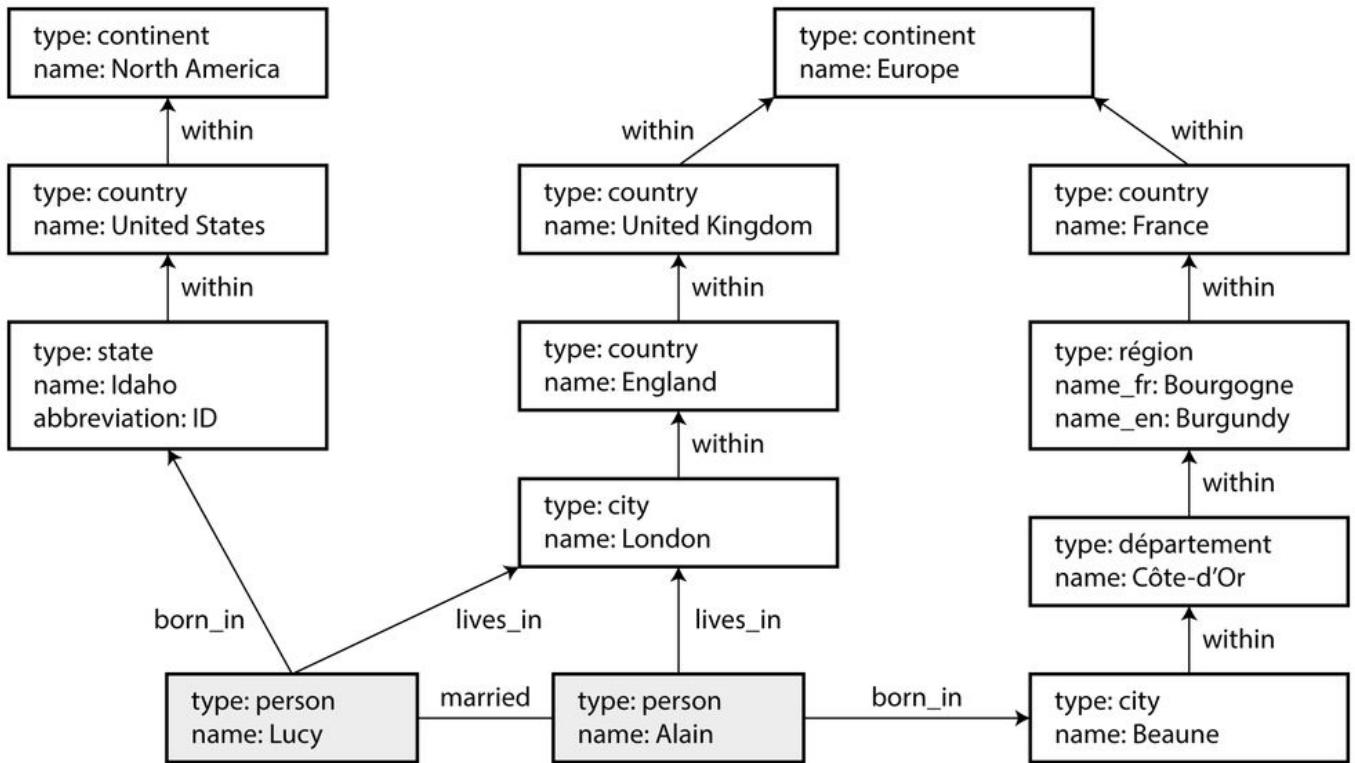


Figure 2-6. Example of graph-structured data (boxes represent vertices, arrows represent edges).

Property graphs

In the property graph model, each vertex consists of:

- a unique identifier,
- a set of outgoing edges,
- a set of incoming edges, and
- a collection of properties (key-value pairs).

Each edge consists of:

- a unique identifier,
- the vertex at which the edge starts (the *tail vertex*),
- the vertex at which the edge ends (the *head vertex*),
- a label to describe the type of relationship between the two vertices, and
- a collection of properties (key-value pairs).

You can think of a graph store as consisting of two relational tables, one for vertices and one for edges, as shown in [Example 2-2](#) (this schema uses the PostgreSQL json datatype to store the properties of each vertex or edge). The head and tail vertex are stored on each edge; if you want

the set of incoming or outgoing edges for a vertex, you can query the edges table by head_vertex or tail_vertex respectively.

Example 2-2. Representing a property graph using a relational schema.

```
CREATE TABLE vertices (
    vertex_id    integer PRIMARY KEY,
    properties   json
);
```

```
CREATE TABLE edges (
    edge_id      integer PRIMARY KEY,
    tail_vertex integer REFERENCES vertices (vertex_id),
    head_vertex integer REFERENCES vertices (vertex_id),
    type        text,
    properties   json
);
```

```
CREATE INDEX edges_tails ON edges (tail_vertex);
```

```
CREATE INDEX edges_heads ON edges (head_vertex);
```

Some important aspects of this model are:

1. Any vertex can have an edge connecting it with any other vertex. There is no schema that restricts which kinds of things can or cannot be associated.
2. Given any vertex, you can efficiently find both its incoming and its outgoing edges, and thus *traverse* the graph—follow a path through a chain of vertices—both forwards and backwards. (That’s why [Example 2-2](#) has indexes on both the tail_vertex and the head_vertex columns.)
3. By using different labels for different kinds of relationship, you can store several different kinds of information in a single graph, while still maintaining a clean data model.

Those features give graphs a great deal of flexibility for data modeling, as illustrated in [Figure 2-6](#). The figure shows a few things that would be difficult to express in a traditional relational schema, such as different kinds of regional structures in different countries (France has *départements* and *régions* whereas the US has *counties* and *states*), quirks of history such as a country within a country (ignoring for now the intricacies of sovereign states and nations), and varying granularity of data (Lucy’s current residence is specified as a city, whereas her place of birth is specified only at the level of a state).

You could imagine extending the graph to also include many other facts about Lucy and Alain, or other people. For instance, you could use it to indicate any food allergies they have (by

introducing a vertex for each allergen, and an edge between a person and an allergen to indicate an allergy), and link the allergens with a set of vertices that show which foods contain which substances. Then you can write a query to find out what is safe for each person to eat. Graphs are good for *plasticity*: as you add features to your application, a graph can easily be extended to accommodate changes in your application's data structures.

The Cypher query language

Cypher is a declarative query language for property graphs, created for the Neo4j graph database. [58] (It is named after a character in the movie *The Matrix*, and is not related to ciphers in cryptography. [59])

[Example 2-3](#) shows the Cypher query to insert the left-hand portion of [Figure 2-6](#) into a graph database. The rest of the graph can be added similarly, and is omitted for readability. Each vertex is given a symbolic name like USA or Idaho, and other parts of the query can use those names to create edges between the vertices, using an arrow notation: (Idaho) -[:WITHIN]-> (USA) creates an edge of type WITHIN, with Idaho as tail node and USA as head node.

Example 2-3. A subset of the data in [Figure 2-6](#), represented as a Cypher query.

CREATE

```
(NAmerica:Location {name:'North America', type:'continent'}),  
(USA:Location      {name:'United States', type:'country'  }),  
(Idaho:Location    {name:'Idaho',          type:'state'    }),  
(Lucy:Person        {name:'Lucy' }),  
(Idaho) -[:WITHIN]-> (USA)  -[:WITHIN]-> (NAmerica),  
(Lucy)  -[:BORN_IN]-> (Idaho)
```

When all the vertices and edges of [Figure 2-6](#) are added to the database, we can start asking interesting questions. For example, *find the names of all the people who emigrated from the United States to Europe*. To be precise: find all the vertices that have a BORN_IN edge to a location within the US, and also a LIVING_IN edge to a location within Europe, and return the name property of those vertices.

[Example 2-4](#) shows how to express that query in Cypher. The same arrow notation is used in a MATCH clause to find patterns in the graph: (person) -[:BORN_IN]-> () matches any two vertices that are related by an edge of type BORN_IN. The tail vertex of that edge is bound to the variable person, and the head vertex is left unnamed.

Example 2-4. Cypher query to find people who emigrated from the US to Europe.

MATCH

```
(person) -[:BORN_IN]-> () -[:WITHIN*o..]-> (us:Location {name:'United States'}),
(person) -[:LIVES_IN]-> () -[:WITHIN*o..]-> (eu:Location {name:'Europe'})
RETURN person.name
```

The query can be read as follows: “Find any vertex (call it *person*) that meets *both* of the following conditions:

1. *person* has an outgoing BORN_IN edge to some vertex. From that vertex, you can follow a chain of outgoing WITHIN edges until eventually you reach a vertex of type Location, whose name property is equal to “United States”.
2. That same *person* vertex also has an outgoing LIVES_IN edge. Following that edge, and then a chain of outgoing WITHIN edges, you eventually reach a vertex of type Location, whose name property is equal to “Europe”.

For each such *person* vertex, return the *name* property.”

There are several possible ways of executing the query. The description above suggests that you start by scanning all the people in the database, examine each person’s birthplace and residence, and return only those people who meet the criteria.

But equivalently, you could start with the two Location vertices and work backwards. If there is an index on the name property, you can probably efficiently find the two vertices representing the US and Europe. Then you can proceed to find all locations (states, regions, cities, etc.) in the US and Europe respectively by following all incoming WITHIN edges. Finally, you can look for people who can be found through an incoming BORN_IN or LIVES_IN edge on one of the locations.

As typical for a declarative query language, you don’t need to specify such execution details when writing the query: the query optimizer automatically chooses the strategy that is predicted to be the most efficient, and you can get on with writing the rest of your application.

Graph queries in SQL

[Example 2-2](#) suggested that graph data can be represented in a relational database. But if we put graph data in a relational structure, can we also query it using SQL?

The answer is: yes, but with some difficulty. In a relational database, you usually know in advance which joins you need in your query. In a graph query, you may need to traverse a variable number of edges before you find the vertex you’re looking for, i.e. the number of joins is not fixed in advance.

In our example, that happens in the `() -[:WITHIN*o..]-> ()` rule in the Cypher query. A person's `LIVES_IN` edge may point at any kind of location: a street, a city, a district, a region, a state, etc. A city may be `WITHIN` a region, a region `WITHIN` a state, a state `WITHIN` a country, etc. The `LIVES_IN` edge may point directly at the location vertex you're looking for, or it may be several levels removed in the location hierarchy.

In Cypher, `:WITHIN*o..` expresses that fact very concisely: it means "follow a `WITHIN` edge, zero or more times". It is like the `*` operator in a regular expression.

This idea of variable-length traversal paths in a query can be expressed since SQL:1999 using something called *recursive common table expressions* (the `WITH RECURSIVE` syntax). [Example 2-5](#) shows the same query—finding the names of people who emigrated from the US to Europe—expressed in SQL using this technique (supported in PostgreSQL, IBM DB2, Oracle and SQL Server). However, the syntax is very clumsy by comparison to Cypher.

Example 2-5. The same query as [Example 2-4](#), expressed in SQL using recursive common table expressions.

WITH RECURSIVE

```
-- in_usa is the set of vertex IDs of all locations within the United States
in_usa(vertex_id) AS (
    SELECT vertex_id FROM vertices WHERE properties->>'name' = 'United States'
①UNION
    SELECT edges.tail_vertex FROM edges ② JOIN in_usa ON edges.head_vertex =
in_usa.vertex_id
        WHERE edges.type = 'within'
),
-- in_europe is the set of vertex IDs of all locations within Europe
in_europe(vertex_id) AS (
    SELECT vertex_id FROM vertices WHERE properties->>'name' = 'Europe' ③UNION
    SELECT edges.tail_vertex FROM edges
        JOIN in_europe ON edges.head_vertex = in_europe.vertex_id
        WHERE edges.type = 'within'
),
-- born_in_usa is the set of vertex IDs of all people born in the US
born_in_usa(vertex_id) AS ( ④SELECT edges.tail_vertex FROM edges
    JOIN in_usa ON edges.head_vertex = in_usa.vertex_id
    WHERE edges.type = 'born_in'
),
-- lives_in_europe is the set of vertex IDs of all people living in Europe
lives_in_europe(vertex_id) AS ( ⑤SELECT edges.tail_vertex FROM edges
```

```

JOIN in_europe ON edges.head_vertex = in_europe.vertex_id
WHERE type = 'lives_in'
)
SELECT vertices.properties->>'name'
FROM vertices
-- join to find those people who were both born in the US *and* live in Europe
JOIN born_in_usa          ON vertices.vertex_id = born_in_usa.vertex_id ❶ JOIN
lives_in_europe ON vertices.vertex_id = lives_in_europe.vertex_id;

```

❶

First find the vertex whose name property has the value “United States”, and add it to the set of vertices in_usa.

❷

Follow all incoming within edges from vertices in the set in_usa, and add them to the same set, until all incoming within edges have been visited.

❸

Do the same starting with the vertex whose name property has the value “Europe”, and build up the set of vertices in_europe.

❹

For each of the vertices in the set in_usa, follow incoming born_in edges, to find people who were born in some place within the United States.

❺

Similarly, for each of the vertices in the set in_europe, follow incoming lives_in edges.

❻

Finally, intersect the set of people born in the USA with the set of people living in Europe, by joining them.

If the same query can be written in four lines in one query language, but requires 29 lines in another, that just shows that different data models are designed to satisfy different use cases. It’s important to pick a data model that is suitable for your application.

Graph databases compared to the network model

In [Historical interlude](#) we discussed how CODASYL and the relational model competed to solve the problem of many-to-many relationships in IMS. At first glance, CODASYL's network model looks similar to the graph model. Are graph databases the second coming of CODASYL in disguise?

No. They differ in several important ways:

- In CODASYL, a database had a schema that specified which record type could be nested within which other record type. In a graph database, there are no such restrictions: any vertex can have an edge to any other vertex. This gives much greater flexibility for applications to adapt to changing requirements.
- In CODASYL, the only way to reach a particular record was to traverse one of the access paths to it. In a graph database, you can refer directly to any vertex by its unique ID, or you can use a property index to find vertices with a particular value.
- In CODASYL, the children of a record were an ordered set, so the database had to maintain that ordering (which had consequences for the storage layout) and applications that inserted new records into the database had to worry about the position of the new record in these sets. In a graph database, there is no defined ordering of vertices or edges (you can only sort the results when making a query).
- In CODASYL, all queries were imperative, difficult to write and easily broken by changes in the schema. In a graph database, you can write your traversal in imperative code if you want to, but most graph databases also support high-level, declarative query languages such as Cypher or SPARQL.

Triple-stores and SPARQL

The triple-store model is mostly equivalent to the property graph model, using different words to describe the same ideas. It is nevertheless worth discussing, because there are various tools and languages for triple-stores that can be valuable additions to your toolbox for building applications.

In a triple-store, all information is stored in the form of very simple three-part statements: (*subject, predicate, object*). For example, in the triple (*Jim, likes, bananas*), *Jim* is the subject, *likes* is the predicate (verb), and *bananas* is the object.

The subject of a triple is equivalent to a vertex in a graph. The object is one of two things:

1. The object can be a value in a primitive datatype, such as a string or a number. In that case, the predicate and object of the triple are equivalent to the key and value of a property on the subject vertex. For example, (*lucy, age, 33*) is like a vertex *lucy* with properties {"age":33}.
2. The object can be another vertex in the graph. In that case, the predicate is an edge in the graph, the subject is the tail vertex and the object is the head vertex. For example, in (*lucy, marriedTo, alain*) the

subject and object *lucy* and *alain* are both vertices, and the predicate *marriedTo* is the label of the edge that connects them.

For example, [Example 2-6](#) shows the same data as in [Example 2-3](#), written as triples in a format called *Turtle*, a subset of *Notation3 (N3)*. [\[60\]](#)

Example 2-6. A subset of the data in [Figure 2-6](#), represented as Turtle triples.

```
@prefix : <urn:x-example:>.  
_:lucy a :Person.  
_:lucy :name "Lucy".  
_:lucy :bornIn _:idaho.  
_:idaho a :Location.  
_:idaho :name "Idaho".  
_:idaho :type "state".  
_:idaho :within _:usa.  
_:usa a :Location.  
_:usa :name "United States".  
_:usa :type "country".  
_:usa :within _:namerica.  
_:namerica a :Location.  
_:namerica :name "North America".  
_:namerica :type "continent".
```

In this example, vertices of the graph are written as `_:someName`—the name doesn't mean anything outside of this file, it exists only because we otherwise wouldn't know which triples refer to the same vertex. When the predicate represents an edge, the object is a vertex, as in `_:idaho :within _:usa`. When the predicate is a property, the object is a string literal, as in `_:usa :name "United States"`.

It's quite repetitive to repeat the same subject over and over again, but fortunately you can use semicolons to say multiple things about the same subject. This makes the Turtle format quite nice and readable: see [Example 2-7](#).

Example 2-7. A more concise way of writing the data in [Example 2-6](#).

```
@prefix : <urn:x-example:>.  
_:lucy a :Person; :name "Lucy"; :bornIn _:idaho.  
_:idaho a :Location; :name "Idaho"; :type "state"; :within _:usa.  
_:usa a :Location; :name "United States"; :type "country"; :within _:namerica.  
_:namerica a :Location; :name "North America"; :type "continent".
```

The semantic web

If you read more about triple-stores, you may get sucked into a maelstrom of articles written about the *semantic web*. The triple-store data model is completely independent of the semantic web—for example, Datomic [61] is a triple-store that does not claim to have anything to do with the semantic web. But since the two are so closely linked in many people’s minds, we should discuss them briefly.

The semantic web is fundamentally a simple and reasonable idea: websites already publish information as text and pictures for humans to read—why don’t they also publish information as machine-readable data for computers to read? The *Resource Description Framework* (RDF) [62] was intended as a mechanism for different websites to publish data in a consistent format, allowing data from different websites to be automatically combined into a *web of data*, a kind of internet-wide ‘database of everything’.

Unfortunately, the semantic web was over-hyped in the early 2000s, but so far hasn’t shown any sign of being realized in practice, which has made many people cynical about it. It has also suffered from a dizzying plethora of acronyms, overly complex standards proposals, and hubris.

However, if you look past those failings, there is also a lot of good work that has come out of the semantic web project. Triples can be a good internal data model for applications, even if you have no interest in publishing RDF data on the semantic web.

The RDF data model

The Turtle language we used in [Example 2-7](#) is a human-readable format for RDF data. Sometimes RDF is also written in an XML format, which does the same thing much more verbosely—see [Example 2-8](#). Turtle/N3 is preferable as it is much easier on the eyes, and tools like Apache Jena [63] can automatically convert between different RDF formats if necessary.

Example 2-8. The data of [Example 2-7](#), expressed using RDF/XML syntax.

```
<rdf:RDF xmlns="urn:x-example:">  
  xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#">  
  
<Location rdf:nodeID="idaho">  
  <name>Idaho</name>  
  <type>state</type>  
  <within>  
    <Location rdf:nodeID="usa">
```

```

<name>United States</name>
<type>country</type>
<within>
  <Location rdf:nodeID="namerica">
    <name>North America</name>
    <type>continent</type>
  </Location>
</within>
</Location>
</within>
</Location>

<Person rdf:nodeID="lucy">
  <name>Lucy</name>
  <bornIn rdf:nodeID="idaho"/>
</Person>
</rdf:RDF>

```

RDF has a few quirks due to the fact that it is designed for internet-wide data exchange. The subject, predicate and object of a triple are often URIs: rather than a predicate being just WITHIN or LIVES_IN, it is actually something like

<<http://my-company.com/namespace#within>> or
<http://my-company.com/namespace#lives_in>. The idea behind this: you should be able to combine your data with someone else's data, and if they attach a different meaning to the word within or lives_in, you won't get a conflict because their predicates are actually
<<http://other.org/foo#within>> and <http://other.org/foo#lives_in>.

The URL <<http://my-company.com/namespace>> doesn't necessarily need to resolve to anything—from RDF's point of view, it is simply a namespace. To avoid getting confused by <http://> URLs, we use URIs like `urn:x-example:within` in the examples above. Fortunately, you can just specify this prefix once at the top of the file, and then forget about it.

The SPARQL query language

SPARQL is a query language for triple-stores using the RDF data model. [\[\[64\]\]](#) (It is an acronym for *SPARQL Protocol and RDF Query Language*, and pronounced “sparkle”.) It predates Cypher, and since Cypher's pattern-matching is borrowed from SPARQL, they look quite similar. [\[\[58\]\]](#)

The same query as before—finding people who moved from the US to Europe—is even more concise in SPARQL than it is in Cypher: see [Example 2-9](#).

Example 2-9. The same query as [Example 2-4](#), expressed in SPARQL.

PREFIX : <urn:x-example:>

```
SELECT ?personName WHERE {  
    ?person :name ?personName.  
    ?person :bornIn / :within* / :name "United States".  
    ?person :livesIn / :within* / :name "Europe".  
}
```

The structure is very similar. The following two expressions are equivalent (variables start with a question mark in SPARQL):

(person) -[:BORN_IN]-> () -[:WITHIN*o..]-> (location) # Cypher

?person :bornIn / :within* ?location. # SPARQL

Because RDF doesn’t distinguish between properties and edges, but just uses predicates for both, you can use the same syntax for matching properties. In the following expression, the variable usa is bound to any vertex with the name property set to "United States":

(usa {name:'United States'}) # Cypher

?usa :name "United States". # SPARQL

SPARQL is a nice query language—even if the semantic web never happens, it can be a powerful tool for applications to use internally.

The foundation: Datalog

Datalog is a much older language than SPARQL or Cypher, having been studied extensively by academics in the 1980s. [\[65\]](#), [\[66\]](#) It is less well-known among software engineers, but it is nevertheless important, because it provides the foundation that later query languages build upon.

Every year we have more cores within each CPU, more CPUs in each machine, and more machines in a networked cluster. As programmers we still haven’t figured out a good answer to the problem of how to best work with all that parallelism. But it has been suggested that declarative languages based on Datalog may be the future for parallel programming, which has

rekindled interest in Datalog recently. [52] There has also been a lot of research into evaluating Datalog queries efficiently. [65]

In practice, Datalog is used in a few data systems: for example, it is the query language of Datomic [61], and Cascalog [67] is a Datalog implementation for querying large datasets in Hadoop.^[68]

Datalog's data model is similar to the triple-store model, generalized a bit. Instead of writing a triple as $(\text{subject}, \text{predicate}, \text{object})$, we write it as $\text{predicate}(\text{subject}, \text{object})$. [Example 2-10](#) shows how to write the data from our example in Datalog.

Example 2-10. A subset of the data in [Figure 2-6](#), represented as Datalog facts.

```
name(namerica, 'North America').  
type(namerica, continent).
```

```
name(usa, 'United States').  
type(usa, country).  
within(usa, namerica).
```

```
name(idaho, 'Idaho').  
type(idaho, state).  
within(idaho, usa).
```

```
name(lucy, 'Lucy').  
born_in(lucy, idaho).
```

Now that we have defined the data, we can write the same query as before, as shown in [Example 2-11](#). It looks a bit different from the equivalent in Cypher or SPARQL, but don't let that put you off. Datalog is a subset of Prolog, which you might have seen before if you studied computer science.

Example 2-11. The same query as [Example 2-4](#), expressed in Datalog.

```
within_recursive(Location, Name) :- name(Location, Name).      /* Rule 1 */
```

```
within_recursive(Location, Name) :- within(Location, Via),      /* Rule 2 */  
                                within_recursive(Via, Name).
```

```
migrated(Name, BornIn, LivingIn) :- name(Person, Name),        /* Rule 3 */  
                                    born_in(Person, BornLoc),  
                                    within_recursive(BornLoc, BornIn),
```

```

lives_in(Person, LivingLoc),
within_recursive(LivingLoc, LivingIn).

```

```

?- migrated(Who, 'United States', 'Europe').
/* Who = 'Lucy'. */

```

Cypher and SPARQL jump in right away with SELECT, but Datalog takes a small step at a time. We define *rules* that tell the database about new predicates: here, we define two new predicates, within_recursive and migrated. These predicates aren't triples stored in the database, but instead, they are derived from data or from other rules. Rules can refer to other rules, just like functions can call other functions or recursively call themselves. Like this, complex queries can be built up a small piece at a time.

In rules, words that start with an uppercase letter are variables, and predicates are matched like in Cypher and SPARQL. For example, name(Location, Name) matches the triple name(namerica, 'North America') with variable bindings Location = namerica and Name = 'North America'.

A rule applies if the system can find a match for *all* predicates on the right-hand side of the :- operator. When the rule applies, it's as though the left-hand side of the :- was added to the database (with variables replaced by the values they matched).

One possible way of applying the rules is thus:

1. name(namerica, 'North America') exists in the database, so rule 1 applies, and generates within_recursive(namerica, 'North America').
2. within(usa, namerica) exists in the database, and within_recursive(namerica, 'North America') was generated by the previous step, so rule 2 applies, and generates within_recursive(usa, 'North America').
3. within(idaho, usa) exists in the database, and within_recursive(usa, 'North America') was generated by the previous step, so rule 2 applies, and generates within_recursive(idaho, 'North America').

By repeated application of rules 1 and 2, the within_recursive predicate can tell us all the locations in North America (or any other location name) contained in our database. This is illustrated in [Figure 2-7](#).

After applying Rule 1:

within_recursive	
Location	Name
namerica	North America
usa	United States
idaho	Idaho

within(usa, namerica).

within(idaho, usa).

After applying Rule 2 once:

within_recursive	
Location	Name
namerica	North America
usa	North America
usa	United States
idaho	United States
idaho	Idaho

within(idaho, usa).

After applying Rule 2 twice:

within_recursive	
Location	Name
namerica	North America
usa	North America
idaho	North America
usa	United States
idaho	United States
idaho	Idaho

Figure 2-7. Determining that Idaho is in North America, using the Datalog rules from [Example 2-11](#).

Now rule 3 can find people who were born in some location BornIn, and live in some location LivingIn. By querying with BornIn = 'United States' and LivingIn = 'Europe', and leaving the person as a variable Who, we ask the Datalog system to find out which values can appear for the variable Who. So, finally we get the same answer as in the Cypher and SPARQL queries above.

The Datalog approach requires a different kind of thinking to the other query languages discussed in this chapter, but it's a very powerful approach, because rules can be combined and reused in different queries. It's less convenient for simple one-off queries, but it can cope better if your data is complex.

Summary

Data models are a huge subject, and in this chapter we have taken a quick look at a broad variety of different models. We didn't have space to go into all the details of each model, but hopefully the overview has been enough to whet your appetite to find out more about the model that best fits your application's requirements.

Historically, data started out being represented as one big tree (the hierarchical model), but that wasn't good for representing many-to-many relationships, so the relational model was invented to solve that problem. More recently, developers found that some applications don't fit well in the relational model either. New non-relational "NoSQL" data stores have diverged in two main directions:

1. Document databases target use cases where data comes in self-contained documents, and relationships between one document and another are rare.
2. Graph databases go in the opposite direction, targeting use cases where anything is potentially related to everything.

All three models (document, relational and graph) are widely used today, and each is good in its respective domain. One model can be emulated in terms of another model, but the result is often awkward. That's why we have different systems for different purposes, not a single one-size-fits-all solution.

One thing that document and graph databases have in common is that they typically don't enforce a schema for the data they store, which can make it easier to adapt applications to changing requirements.

Each data model comes with its own query language or framework, and we discussed several examples: SQL, MapReduce, MongoDB's aggregation pipeline, Cypher, SPARQL and Datalog. We also touched on CSS and XPath, which aren't database query languages, but have interesting parallels.

Although we have covered a lot of ground, there are still many data models left unmentioned. To give just two brief examples:

- Researchers working with genome data often need to perform *sequence-similarity searches*, which means taking one very long string (representing a DNA molecule) and matching it against a large database of strings that are similar, but not identical. None of the databases described above can handle this kind of usage, which is why researchers have written specialized genome database software like GenBank. [[\[69\]](#)]
- Particle physicists have been doing *Big Data*-style large scale data analysis for decades, and projects like the Large Hadron Collider (LHC) now work with hundreds of petabytes! At such scale, custom solutions are required, to stop the hardware cost spiraling out of control. [[\[70\]](#)]

But we have to leave it there for now. In the next chapter we will discuss some of the trade-offs that come into play when *implementing* the data models described in this chapter.

[[21](#)] Edgar F Codd: “[A Relational Model of Data for Large Shared Data Banks](#),” *Communications of the ACM*, volume 13, number 6, pages 377–387, June 1970. [doi:10.1145/362384.362685](#)

[[22](#)] Michael Stonebraker and Joseph M Hellerstein: “[What Goes Around Comes Around](#),” in *Readings in Database Systems*, Fourth Edition, MIT Press, pages 2–41, 2005. ISBN: 9780262693141

[[23](#)] Pramod J Sadalage and Martin Fowler: *NoSQL Distilled*. Addison-Wesley, August 2012. ISBN: 9780321826626

[24] James Phillips: “[Surprises in our NoSQL adoption survey](#),” blog.couchbase.com, 8 February 2012.

[25] A term borrowed from electronics. Every electric circuit has a certain impedance (resistance to alternating current) on its inputs and outputs. When you connect one circuit’s output to another one’s input, the power transfer across the connection is maximized if the output and input impedances of the two circuits match. An impedance mismatch can lead to signal reflections and other troubles.

[26] Michael Wagner: *SQL/XML:2006 – Evaluierung der Standardkonformität ausgewählter Datenbanksysteme*. Diplomica Verlag, Hamburg, 2010. ISBN: 978-3-8366-4609-3

[27] “[XML Data in SQL Server](#),” SQL Server 2012 documentation, technet.microsoft.com, 2013.

[28] “[PostgreSQL 9.3.1 Documentation](#),” The PostgreSQL Global Development Group, 2013.

[29] “[The MongoDB 2.4 Manual](#),” MongoDB, Inc., 2013.

[30] “[RethinkDB 1.11 Documentation](#),” www.rethinkdb.com, 2013.

[31] “[Apache CouchDB 1.6 Documentation](#),” docs.couchdb.org, 2013.

[32] Lin Qiao, Kapil Surlaker, Shirshanka Das, et al.: “[On Brewing Fresh Espresso: LinkedIn’s Distributed Data Serving Platform](#),” at *ACM International Conference on Management of Data* (SIGMOD), June 2013.

[33] Literature on the relational model distinguishes many different normal forms, but the distinctions are of little practical interest. As a rule of thumb, if you’re duplicating values that could be stored in just one place, the schema is not normalized.

[34] At the time of writing, joins are supported in RethinkDB, not supported in MongoDB, and only supported in pre-declared views in CouchDB.

[35] Rick Long, Mark Harrington, Robert Hain, and Geoff Nicholls: [IMS Primer](#). IBM Redbook SG24-5352-00, IBM International Technical Support Organization, January 2000.

[36] Stephen D Bartlett: “[IBM’s IMS – Myths, Realities, and Opportunities](#),” The Clipper Group Navigator, TCG2013015LI, July 2013.

[37] Sarah Mei: “[Why you should never use MongoDB](#),” sarahmei.com, 11 November 2013.

[38] J S Knowles and D M R Bell: “The CODASYL Model,” in *Databases - Role and Structure: an advanced course*, edited by P M Stocker, P M D Gray, and M P Atkinson, Cambridge University Press, pages 19–56, 1984. ISBN: 0521254302

[39] Charles W Bachman: “[The Programmer as Navigator](#),” *Communications of the ACM*, volume 16, number 11, pages 653–658, November 1973. [doi:10.1145/355611.362534](https://doi.org/10.1145/355611.362534)

[40] Foreign key constraints allow you to restrict modifications, but such constraints are not required by the relational model. Even with constraints, joins on foreign keys are performed at query time, whereas in CODASYL, the join was effectively done at insert time.

[41] Joseph M Hellerstein, Michael Stonebraker, and James Hamilton: “[Architecture of a Database System](#),” *Foundations and Trends in Databases*, volume 1, number 2, pages 141–259, November 2007. [doi:10.1561/1900000002](https://doi.org/10.1561/1900000002)

[42] Sandeep Parikh and Kelly Stirman: “[Schema design for time series data in MongoDB](#),” blog.mongodb.org, 30 October 2013.

[43] Martin Odersky: “[The Trouble With Types](#),” at *Strange Loop*, September 2013.

[44] Conrad Irwin: “[MongoDB — confessions of a PostgreSQL lover](#),” at *HTML5DevConf*, October 2013.

[45] “[Percona Toolkit Documentation: pt-online-schema-change](#),” Percona Ireland Ltd., 2013.

[46] Rany Keddo, Tobias Bielohlawek, and Tobias Schmidt: “[Large Hadron Migrator](#),” SoundCloud, 2013.

[47] James C Corbett, Jeffrey Dean, Michael Epstein, et al.: “[Spanner: Google’s Globally-Distributed Database](#),” at *10th USENIX Symposium on Operating System Design and Implementation (OSDI)*, October 2012.

[48] Donald K Burleson: “[Reduce I/O with Oracle cluster tables](#),” dba-oracle.com.

[49] Fay Chang, Jeffrey Dean, Sanjay Ghemawat, et al.: “[Bigtable: A Distributed Storage System for Structured Data](#),” at *7th USENIX Symposium on Operating System Design and Implementation (OSDI)*, November 2006.

[50] Bobbie J Cochrane and Kathy A McKnight: “[DB2 JSON capabilities, Part 1: Introduction to DB2 JSON](#),” IBM developerWorks, 20 June 2013.

[51] Codd's original description of the relational model [21] actually allowed something quite similar to JSON documents within a relational schema. He called it *nonsimple domains*. The idea was: a value in a row doesn't have to just be a primitive datatype like a number or a string, but it could also be a nested relation (table) — and so you can have an arbitrarily nested tree structure as a value, much like the JSON or XML support that was added to SQL over 30 years later.

[52] Joseph M Hellerstein: “[The Declarative Imperative: Experiences and Conjectures in Distributed Logic](#),” Electrical Engineering and Computer Sciences, University of California at Berkeley, Tech report UCB/EECS-2010-90, June 2010.

[53] IMS and CODASYL both used imperative query APIs. Applications typically used COBOL code to iterate over records in the database, one record at a time. [22], [38]

[54] Jeffrey Dean and Sanjay Ghemawat: “[MapReduce: Simplified Data Processing on Large Clusters](#),” at *6th USENIX Symposium on Operating System Design and Implementation* (OSDI), December 2004.

[55] Craig Kerstiens: “[JavaScript in your Postgres](#),” postgres.heroku.com, 5 June 2013.

[56] Nathan Bronson, Zach Amsden, George Cabrera, et al.: “[TAO: Facebook’s Distributed Data Store for the Social Graph](#),” at *USENIX Annual Technical Conference* (USENIX ATC), June 2013.

[57] “[Gremlin graph traversal language](#),” TinkerPop, gremlin.tinkerpop.com, 2013.

[58] “[The Neo4j Manual v2.0.0](#),” Neo Technology, 2013.

[59] Emil Eifrem: [Twitter correspondence](#).

[60] David Beckett and Tim Berners-Lee: “[Turtle – Terse RDF Triple Language](#),” W3C Team Submission, 28 March 2011.

[61] “[Datomic Development Resources](#),” Metadata Partners, LLC, 2013.

[62] W3C RDF Working Group: “[Resource Description Framework \(RDF\)](#),” www.w3.org, 10 February 2004.

[63] “[Apache Jena](#),” Apache Software Foundation.

[64] Steve Harris, Andy Seaborne, and Eric Prud’hommeaux: “[SPARQL 1.1 Query Language](#),” W3C Recommendation, March 2013.

[65] Todd J Green, Shan Shan Huang, Boon Thau Loo, and Wenchoao Zhou: “Datalog and Recursive Query Processing,” *Foundations and Trends in Databases*, volume 5, number 2, pages 105–195, November 2013. [doi:10.1561/1900000017](https://doi.org/10.1561/1900000017)

[66] Stefano Ceri, Georg Gottlob, and Letizia Tanca: “[What You Always Wanted to Know About Datalog \(And Never Dared to Ask\)](#),” *IEEE Transactions on Knowledge and Data Engineering*, volume 1, number 1, pages 146–166, March 1989. [doi:10.1109/69.43410](https://doi.org/10.1109/69.43410)

[67] Nathan Marz: “Cascalog,” Apache License Version 2.0. cascalog.org

[68] Datomic and Cascalog use a Clojure S-expression syntax for Datalog. In the following examples we use a Prolog syntax, which is a little easier to read, but makes no functional difference.

[69] Dennis A Benson, Ilene Karsch-Mizrachi, David J Lipman, James Ostell, and David L Wheeler: “[GenBank](#),” *Nucleic Acids Research*, volume 36, Database issue, pages D25–D30, December 2007. [doi:10.1093/nar/gkm929](https://doi.org/10.1093/nar/gkm929)

[70] Fons Rademakers: “[ROOT for Big Data Analysis](#),” at *Workshop on the future of Big Data management*, London, UK, June 2013.

Chapter 3. Storage and Retrieval

On the most fundamental level, a database needs to do two things: when you give it some data, it should store the data—and when you ask it again later, it should give the data back to you.

In [Chapter 2](#) we discussed data models and query languages, i.e. the format in which you (the application developer) give the database your data, and the mechanism by which you can ask for it again later. In this chapter we discuss the same from the database's point of view: how we can store the data that we're given, and how we can find it again when we're asked for it.

Why should you, as application developer, care how the database handles storage and retrieval internally? You're probably not going to implement your own storage engine from scratch, but you *do* need to select a storage engine that is appropriate to your application, from the many that are available. In order to tune a storage engine to perform well on your kind of workload, you need to have a rough idea of what the storage engine is doing under the hood.

Data Structures that Power Your Database

Consider the world's simplest database, implemented as two Bash functions:

```
#!/bin/bash

db_set () {
    echo "$1,$2" >> database
}

db_get () {
    grep "^\$1," database | sed -e "s/^\$1,//" | tail -n 1
}
```

These two functions implement a key-value store. You can call `db_set` key value, which will store key and value in the database. The key and value can be (almost) anything you like—for example, the value could be a JSON document. You can then call `db_get` key, which looks up the most recent value associated with that particular key, and returns it.

And it works:

```
$ db_set 123456 '{"name":"London","attractions":["Big Ben","London Eye"]}'
```

```
$ db_set 42 '{"name":"San Francisco","attractions":["Golden Gate Bridge"]}'
```

```
$ db_get 42
```

```
{"name":"San Francisco","attractions":["Golden Gate Bridge"]}
```

The underlying storage format is very simple: a text file where each line contains a key-value pair, separated by a comma (roughly like a CSV file, ignoring escaping issues). Every call to db_set appends to the end of the file, so if you update a key several times, the old versions of the value are not overwritten—you need to look at the last occurrence of a key in a file to find the latest value (hence the tail -n 1 in db_get).

Our db_set function actually has pretty good performance for something that is so simple, because appending to a file is generally very efficient. Many databases internally use a *log*,^[71] an append-only data file, quite similar to what db_set does. Real databases have more issues to deal with (such as concurrency control, reclaiming disk space so that the log doesn't grow forever, handling errors, partially written records, and so on) but the basic principle is the same. Logs are incredibly useful, and we will come back to them later.

On the other hand, our db_get function has terrible performance if you have a large number of records in your database. Every time you want to look up a key, db_get has to scan the entire database file from beginning to end, looking for occurrences of the key. In algorithmic terms, the cost of a lookup is $O(n)$: if you double the number of records n in your database, a lookup takes twice as long. That's not good.

In order to efficiently find the value for a particular key in the database, we need a different data structure: **an index**. In this chapter we will look at a range of indexing structures and see how they compare. But the general idea behind them is: keep some additional metadata on the side, which acts as a signpost and helps you to locate the data you want. If you want to search the same data in several different ways, you may need several different indexes on different parts of the data.

An **index** is an *additional structure that is derived from the primary data*—many databases allow you to add and remove indexes, and this doesn't affect the contents of the database, it only affects the performance of queries. Maintaining additional structures is overhead, especially on writes. For writes, it's hard to beat the performance of simply appending to a file, so any kind of index usually slows down writes.

This is an important trade-off in storage systems: **well-chosen indexes can speed up read queries, but every index slows down writes**. For this reason, databases don't usually index everything by

default, but require you—the application developer or database administrator—to choose indexes manually, using your knowledge of the application’s typical query patterns. You can then choose the indexes that give your application the greatest benefit, without introducing more overhead than necessary.

Hash indexes

Let’s start with indexes for key-value data. This is not the only kind of data you can index, but it’s very common, and it’s a useful building block for more complex indexes.

Key-value stores are quite similar to the *dictionary* type that you can find in most programming languages, and which is usually implemented as a hash map (hash table). Hash maps are described in many algorithms textbooks, for example [72], so we won’t go into detail of how they work here. Since we already have hash maps for our in-memory data structures, why not use them to index our data on disk?

Let’s say our data storage consists only of appending to a file, as in the example above. Then the simplest possible indexing strategy is this: keep an in-memory hash map where every key is mapped to a byte offset in the data file—the location at which the value can be found. This is illustrated in [Figure 3-1](#).

Whenever you append a new key-value pair to the file, you also update the hash map to reflect the offset of the data you just wrote (this works both for inserting new keys and for updating existing keys). When you want to look up a value, use the hash map to find the offset in the data file, seek to that location, and read the value.

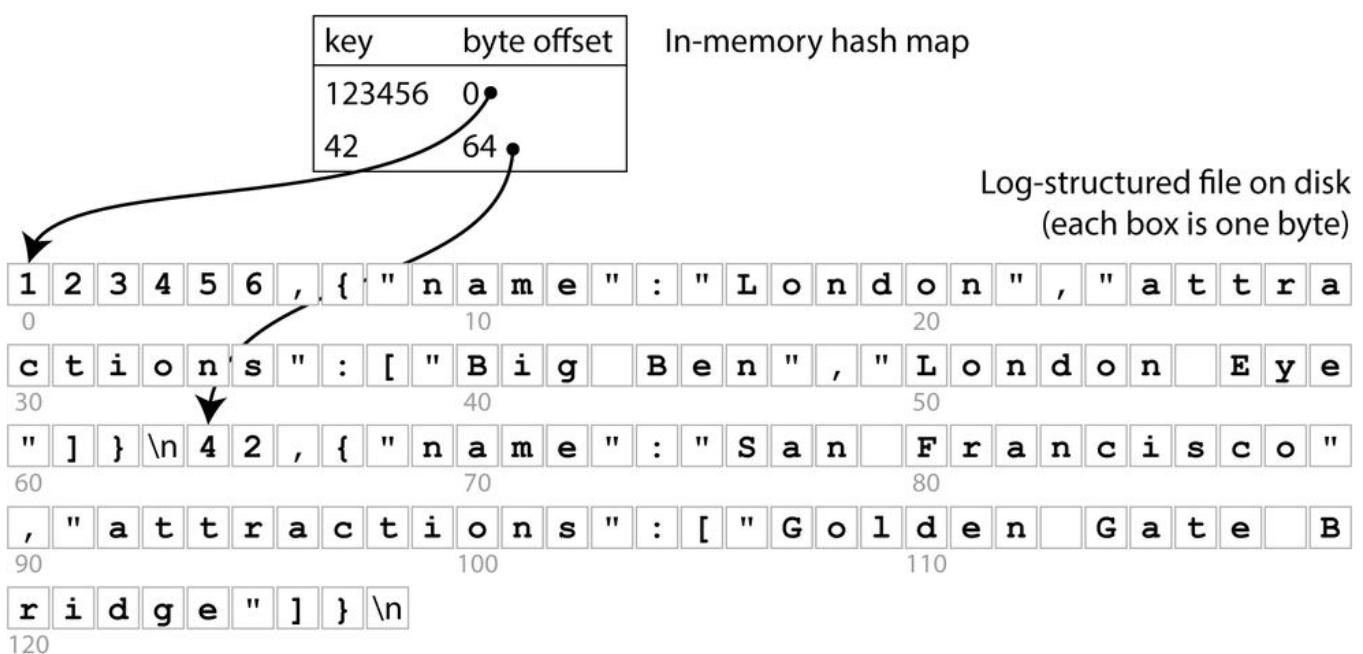


Figure 3-1. Storing a log of key-value pairs in a CSV-like format, indexed with an in-memory hash map.

This may sound simplistic, but it is a viable approach. In fact, this is essentially what Bitcask (the default storage engine in Riak) does. [73] Bitcask offers high-performance reads and writes, subject to the requirement that all the keys fit in the available RAM, since the hash map is kept completely in memory. The values can use more space than available memory, since they can be loaded from disk with just one disk seek. If that part of the data file is already in the filesystem cache, a read doesn't require any disk I/O at all.

A storage engine like Bitcask is well suited in situations where the value for each key is updated frequently. For example, the key might be the URL of a cat video, and the value might be the number of times it has been played (incremented every time someone hits the play button).

As described so far, we only ever append to a file—so how do we avoid eventually running out of disk space? A good solution is to break the log into segments of a certain size, and to periodically run a background process for *compaction and merging* of segments, illustrated in [Figure 3-2](#). Compaction means throwing away all key-value pairs in the log except for the most recent update for each key. This makes the segments much smaller (assuming that every key is updated multiple times on average), so we can also merge several segments into one.

Segments are never modified after they have been written, so the merged segment is written to a new file. While the merge is going on, we can still continue to serve read and write requests as normal, using the old segment files. After the merging process is complete, we switch read requests to using the new merged segment instead of the old segments—and then the old segment files can simply be deleted.

Data file segment 1

mew: 1078	purr: 2103	purr: 2104	mew: 1079	mew: 1080	mew: 1081
purr: 2105	purr: 2106	purr: 2107	yawn: 511	purr: 2108	mew: 1082

Data file segment 2

purr: 2109	purr: 2110	mew: 1083	scratch: 252	mew: 1084	mew: 1085
purr: 2111	mew: 1086	purr: 2112	purr: 2113	mew: 1087	purr: 2114

+ Compaction and merging process

Merged segments 1 and 2

yawn: 511	scratch: 252	mew: 1087	purr: 2114
-----------	--------------	-----------	------------

Figure 3-2. Merging segments of a key-value update log (counting the number of times each cat video was

played), retaining only the most recent value for each key.

Each segment now has its own in-memory hash table, mapping keys to file offsets. In order to find the value for a key, we first check the most recent segment's hash map; if the key is not present, check the second-most-recent segment, etc. The merging process keeps the number of segments small, so lookups don't need to check many hash maps.

Lots of detail goes into making this simple idea work in practice. To briefly mention some of the issues that are important in a real implementation:

File format

CSV is not the best format for a log. It's faster and simpler to use a binary format which first encodes the length of a string in bytes, followed by the raw string (without need for escaping).

Deleting records

If you want to delete a key and its associated value, you have to append a special deletion record to the data file (sometimes called a *tombstone*). When log segments are merged, the tombstone tells the merging process to discard any previous values for the deleted key.

Crash recovery

If the database is restarted, the in-memory hash maps are lost. In principle, you can restore each segment's hash map by reading the entire segment file from beginning to end, and noting the offset of the most recent value for every key as you go along. However, that might take a long time if the segment files are large, which would make server restarts painful. Bitcask speeds up recovery by storing a snapshot of each segment's hash map on disk, which can be loaded into memory quicker.

Partially written records

The database may crash at any time, including halfway through appending a record to the log. Bitcask files include checksums which allow such corrupted parts of the log to be detected and ignored.

Concurrency control

Writes are appended to the log in a strictly sequential order (there is only one writer thread), there are no transactions, and data file segments are append-only and otherwise immutable. These facts make concurrency fairly simple.

An append-only log seems wasteful at first glance: why don't you update the file in place, overwriting the old value with the new value? But an append-only design turns out to be good for several reasons:

- Appending and segment merging are sequential write operations, which are generally much faster than random writes. This performance difference applies both to traditional spinning-disk hard drives and to flash-based *solid state drives* (SSDs). [[74](#)]

- Concurrency and crash recovery are much simpler if files are immutable. For example, you don't have to worry about the case where a crash happened while a value was being overwritten, leaving you with a file containing part of the old and part of the new value spliced together.
- Merging old segments avoids problems of data files getting fragmented over time.

However, the hash table index also has limitations:

- The **hash table must fit in memory**, so if you have a very large number of keys, you're out of luck. In principle, you could maintain a hash map on disk, but unfortunately it is difficult to make an on-disk hash map perform well. It requires a lot of random access I/O, it is expensive to grow when it becomes full, and hash collisions require fiddly logic. [[75](#)]
- Range queries are not efficient. For example, you cannot easily fetch the values for all keys between kittyooooo and kitty99999—you'd have to look up each key individually in the hash maps.

In the next section we will look at an indexing structure that doesn't have those limitations.

SSTables and LSM-trees

In [Figure 3-2](#), each log-structured storage segment is a sequence of key-value pairs. These pairs appear in the order that they were written, and values later in the log take precedence over values for the same key earlier in the log. Apart from that, the order of key-value pairs in the file does not matter.

Now we can make a simple change to the format of our segment files: we require that the sequence of key-value pairs is *sorted by key*. We call this format *Sorted String Table*, or *SSTable* for short. We also require that each key only appears once within each merged segment file (the merging process already ensures that).

SSTables have several big advantages:

- Merging segments is simple and efficient, even if the files are bigger than the available memory. This is illustrated in [Figure 3-3](#). You start reading the input files side-by-side, look at the first key in each file, copy the lowest-numbered key to the output file, and repeat. If the same key appears in several input files, keep the one from the most recent input file, and discard the values in older segments. This produces a new merged segment which is also sorted by key, and which also has exactly one value per key.
- In order to find a particular key in the file, you no longer need to keep an index of all the keys in memory. See [Figure 3-4](#) for example: say you're looking for the key *handiwork*, but you don't know the exact offset of that key in the segment file. However, you do know the offsets for the keys *handbag* and *handsome*, and because of the sorting you know that

handiwork must appear between those two. So you can jump to the offset for *handbag* and scan from there until you find *handiwork* (or not, if the key is not present in the file).

You still need an in-memory index to tell you the offsets for some of the keys, but it can be sparse: one key for every few kilobytes of segment file is sufficient, because a few kilobytes can be scanned very quickly.^[76]

- Since read requests need to scan over several key-value pairs in the requested range anyway, it is possible to group those records into a block and compress it before writing it to disk (indicated by the shaded area in [Figure 3-4](#)). Each entry of the sparse in-memory index then points at the start of a compressed block. Nowadays, disk bandwidth is usually a worse bottleneck than CPU, so it is worth spending a few additional CPU cycles to reduce the amount of data you need to write to and read from disk.

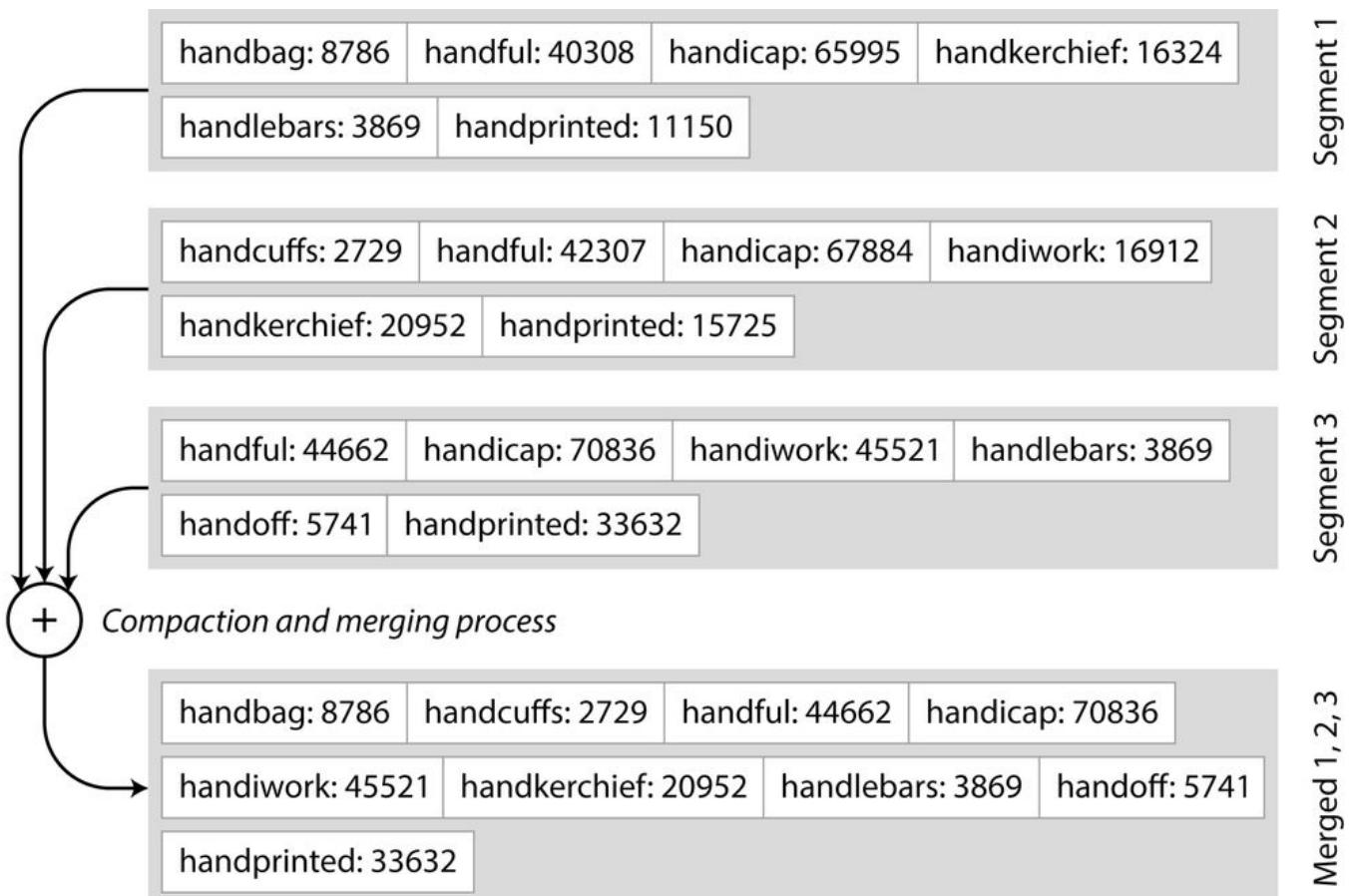


Figure 3-3. Merging several Sorted String Table (SSTable) segments, retaining only the most recent value for each key.

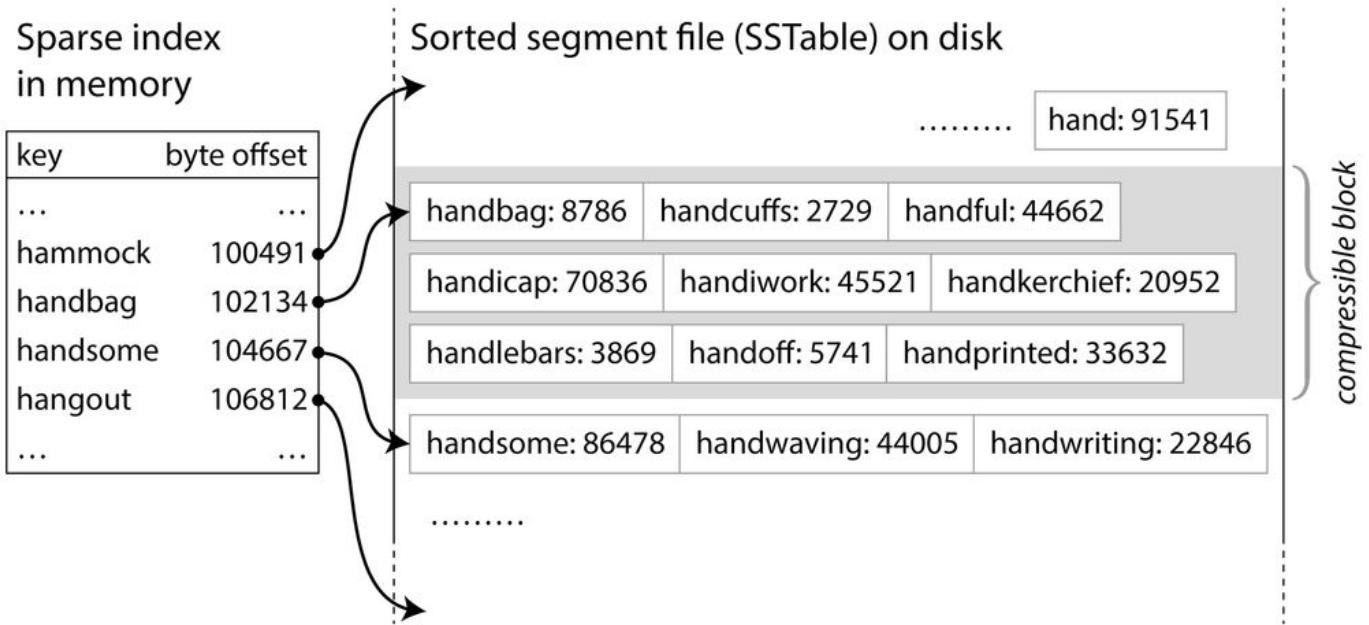


Figure 3-4. A Sorted String Table (SSTable) with in-memory index.

Fine so far—but how do you get your data to be sorted by key in the first place? Our incoming writes can occur in any order.

Maintaining a sorted structure on disk is possible (see next section), but maintaining it in memory is much easier. There are plenty of well-known tree data structures that you can use, such as Red-Black trees or AVL trees. [77] With these data structures, you can insert keys in any order, and read them back in sorted order.

We can now make our storage engine work as follows:

- When a write comes in, add it to an in-memory balanced tree data structure, for example a Red-Black tree. This in-memory tree is sometimes called a *memtable*.
- When the memtable gets bigger than some threshold—typically a few megabytes—write it out to disk as an SSTable file. This can be done efficiently because the tree already maintains the key-value pairs sorted by key. The new SSTable file becomes the most recent segment of the database. When the new SSTable is ready, the memtable can be emptied.
- In order to serve a read request, first try to find the key in the memtable, then in the most recent on-disk segment, then in the next-older segment, etc.
- From time to time, run a merging and compaction process in the background to combine segment files and to discard overwritten or deleted values.

This scheme works very well. It only suffers from one problem: if the database crashes, the most recent writes (which are in the memtable but not yet written out to disk) are lost. In order to avoid that problem, we can keep a separate log on disk to which every write is immediately

appended, just like in the previous section. That log is not in sorted order, but that doesn't matter, because its only purpose is to restore the memtable after a crash. Every time the memtable is written out to an SSTable, the corresponding log can be discarded.

The algorithm described here is essentially what is used in LevelDB [[\[78\]](#)] and RocksDB [[\[79\]](#)], key-value storage engine libraries that are designed to be embedded into other applications. Among other things, LevelDB can be used in Riak, as alternative to Bitcask. Similar storage engines are used in Cassandra and HBase, both of which were inspired by Google's Bigtable paper [[\[80\]](#)] (which introduced the terms *SSTable* and *memtable*). Originally this indexing structure was described by Patrick O'Neil et al. under the name *Log-Structured Merge-Tree (LSM-Tree)* [[\[81\]](#)], building on earlier work on log-structured file systems [[\[82\]](#)].

Lucene, an indexing engine for full-text search used by Elasticsearch and Solr, uses a similar method for storing its *term dictionary*. [[\[83\]](#), [\[84\]](#)] A full-text index is much more complex than a key-value index, but at its core is a similar idea: given a word in a search query, find all the documents (web pages, product descriptions, etc.) that mention the word. This is implemented with a key-value structure where the key is a word (a *term*), and the value is the IDs of all the documents that contain the word (the *postings list*). In Lucene, this mapping from term to postings list is kept in SSTable-like sorted files, which are merged in the background as needed. [[\[85\]](#)]

As always, a lot of detail goes into making a storage engine perform well in practice. For example, the LSM-tree algorithm can be slow when looking up keys that do not exist in the database: you have to check the memtable, then the segments all the way back to the oldest (possibly having to read from disk for each one) before you can be sure that the key does not exist. In order to optimize this, LevelDB maintains additional Bloom filters, which allows it to avoid many unnecessary disk reads for non-existent keys.

However, the basic idea—keeping a cascade of SSTables that are merged in the background—is simple and effective. Even when the dataset is much bigger than memory it continues to work well. Since data is stored in sorted order, you can efficiently perform range queries (scanning all keys above some minimum and up to some maximum). And because the disk writes are sequential, the LSM-tree can support remarkably high write throughput.

B-trees

The log-structured indexes we have discussed so far are gaining acceptance, but they are not the most common type of index. The most widely-used indexing structure is quite different: the *B-tree*.

Introduced in 1970 [86] and called “ubiquitous” less than 10 years later [87], B-trees have stood the test of time very well. They remain the standard index implementation in almost all relational databases, and many non-relational databases use them too.

Like SSTables, B-trees keep key-value pairs sorted by key, which allows efficient key-value lookups and range queries. But that’s where the similarity ends: B-trees have a very different design philosophy.

The log-structured indexes we saw earlier break the database down into variable-size *segments*, typically several megabytes or more in size, and always write a segment sequentially. By contrast, B-trees break the database down into fixed-size *blocks* or *pages*, traditionally 4 kB in size, and read or write one page at a time. This corresponds more closely to the underlying hardware, as disks are also arranged in fixed-size blocks.

Each page can be identified using an address or location, which allows one page to refer to another—similar to a pointer, but on disk instead of in memory. We can use this to construct a tree of pages, similar to a Red-Black tree or a 2-3 tree, but with a larger branching factor: each page may have hundreds of children, not just two. This is illustrated in [Figure 3-5](#).

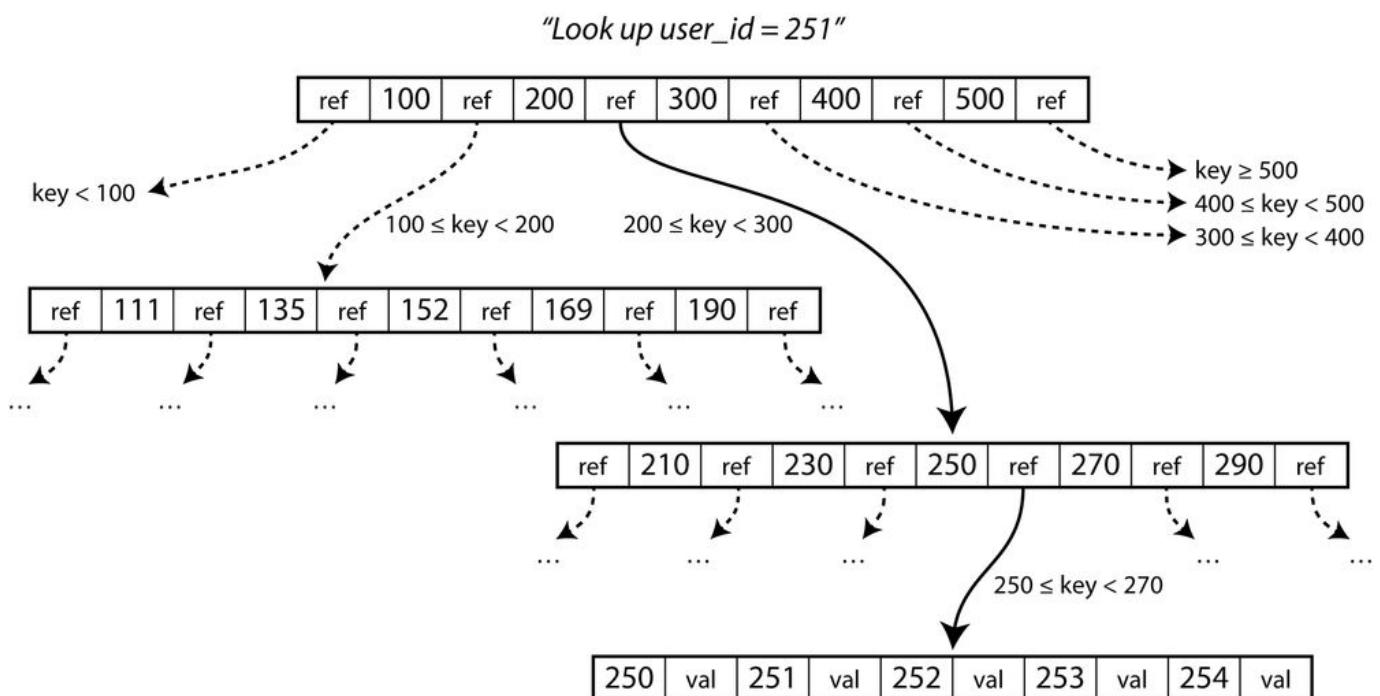


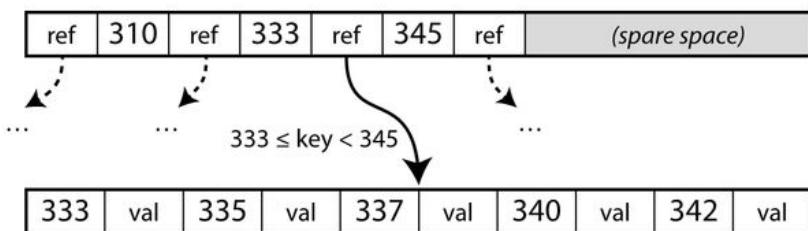
Figure 3-5. Looking up a key using a B-tree index.

One page is designated as the root of the B-tree; whenever you want to look up a key in the index, you start here. The page contains k keys and $k + 1$ references to child pages (in [Figure 3-5](#), $k = 5$, but in reality k would typically be in the hundreds). Each child is responsible for a continuous range of keys, and the keys in the root page indicate where the boundaries between those ranges lie.

In the example of [Figure 3-5](#), we are looking for the key 251, so we know that we need to follow the page reference between the boundaries 200 and 300. That takes us to a similar-looking page which further breaks down the 200–300 range into sub-ranges. Eventually we are down to a page containing individual keys (a *leaf page*), which either contains the value for each key inline, or contains references to the pages where each value can be found.

If you want to update the value for an existing key in a B-tree, you search for the leaf page containing that key, and update the value in place. If you want to add a new key, you need to find the page whose range encompasses the new key, and add it to that page. If there isn't enough free space in the page to accommodate the new key, it is split into two half-full pages, and the parent page is updated to account for the new subdivision of key ranges—see [Figure 3-6](#).

This algorithm ensures that a B-tree with n keys always has a height of $O(\log n)$ —i.e. even if the tree is very large, you don't need to follow many page references to find the page you are looking for.



After adding key 334:

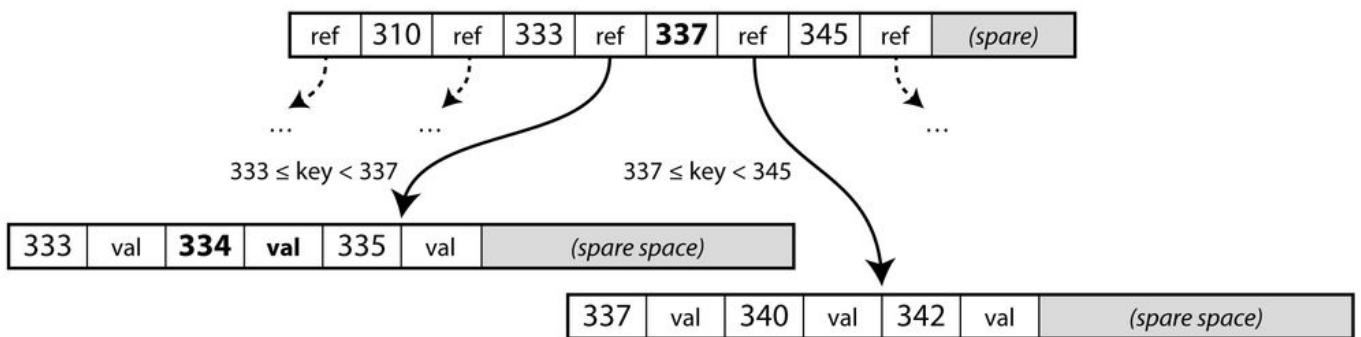


Figure 3-6. Growing a B-tree by splitting a page.

Update-in-place vs. append-only logging

The basic underlying write operation of a B-tree is to overwrite a page on disk with new data. It is assumed that the overwrite does not change the location of the page, i.e. all references to that page remain intact when the page is overwritten. This is in stark contrast to log-structured

indexes such as LSM-trees, which only append to files (and eventually delete obsolete files), but never modify files in place.

You can think of overwriting a page on disk as an actual hardware operation. On a magnetic hard drive, this means moving the disk head to the right place, waiting for the right position on the spinning platter to come around, and then overwriting the appropriate sector with new data. On SSDs, what happens is somewhat more complicated, but it is similarly slow. [\[88\]](#)

Moreover, some operations require several different pages to be overwritten. For example, if you split a page because an insertion caused it to be over-full, you need to write the two pages that were split, and also overwrite their parent page to update the references to the two child pages. This is a dangerous operation, because if the database crashes after writing only some of the pages, you end up with a corrupted index (e.g. there may be an *orphan* page which is not a child of any parent).

In order to make the database resilient to crashes, it is normal for B-tree implementations to include an additional data structure on disk: a *write-ahead log* (WAL, also known as *redo log*). This is an append-only file to which every B-tree modification must be written before it can be applied to the pages of the tree itself. When the database comes back up after a crash, this log is used to restore the B-tree back to a consistent state. [\[75\]](#)

A B-tree index must therefore write every piece of data at least twice: once to the log, and once to the tree page itself (and perhaps again as pages are split). On the other hand, log-structured indexes also re-write data multiple times due to repeated background merging. [\[89\]](#) It's not clear whether B-trees or LSM-trees are better in this regard—it depends on the workload and the tuning of the storage engine.

An additional complication of updating pages in-place is that careful concurrency control is required if multiple threads are going to access the B-tree at the same time, otherwise a thread may see the tree in an inconsistent state. This is typically done by protecting the tree's data structures with *latches* (lightweight locks). Log-structured approaches are simpler in this regard, because they do all the merging in the background without interfering with incoming queries, and atomically swap old segments for new segments from time to time.

B-tree optimizations

As B-trees have been around for so long, it's not surprising that many optimizations have been developed over the years. To mention just a few:

- We can save space in pages by not storing the entire key, but abbreviating it. Especially in pages on the interior of the tree, keys only need to provide enough information to act as boundaries between key ranges. Packing more keys into a page allows the tree to have a higher branching factor, and thus fewer levels.^[90]
- In general, pages could be positioned anywhere on disk; there is nothing requiring pages with nearby key ranges to be nearby on disk. If a query needs to scan over a large part of the key range in sorted order, that page-by-page layout can be inefficient, because a disk seek may be required for every page that is read. Many B-tree implementations therefore try to lay out the tree so that leaf pages appear in sequential order on disk. However, it's difficult to maintain that order as the tree grows. By contrast, since LSM-trees rewrite large segments of the storage in one go during merging, it's easier for them to keep sequential keys nearby on disk.
- Additional pointers have been added to the tree, for example each leaf page may have references to its sibling pages to the left and right, which allows scanning keys in order without jumping back to parent pages.

Comparing B-trees to LSM-trees

B-tree implementations are generally more mature than LSM-tree implementations, but LSM-trees are very promising due to their performance characteristics.

For random reads (the most common type of request in many applications) there is not a big performance difference between LSM-trees and B-trees—benchmarks are inconclusive. ^[91] However, LSM-trees are typically able to sustain much higher throughput of random writes compared to B-trees, because they turn all random writes into sequential writes on the underlying device. This makes them appealing for write-intensive applications.

An advantage of B-trees is that each key exists in exactly one place in the index, whereas a log-structured storage engine may have multiple copies of the same key in different segments. This makes B-trees attractive in databases that want to offer strong transactional semantics: in many relational databases, transaction isolation is implemented using locks on ranges of keys, and in a B-tree index, those locks can be directly attached to the tree. ^[75] In [Link to Come] we will discuss this in detail.

B-trees are very ingrained in the architecture of databases, and provide consistently good performance for many workloads, so it's unlikely that they will go away anytime soon. In new datastores, log-structured indexes are becoming increasingly popular.

Other indexing structures

So far we have only discussed key-value indexes, which are like a *primary key* index in the relational model. A primary key uniquely identifies one row in a relational table, or one document in a document database, or one vertex in a graph database. Other records in the database can refer to that row/document/vertex by its primary key (or ID), and the index is used to resolve such references.

It is also very common to have *secondary indexes*. In relational databases, you can create several secondary indexes on the same table, using the CREATE INDEX command, and they are often crucial for performing joins efficiently. For example, in [Figure 2-1](#) in [Chapter 2](#) you would most likely have a secondary index on the user_id columns, so that you can find all the rows belonging to the same user in each of the tables.

A secondary index can easily be constructed from a key-value index: the main difference is that keys are not unique, i.e. there might be many rows (documents, vertices) with the same key. This can be solved two ways: either by making each value in the index a list of matching row identifiers (like a posting list in a full-text index), or by making each key unique by appending a row identifier to it. Either way, both B-trees and log-structured indexes can be used as secondary indexes.

Storing values within the index

The key in an index is the thing that queries search for, but the value could be one of two things: it could be the actual row (document, vertex) in question, or it could be a reference to the row stored elsewhere. In the latter case, the place where rows are stored is known as a *heap file*, and it stores data in no particular order (it may be append-only, or it may keep track of deleted rows in order to overwrite them with new data later). The heap file approach is common, because it avoids duplicating data when multiple secondary indexes are present: **each index just references a location in the heap file, and the actual data is kept in one place.**

When updating a value without changing the key, the heap file approach can be quite efficient: the record can be overwritten in-place, provided that the new value is not larger than the old value. The situation is more complicated if the new value is larger, as it probably needs to be moved to a new location in the heap where there is enough space. In that case, either all indexes need to be updated to point at the new heap location of the record, or a forwarding pointer is left behind in the old heap location. [\[75\]](#)

In some situations, the extra hop from the index to the heap file is too much of a performance penalty for reads, so it can be desirable to store the indexed row directly within an index. This is known as a *clustered index*. For example, in **MySQL's InnoDB storage engine**, the primary key

of a table is always a **clustered index**, and secondary indexes refer to the primary key (rather than a heap file location). [92] In SQL Server, you can specify one clustered index per table. [93]

A compromise between a clustered index (storing all row data within the index) and a nonclustered index (storing only references to the data within the index) is known as a *covering index* or *index with included columns*, which stores *some* of a table's columns within the index. [94] This allows some queries to be answered by using the index alone (in which case, the index is said to *cover* the query). [93]

As with any kind of duplication of data, clustered and covering indexes **can speed up reads, but they require additional storage and can add overhead on writes.** Databases also need to go to additional effort to enforce transactional guarantees, because applications should not see inconsistencies due to the duplication.

Multi-column indexes

The indexes discussed so far only map a single key to a value. That is not sufficient if we need to query multiple columns of a table (or multiple fields in a document) simultaneously.

The most common type of multi-column index is called a **concatenated index**, which simply combines several fields into one key by appending one column to another (the index definition specifies in which order the fields are concatenated). This is like an old-fashioned paper phone book, which provides an index from *(lastname, firstname)* to phone number. Due to the sort order, the index can be used to find all the people with a particular last name, or all the people with a particular lastname-firstname combination. However, the index is useless if you want to find all the people with a particular first name.

Multi-dimensional indexes are a more general way of querying several columns at once, which is particularly important for geospatial data. For example, a restaurant-search website may have a database containing the latitude and longitude of each restaurant. When a user is looking at the restaurants on a map, the website needs to search for all the restaurants within the rectangular map area that the user is currently viewing. This requires a two-dimensional range query like the following:

```
SELECT * FROM restaurants WHERE latitude > 51.4946 AND latitude < 51.5079  
AND longitude > -0.1162 AND longitude < -0.1004;
```

A standard B-tree or LSM-tree index is not able to answer that kind of query efficiently: it can give you either all the restaurants in a range of latitudes (but at any longitude), or all the

restaurants in a range of longitudes (but anywhere between north and south pole), but not both simultaneously.

One option is to translate a two-dimensional location into a single number using a space-filling curve, and then to use a regular [B-tree index](#). [\[95\]](#) More commonly, specialized spatial indexes such as R-trees are used. For example, PostGIS implements geospatial indexes as R-trees using PostgreSQL's Generalized Search Tree indexing facility. [\[96\]](#) We don't have space to describe R-trees in detail here, but there is plenty of literature on them.

An interesting idea is that multidimensional indexes are not just for geographic locations. For example, on an e-commerce website you could use a three-dimensional index on the dimensions (*red, green, blue*) to search for products in a certain range of colors. Or in a database of weather observations, you could have a two-dimensional index on (*date, temperature*) in order to efficiently search for all the observations during the year 2013 where the temperature was between 25 and 30°C. With a one-dimensional index, you would have to either scan over all the records from 2013 (regardless of temperature) and then filter them by temperature, or vice versa. A 2D index could narrow down by timestamp and temperature simultaneously.

Fuzzy indexes

All the indexes discussed so far assume that you have exact data, and allow you to query for exact values of a key, or a range of values of a key with a sort order. What they don't allow you to do is search for *similar* keys, such as misspelled words. Such *fuzzy* querying requires different techniques.

To mention just one example, Lucene is able to search text for words within a certain edit distance (an edit distance of 1 means that one letter has been added, removed or replaced). [\[97\]](#)

As mentioned in [SSTables and LSM-trees](#), Lucene uses a SSTable-like structure for its term dictionary. This structure requires a small in-memory index which tells queries at which offset in the sorted file they need to look for a key. In LevelDB, this in-memory index is a sparse collection of some of the keys, but in Lucene, the in-memory index is a finite state automaton over the characters in the keys, similar to a *trie*. [\[98\]](#) This automaton can be transformed into a *Levenshtein automaton*, which supports efficient search for words within a given edit distance. [\[99\]](#)

Other fuzzy search techniques go in the direction of document classification and machine learning. Information retrieval books such as [\[100\]](#) go into more detail.

Keeping everything in memory

The data structures discussed so far in this chapter have all been answers to the limitations of disks. Compared to main memory, disks are awkward to deal with. Both with magnetic disks and SSDs, data on disk needs to be laid out carefully if you want good performance on reads and writes. However, we tolerate this awkwardness because disks have two significant advantages: they are durable (their contents are not lost if the power is turned off), and they have a lower cost per gigabyte than RAM.

As RAM becomes cheaper, the cost-per-gigabyte argument is eroded. Many datasets are simply not that big, so it's quite feasible to keep them entirely in memory, potentially distributed across several machines. This has led to the development of *in-memory databases*.

Some **in-memory key-value stores**, such as Memcached, are intended for caching use only, where it's acceptable for data to be lost if a machine is restarted. But other in-memory databases aim for durability, which can be achieved with special hardware (such as battery-powered RAM, which is still unusual), by writing a log of changes to disk, **by writing periodic snapshots to disk, or by replicating the in-memory state to other machines.**

When an in-memory database is restarted, it needs to reload its state, either from disk or over the network from a replica (unless special hardware is used). Despite writing to disk it's still an in-memory database, because the disk is merely used as an append-only log for durability, and reads are served entirely from memory. Writing to disk also has operational advantages: files on disk can easily be backed up, inspected and analyzed by external utilities.

Vendors such as VoltDB, MemSQL and Oracle TimesTen are in-memory databases with a relational model, and they claim that they can offer big performance improvements by removing all the overheads associated with managing on-disk data structures. [[101], [102]] RAMCloud is an open-source in-memory key-value store with durability (using a log-structured approach for the data in memory as well as the data on disk). [[103]]

Counter-intuitively, the performance advantage of in-memory databases is not due to the fact that they don't need to read from disk. Even a disk-based storage engine may never need to read from disk if you have enough memory, because the operating system caches recently used disk blocks in memory anyway. Rather, they can be faster because they can avoid the overheads of encoding in-memory data structures in a form that can be written to disk. [[104]]

Besides performance, another interesting area for in-memory databases is providing data models that are difficult to implement with disk-based indexes. For example, Redis offers a **database-like interface** to various data structures such as **priority queues and sets**. By keeping all data in memory, its implementation is comparatively simple.

Recent research indicates that an in-memory database architecture could be extended to support datasets larger than memory, without bringing back the overheads of a disk-centric architecture. [105] The so-called *anti-caching* approach works by evicting the least-recently used data from memory to disk when there is not enough memory, and loading it back into memory when it is accessed again in future. This is similar to what operating systems do with virtual memory and swap files, but the database can manage memory more efficiently than the OS, as it can work at the granularity of individual records rather than entire memory pages. This approach still requires indexes to fit entirely in memory (like the Bitcask example at the beginning of the chapter).

At present, in-memory databases are still a fairly new technology, but they are worth keeping an eye on in future.

Transaction Processing or Analytics?

In the early days of business data processing, a write to the database typically corresponded to a *commercial transaction* taking place: making a sale, placing an order with a supplier, paying an employee's salary, etc. As databases expanded into areas that didn't involve money changing hands, the term *transaction* nevertheless stuck, referring to a group of reads and writes that form a logical unit.

Note

A transaction needn't necessarily have ACID (atomicity, consistency, isolation and durability) properties. *Transaction processing* just means allowing clients to make low-latency reads and writes—as opposed to *batch processing* jobs, which only run periodically, for example once per day. We discuss ACID later, in [Link to Come].

Even though databases started being used for many different kinds of data—comments on blog posts, or actions in a game, or contacts in an address book, etc.—the basic access pattern remained similar to processing business transactions. An application typically looks up a small number of records by some key, using an index. Records are inserted or updated based on the user's input. Because these applications are interactive, the access pattern became known as *online transaction processing* (OLTP).

However, databases also started being increasingly used for *data analytics*, which has very different access patterns. Usually an analytic query needs to scan over a huge number of records, and calculates aggregate statistics (such as count, sum or average) rather than returning the raw data to the user. For example, if your data is a table of sales transactions, then analytic queries might be:

- What was the total revenue of each of our stores in January?
- How much more bananas than usual did we sell during our latest promotion?
- Which brand of baby food is most often purchased together with brand X diapers?

These queries are often written by business analysts, and feed into reports that help the management of a company make better decisions (*business intelligence*). In order to differentiate this pattern of using databases from transaction processing, it has been called *online analytic processing* (OLAP).^[106] ^[107] The difference between OLTP and OLAP is not always clear-cut, but some typical characteristics are listed in [Table 3-1](#).

Table 3-1. Comparing characteristics of transaction-processing versus analytic systems.

Property	Transaction processing systems (OLTP)	Analytic systems  AP
Main read pattern	Small number of records per query, fetched by key	Aggregate over large number of records
Main write pattern	Random-access, low-latency writes from user input	Bulk import (ETL) or event stream
Primarily used by	End user/customer, via web application	Internal analyst, for decision support
What data represents	Latest state of data (current point in time)	History of events that happened over time
Dataset size	Gigabytes to terabytes	Terabytes to petabytes

At first, the same databases were used for both transaction-processing and analytic queries. SQL turned out to be quite flexible in this regard: it works well for OLTP-type queries as well as OLAP-type queries. Nevertheless, in the late 1980s and early 1990s, there was a trend for companies to stop using their OLTP systems for analytics purposes, and to run the analytics on a separate database instead. This separate database was called a *data warehouse*.

Data warehousing

An enterprise may have dozens of different transaction-processing systems, for example systems powering the customer-facing website, controlling point of sale (checkout) systems in physical stores, *tracking inventory in warehouses*, *planning routes for vehicles*, managing suppliers, administering employees, etc. Each of these systems is complex and needs a team of people to maintain it, so the systems end up operating mostly autonomously from each other.

These OLTP systems are usually expected to be highly available and to process transactions with low latency, since they are often critical to the operation of the business. Database administrators therefore closely guard their OLTP databases. They are usually reluctant to let

business analysts run ad-hoc analytic queries on an OLTP database, since those queries are often expensive, scanning large parts of the dataset, which can harm the performance of concurrently executing transactions.

A *data warehouse*, by contrast, is a separate database that analysts can query to their heart's content, without affecting OLTP operations. [108] The data warehouse contains a read-only copy of the data in all the various OLTP systems in the company. Data is extracted from OLTP databases (using either a periodic data dump or a continuous stream of updates), transformed into an analysis-friendly schema, cleaned up, and then loaded into the data warehouse. This process of getting data into the warehouse is known as *Extract-Transform-Load* (ETL), and is illustrated in [Figure 3-7](#).

Data warehouses now exist in almost all large enterprises, but in small companies they are almost unheard of. This is probably because most small companies don't have so many different OLTP systems, and most small companies have a small amount of data—small enough that it can be queried in a conventional SQL database, or even analyzed in a spreadsheet. In a large company, a lot of heavy lifting is required to do something that is simple in a small company.

A big advantage of using a separate data warehouse, rather than querying OLTP systems directly for analytics, is that the data warehouse can be optimized for analytic access patterns. It turns out that the indexing algorithms discussed in the first half of this chapter work well for OLTP, but are not very good at answering analytic queries. In the rest of this chapter we will look at storage engines that are optimized for analytics instead.

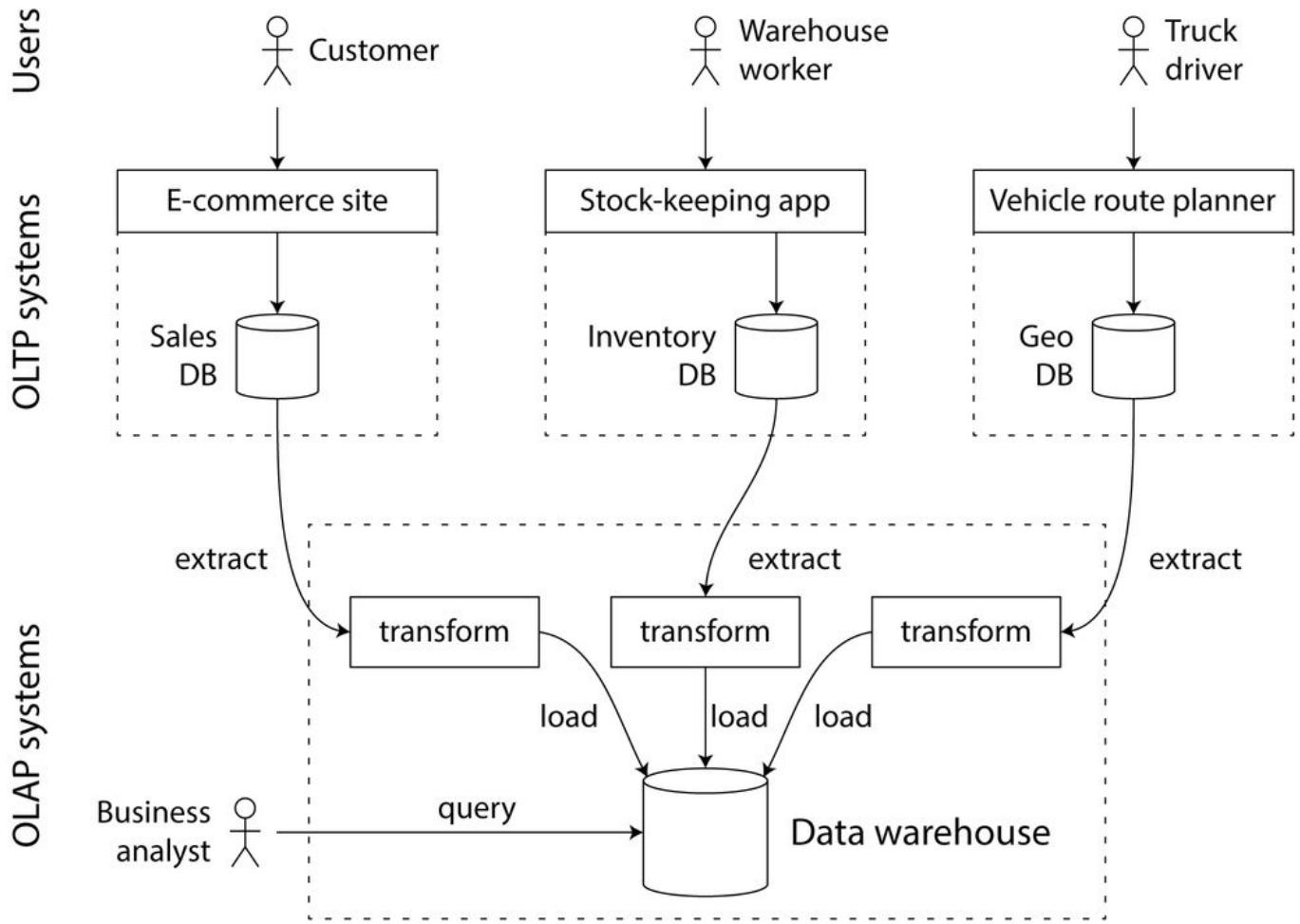


Figure 3-7. Simplified outline of ETL into a data warehouse.

The divergence between OLTP databases and data warehouses

The data model of a data warehouse is most commonly relational, because SQL is generally a good fit for analytic queries. There are many graphical data analysis tools which generate SQL queries, visualize the results, and allow analysts to explore the data (through operations such as *drill-down* and *slicing and dicing*).

On the surface, a data warehouse and a relational OLTP database look similar, because they both have a SQL query interface. However, the internals of the systems can look quite different, because they are optimized for very different query patterns. Many database vendors now focus on supporting either transaction processing or analytics workloads, but not both.

Some databases, such as Microsoft SQL Server and SAP HANA, have support for transaction processing and data warehousing in the same product. However, they are increasingly becoming two separate storage and query engines, which happen to be accessible through a common SQL interface. [[109], [110], [111]]

Data warehouse vendors such as Teradata, Vertica, SAP HANA and ParAccel typically sell their systems under expensive commercial licenses. Amazon RedShift is a hosted version of ParAccel. More recently, a plethora of open source SQL-on-Hadoop projects have emerged; they are young, but aiming to compete with commercial data warehouse systems. These include Apache Hive, AMPLab's Shark, Cloudera Impala, Hortonworks Stinger, Facebook Prestro, Apache Tajo and Apache Drill. [\[112\]](#) Some of them are based on ideas from Google's Dremel [\[113\]](#).

Stars and snowflakes: schemas for analytics

As explored in [Chapter 2](#), a wide range of different data models are used in the realm of transaction processing, depending on the needs of the application. On the other hand, in analytics, there is much less diversity of data models. Many data warehouses are used in a fairly formulaic style, known as a *star schema* (also known as *dimensional modeling*). [\[114\]](#)

An example schema in [Figure 3-8](#) shows a data warehouse that might be found at a grocery retailer. At the center of the schema is a so-called *fact table* (here, fact_sales). Each row of the fact table represents an event that occurred at a particular time (here, each row represents a product that was purchased by a customer). If we were analyzing website traffic rather than retail sales, each row may represent a page view or a click by a user.

Usually, facts are captured as individual events, because this allows maximum flexibility of analysis later on. However, this means that the fact table can become extremely large. A big enterprise like Apple, Walmart or eBay may have tens of petabytes of transaction history in its data warehouse, most of which is in fact tables. [\[115\]](#)

Some of the columns in the fact table are attributes, such as the price at which the product was sold, and the cost of buying it from the supplier (allowing the profit margin to be calculated). Other columns in the fact table are foreign key references to other tables, called *dimension* tables. As each row in the fact table represents an event, the dimensions represent the *who*, *what*, *where*, *when*, *how* and *why* of the event.

For example in [Figure 3-8](#), one of the dimensions is the product that was sold. Each row in the dim_product table represents one type of product that is for sale, including its stock-keeping unit (SKU), description, brand name, category, fat content, package size, etc. Each row in the fact_sales table uses a foreign key to indicate which product was sold in that particular transaction. (For simplicity, if the customer buys several different products at once, they are represented as separate rows in the fact table.)

Even date and time are often represented using dimension tables, because this allows additional information about dates (such as public holidays) to be encoded, allowing queries to differentiate between sales on holidays and non-holidays.

The name *star schema* comes from the fact that when the table relationships are visualized, the fact table is in the middle, surrounded by its foreign keys to dimension tables like rays of a star.

A variation of this template is known as *snowflake schema*, where dimensions are further broken down into sub-dimensions. For example, there could be separate dimension tables for brands and product categories, and each row in the dim_product table could reference the brand and category as foreign keys, rather than storing them as strings in the dim_product table. Snowflake schemas are more normalized than star schemas, but in this case, star schemas are often preferred because they are simpler for analysts to work with. [\[114\]](#)

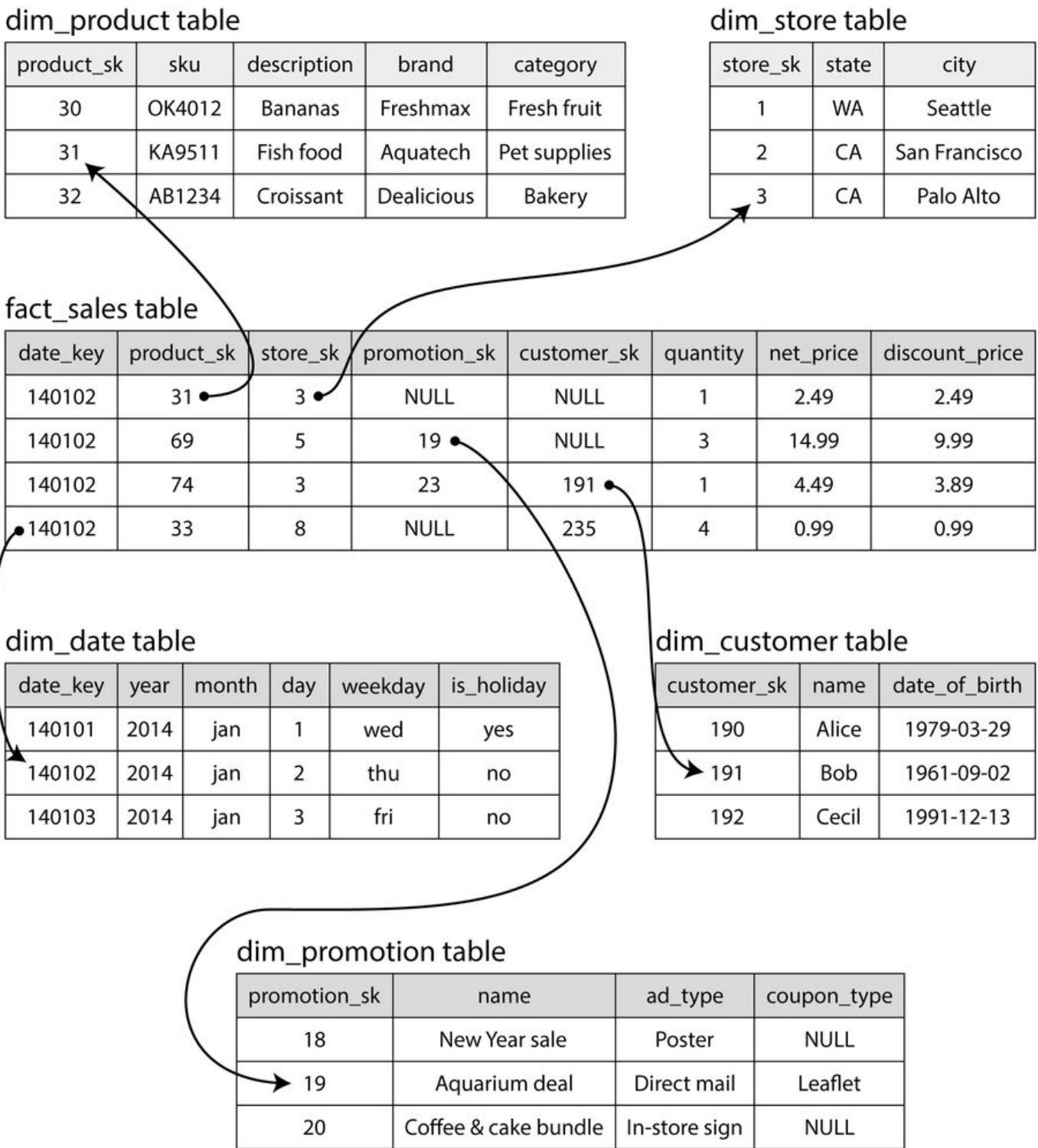


Figure 3-8. Example of a star schema for use in a data warehouse.

In a typical data warehouse, tables are often very wide: fact tables often have over 100 columns, sometimes several hundred. [111] Dimension tables can also be very wide, as they include all relevant metadata that may be relevant for analysis—for example, the `dim_store` table may include details of which services are offered at each store, whether it has an in-store bakery, the square footage, the date when the store was first opened, when it was last remodeled, how far it is from the nearest highway, etc.

Column-oriented storage

If you have trillions of rows and petabytes of data in your fact tables, storing and querying them efficiently becomes a challenging problem. Dimension tables are usually much smaller (millions of rows), so in this section we will concentrate primarily on storage of facts.

Although fact tables are often over 100 columns wide, a typical data warehouse query only accesses 4 or 5 of them at one time ("SELECT *" queries are rarely needed for analytics). [111] Take the query in [Example 3-1](#): it accesses a large number of rows (every occurrence of someone buying fruit or candy during the 2013 calendar year), but it only needs to access three columns of the fact_sales table: date_key, product_sk and quantity. All other columns are ignored by the query.

Example 3-1. Analyzing whether people are more inclined to buy fresh fruit or candy, depending on the day of the week.

SELECT

```
    dim_date.weekday, dim_product.category,  
    SUM(fact_sales.quantity) AS quantity_sold  
FROM fact_sales  
    JOIN dim_date      ON fact_sales.date_key      = dim_date.date_key  
    JOIN dim_product ON fact_sales.product_sk = dim_product.product_sk  
WHERE  
    dim_date.year = 2013 AND  
    dim_product.category IN ('Fresh fruit', 'Candy')  
GROUP BY  
    dim_date.weekday, dim_product.category;
```

How can we execute this query efficiently?

In most OLTP databases, storage is laid out in a *row-oriented* fashion: all the values from one row of a table are stored next to each other. Document databases are similar: an entire document is typically stored as one contiguous sequence of bytes. You can see this in the CSV example of [Figure 3-1](#).

In order to process a query like [Example 3-1](#), you may have indexes on fact_sales.date_key and/or fact_sales.product_sk, which tell the storage engine where to find all the sales for a particular date or for a particular product. But then, a row-oriented storage engine still needs to load all of those rows (each consisting of over 100 attributes) from disk into memory, parse them, and filter out those that don't meet the required conditions. That can take a long time.

The idea behind *column-oriented storage* is simple: don't store all the values from one row together, but store all the values from each *column* together instead. If each column is stored in a separate file, a query only needs to read and parse those columns that are used in that query, which can save a lot of work. This is illustrated in [Figure 3-9](#).

fact_sales table

date_key	product_sk	store_sk	promotion_sk	customer_sk	quantity	net_price	discount_price
140102	69	4	NULL	NULL	1	13.99	13.99
140102	69	5	19	NULL	3	14.99	9.99
140102	69	5	NULL	191	1	14.99	14.99
140102	74	3	23	202	5	0.99	0.89
140103	31	2	NULL	NULL	1	2.49	2.49
140103	31	3	NULL	NULL	3	14.99	9.99
140103	31	3	21	123	1	49.99	39.99
140103	31	8	NULL	233	1	0.99	0.99

Columnar storage layout:

date_key file contents:	140102, 140102, 140102, 140102, 140103, 140103, 140103, 140103
product_sk file contents:	69, 69, 69, 74, 31, 31, 31, 31
store_sk file contents:	4, 5, 5, 3, 2, 3, 3, 8
promotion_sk file contents:	NULL, 19, NULL, 23, NULL, NULL, 21, NULL
customer_sk file contents:	NULL, NULL, 191, 202, NULL, NULL, 123, 233
quantity file contents:	1, 3, 1, 5, 1, 3, 1, 1
net_price file contents:	13.99, 14.99, 14.99, 0.99, 2.49, 14.99, 49.99, 0.99
discount_price file contents:	13.99, 9.99, 14.99, 0.89, 2.49, 9.99, 39.99, 0.99

Figure 3-9. Storing relational data by column, rather than by row.

The column-oriented storage layout relies on each column containing the rows in the same order. Thus, if you need to reassemble an entire row, you can take the 23rd entry from each of the individual column files, and put them together to form the 23rd row of the table.

Note

Column storage is easiest to understand in a relational data model, but it applies equally to non-relational data. For example, Parquet [[\[116\]](#)] is a columnar storage format for a document data model, based on Google's Dremel [[\[113\]](#)].

Column compression

Besides only loading those columns from disk that are required for a query, we can further reduce the demands on disk throughput by compressing data. Fortunately, column-oriented storage often lends itself very well to compression.

In [Figure 3-9](#), see the sequences of values for each column: they often look quite repetitive, which is a good sign for compression. Depending on the data in the column, different compression techniques can be used. One technique that is particularly effective in data warehouses is a *bitmap encoding*, illustrated in [Figure 3-10](#).

Column values:

product_sk: 69 69 69 69 74 31 31 31 31 29 30 30 31 31 31 68 69 69

Bitmap for each possible value:

product_sk = 29: 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0

product_sk = 30: 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0

product_sk = 31: [0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0]

product_sk = 68: [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0]

product_sk = 69: [1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1]

product_sk = 74: [0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

Run-length encoding:

product_sk = 29: 9, 1 (9 zeros, 1 one, rest zeros)

product_sk = 30: 10, 2 (10 zeros, 2 ones, rest zeros)

product_sk = 31: 5, 4, 3, 3 (5 zeros, 4 ones, 3 zeros, 3 ones, rest zeros)

product $sk = 68$: 15, 1 (15 zeros, 1 one, rest zeros)

product_sk = 69: 0, 4, 12, 2 (0 zeros, 4 ones, 12 zeros, 2 ones)

product_sk = 74: 4, 1 (4 zeros, 1 one, rest zeros)

Figure 3-10. Compressed, bitmap-indexed storage of a single column.

Often, the number of distinct values in a column is small compared to the number of rows (for example, a retailer may have billions of sales transactions, but only 100,000 distinct products). We can now take a column with n distinct values, and turn it into n separate bitmaps: one bitmap for each distinct value, with one bit for each row. The bit is 1 if the row has that value, and 0 if not.

If n is very small (for example, a *country* column may have approximately 200 distinct values), those bitmaps can be stored with one bit per row. But if n is bigger, there will be a lot of zeros in most of the bitmaps (we say that they are *sparse*). In that case, the bitmaps can additionally be

run-length encoded, as shown at the bottom of [Figure 3-10](#). This can make the encoding of a column remarkably compact.

Bitmap indexes such as these are very well suited for the kind of queries that are common in a data warehouse:

WHERE product_sk IN (30, 68, 69):

Load the three bitmaps for product_sk = 30, product_sk = 68 and product_sk = 69, and calculate the bitwise *OR* of the three bitmaps, which can be done very efficiently.

WHERE product_sk = 31 AND store_sk = 3:

Load the bitmaps for product_sk = 31 and store_sk = 3, and calculate the bitwise *AND*. This works because the columns contain the rows in the same order, so the k th bit in one column's bitmap corresponds to the same row as the k th bit in another column's bitmap.

There are also various other compression schemes for different kinds of data, but we won't go into them in detail—see [\[117\]](#) for an overview.

Pipelined execution

For data warehouse queries that need to scan over millions of rows, a big bottleneck is the bandwidth for getting data from disk into memory. However, that is not the only bottleneck. Developers of analytical databases also worry about using CPU cycles efficiently: the bandwidth from main memory into the CPU cache, avoiding branch mispredictions and bubbles in the CPU instruction processing pipeline, and making use of single-instruction-multi-data (SIMD) instructions in modern CPUs. [\[118\]](#), [\[119\]](#)

Besides reducing the volume of data that needs to be loaded from disk, column-oriented storage layouts are also good for making efficient use of CPU cycles. For example, the query engine can take a chunk of compressed column data that fits comfortably in the CPU's L1 cache, and iterate through it in a tight loop. This is much faster than code that requires a lot of function calls and conditions for each record that is processed. Operators, such as the bitwise *AND* and *OR* described above, can be designed to operate on such chunks of compressed column data directly. This technique is known as *vectorized processing*. [\[117\]](#), [\[109\]](#)

Sort order in column storage

In a column store, it doesn't necessarily matter in which order the rows are stored. It's easiest to store them in the order in which they were inserted, since then inserting a new row just means appending to each of the column files. However, we can choose to impose an order, like we did with SSTables previously, and use that as an indexing mechanism.

Note that it wouldn't make sense to sort each column independently, because then we would no longer know which items in the columns belong to the same row. We can only reconstruct a row because we know that the k th item in one column belongs to the same row as the k th item in another column.

Rather, the data needs to be sorted an entire row at a time, even though it is stored by column. The administrator of the database can choose the columns by which the table should be sorted, using their knowledge of common queries. For example, if queries often target date ranges, such as the last month, it might make sense to make `date_key` the first sort key. Then the query optimizer can scan only the rows from the last month, which would be much faster than scanning all rows.

A second column can determine the sort order of any rows which have the same value in the first column. For example, if `date_key` is the first sort key in [Figure 3-9](#), it might make sense for `product_sk` to be the second sort key, so that all sales for the same product on the same day are grouped together in storage. That will help queries which need to group or filter sales by product within a certain date range.

Another advantage of sorted order is that it can help with compression of columns. If the primary sort column does not have many distinct values, then after sorting, it will have long sequences where the same value is repeated many times in a row. A simple run-length encoding, like we used for the bitmaps in [Figure 3-10](#), could compress that column down to a few kilobytes—even if the table has billions of rows.

That compression effect is strongest on the first sort key. The second and third sort key will be more jumbled up, and thus not have such long runs of repeated values. Columns further down the sorting priority appear in essentially random order, so they probably won't compress as well. But having the first few columns sorted is still a win overall.

Several different sort orders

A clever extension of this idea was introduced in C-Store, and adopted in the commercial data warehouse Vertica. [[120](#)], [[121](#)]) Different queries benefit from different sort orders, so why not store the same data sorted in *several different* ways? Data needs to be replicated to multiple machines anyway, so that you don't lose data if one machine fails. You might as well store that redundant data sorted in different ways, so that when you're processing a query, you can use the version that best fits the query pattern.

Having multiple sort orders in a column-oriented store is a bit similar to having multiple secondary indexes in a row-oriented store. But the big difference is that the row-oriented store

keeps every row in one place (in the heap file or a clustered index), and secondary indexes just contain pointers to the matching rows. In a column store, there normally aren't any pointers to data elsewhere, only columns containing values.

Writing to column-oriented storage

These optimizations make sense in data warehouses, because most of the load consists of large read-only queries run by analysts. Column-oriented storage, compression and sorting all help to make those read queries faster. However, they have the downside of making writes more difficult.

An update-in-place approach, like B-trees use, is not possible with compressed columns. If you wanted to insert a row in the middle of a sorted table, you would most likely have to rewrite all the column files. As rows are identified by their position within a column, the insertion has to update all columns consistently.

Fortunately, we have already seen a good solution earlier in this chapter: LSM-trees. All writes first go to an in-memory store, where they are added to a sorted structure, and prepared for writing to disk. It doesn't matter whether the in-memory store is row-oriented or column-oriented. When enough writes have accumulated, they are merged with the column files on disk, and written to new files in bulk. This is essentially what Vertica does. [\[121\]](#)

Queries need to examine both the column data on disk and the recent writes in memory, and combine the two. However, the query optimizer hides this distinction from the user. From an analyst's point of view, data that has been modified with inserts, updates or deletes is immediately reflected in subsequent queries.

Aggregation: Data cubes and materialized views

Not every data warehouse is necessarily a column store: traditional row-oriented databases and a few other architectures are also used. However, the market is moving rapidly in the direction of column stores because they offer a good trade-off between query flexibility and performance. [\[111\]](#)

Another aspect of data warehouses that is worth mentioning briefly is *materialized aggregates*. As discussed above, data warehouse queries often involve an aggregate function, such as COUNT, SUM, AVG, MIN or MAX in SQL. If the same aggregates are used by many different queries, it can be wasteful to crunch through the raw data every time. Why not cache some of the counts or sums that are used most often by queries?

One way of creating such a cache is a *materialized view*. In a relational data model, it is often defined like a standard (virtual) view: a table-like object whose contents are the results of some query. The difference is that a materialized view is an actual copy of the query results, written to disk, whereas a virtual view is just a shortcut for writing queries. When you read from a virtual view, the SQL engine expands it into the view's underlying query on the fly, and then processes the expanded query.

When the underlying data changes, a materialized view needs to be updated, because it is a denormalized copy of the data. The database can do that automatically, but such updates make writes more expensive, which is why materialized views are not often used in OLTP databases. In read-heavy data warehouses they can make more sense (whether or not they actually improve read performance depends on the individual case).

A common special case of a materialized view is known as a *data cube* or *OLAP cube*. [\[122\]](#) It is a grid of aggregates grouped by different dimensions. [Figure 3-11](#) shows an example.

The diagram illustrates a data cube with two dimensions of aggregation. The vertical axis is labeled *date_key* and the horizontal axis is labeled *product_sk*.

	32	33	34	35	total
140101	149.60	31.01	84.58	28.18	40710.53
140102	132.18	19.78	82.91	10.96	73091.28
140103	196.75	0.00	12.52	64.67	54688.10
140104	178.36	9.98	88.75	56.16	95121.09
.....
total	14967.09	5910.43	7328.85	6885.39	lots

Three SQL queries are shown, each pointing to a specific cell in the grid:

- `SELECT SUM(net_price) FROM fact_sales WHERE date_key = 140101 AND product_sk = 32` points to the cell containing 149.60.
- `SELECT SUM(net_price) FROM fact_sales WHERE date_key = 140101` points to the cell containing 40710.53.
- `SELECT SUM(net_price) FROM fact_sales WHERE product_sk = 32` points to the cell containing 14967.09.

Figure 3-11. Two dimensions of a data cube, aggregating data by summing.

Imagine for now that each fact has foreign keys to only two dimension tables—in [Figure 3-11](#), these are *date* and *product*. You can now draw a two-dimensional table, with dates along one axis, and products along the other. Each cell contains the aggregate (e.g. SUM) of an attribute (e.g. net_price) of all facts with that date-product combination. Then you can apply the same aggregate along each row or column, and get a summary that has been reduced by one dimension (the sales by product regardless of date, or the sales by date regardless of product).

In general, facts often have more than two dimensions. In [Figure 3-8](#) there are five dimensions: date, product, store, promotion and customer. It's a lot harder to imagine what a five-dimensional hypercube would look like, but the principle remains the same: each cell contains the sales for a particular date-product-store-promotion-customer combination. These values can then repeatedly be summarized along each of the dimensions.

The advantage of a materialized data cube is that certain queries become very fast, because they have effectively been pre-computed. For example, if you want to know the total sales per store yesterday, you just need to look at the totals along the appropriate dimension—no need to scan millions of rows.

The disadvantage is that it doesn't have the same flexibility as querying the raw data. For example, there is no way of calculating which proportion of sales comes from items that cost more than \$100, because the price isn't one of the dimensions. Most data warehouses therefore try to keep as much raw data as possible, and use aggregates such as data cubes only as a performance boost for certain queries.

Summary

In this chapter we tried to get to the bottom of the questions of data storage and retrieval. What happens when you store some data in a database, and what does the database do when you query for the data again later?

On a high level, we saw that storage engines fall into two broad categories: those optimized for transaction processing (OLTP), and those optimized for analytics. There are big differences between the access patterns in those use cases:

- OLTP systems are typically user-facing, which means that they may see a huge volume of requests. In order to handle the load, applications usually only touch a small number of records in each query. The application requests records using some kind of key, and the storage engine uses an index to find the data for the requested key. Disk seek time is often the bottleneck here.
- Data warehouses and similar analytic systems are less well-known, because they are primarily used by business analysts, not by end users. They handle a much lower volume of queries than OLTP systems, but each query is typically very demanding, requiring many millions of records to be scanned in a short time. Disk bandwidth (not seek time) is often the bottleneck here, and column-oriented storage is an increasingly popular solution for this kind of workload.

On the OLTP side, we saw storage engines from two main schools of thought:

- The log-structured school, which only permits appending to files and deleting obsolete files, but never updates a file that has been written. Bitcask, SSTables, LSM-Trees, LevelDB, Cassandra, HBase, Lucene and others belong to this group.
- The update-in-place school, which treats the disk as fixed-size blocks which can be overwritten. B-trees are the biggest example of this philosophy, being used in all major relational databases and also many non-relational ones.

Log-structured storage engines are a comparatively recent development. Their key idea is that they systematically turn random-access writes into sequential writes on disk, which enables higher write throughput due to the performance characteristics of hard drives and SSDs.

Finishing off the OLTP side, we did a brief tour through some more complicated indexing structures, and databases that are optimized for keeping all data in memory.

We then took a detour from the internals of storage engines, to look at the high-level architecture of a typical data warehouse. This background illustrated why analytic workloads are so different from OLTP: when your queries require sequentially scanning across a large number of rows, indexes are much less relevant. Instead it becomes important to encode data very compactly, to minimize the amount of data that the query needs to read from disk. We discussed how column-oriented storage helps achieve this goal.

As an application developer, if you're armed with this knowledge about the internals of storage engines, you are in a much better position to know which tool is best suited for your particular application. If you need to adjust a database's tuning parameters, this understanding allows you to imagine what effect a higher or a lower value may have.

Although this chapter couldn't make you an expert in tuning any one particular storage engine, it has hopefully equipped you with enough vocabulary and ideas that you can make sense of the documentation for the database of your choice.

^[71] The word *log* is often used to refer to application logs, where an application outputs text that describes what's happening. In this book, *log* is used in the more general sense: an append-only sequence of records. It doesn't have to be human-readable, it might be binary and intended only for other programs to read.

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Part II. Systems of Record

On a high level, systems that store and process data can be grouped into two broad categories:

Systems of record

A system of record, also known as *source of truth*, holds the authoritative version of your data. When new data comes in, e.g. as user input, it is first written here. Each fact is represented exactly once (the representation is typically *normalized*).

Derived data systems

If you lose derived data, you can in principle re-create it by processing some other data that you have stored. A classic example is a cache. Indexes, statistics and analytics fall in this category too. Technically speaking, derived data is *redundant*, in the sense that it duplicates existing information. However, it is often essential for getting good performance on read queries. It is often *denormalized*. You can derive several different datasets from a single source of truth, and this allows you to look at the data from different “points of view”.

Often it’s not clear whether a system falls in one category or the other. However, when thinking about the dataflow in a system, it can be very helpful to make this distinction. By being conscious of what constitutes your system of record, and which datasets are derived from it, you can bring clarity to an otherwise confusing system architecture.

In this [Part II](#) of this book, we discuss algorithms and techniques that are most applicable to systems of record. Later, in (to come), we will focus on derived data. The two are not mutually exclusive, but they have different styles of thinking, so it’s worth making the distinction explicit.

Chapter 4. Replication

The major difference between a thing that might go wrong and a thing that cannot possibly go wrong is that when a thing that cannot possibly go wrong goes wrong it usually turns out to be impossible to get at or repair.

— Douglas Adams *Mostly Harmless* (1992)

In [Chapter 3](#) we discussed different ways of storing data on a single machine, on disk and in memory. In this chapter we move up a level and ask: what happens if multiple machines are involved in storage and retrieval of data?

There are various reasons why you might want to distribute a database across multiple machines:

Scalability

If your data volume or your query throughput grows bigger than a single machine can handle, you can potentially spread the load across multiple machines.

Fault tolerance/high availability

If your application needs to continue working, even if one machine (or several machines, or an entire datacenter) goes down, you can use multiple machines to give you redundancy. When one fails, another one can take over.

Latency

If you have users around the world, you might want to have servers at various locations worldwide, so that users can be served from a datacenter that is geographically close to them. That avoids the user having to wait for network packets to travel halfway around the world.

Shared-Nothing Architectures

If all you need is to scale to higher load, the simplest approach is to buy a more powerful machine. Many CPUs, many RAM chips and many disks can be joined together under one operating system, and a fast interconnect allows any CPU to access any part of memory or disk. This is called a *shared-memory architecture*, and it allows all the components to be treated as a single machine.^[123]

The problem with a shared-memory approach is that the cost is super-linear: a machine with twice as many CPUs, twice as much RAM and disk typically costs significantly more than twice as much. Due to bottlenecks, a machine twice the size cannot necessarily handle twice the load.

A shared-memory architecture may offer limited fault tolerance: high-end machines have hot-swappable components (you can replace disks, memory modules and even CPUs without shutting down the machine) but it is definitely limited to a single geographic location.

Another approach is the *shared-disk architecture*, which uses several machines with independent CPUs and RAM, but stores data on an array of disks that is shared between the machines, connected via a fast network.^[124] This architecture is used for some data warehousing workloads, but contention and the overhead of locking limit the scalability of the shared-disk approach.^[125]

By contrast, *shared-nothing architectures* ^[126] have gained a lot of popularity. In this approach, each machine or virtual machine running the database software is called a *node*. Each node uses its CPUs, RAM and disks independently. Any coordination between nodes is done at the software level, using a conventional network.

No special hardware is required by a shared-nothing system, so you can use whatever machines have the best price/performance ratio. You can potentially distribute data across multiple geographic regions, and thus reduce latency for users and potentially be able to survive the loss of an entire datacenter. With ‘cloud’ deployments of virtual machines, you don’t need to be operating at Google scale: even for small companies, a multi-region distributed architecture is now feasible.

In this book, we focus on shared-nothing architectures—not because they are necessarily the best choice for every use case, but rather because they require the most caution from you, the application developer. If your data is distributed across multiple nodes, you need to be aware of the constraints and trade-offs that occur in such a distributed system—the database cannot magically hide these from you.

While a distributed shared-nothing architecture has many advantages, it usually also incurs additional complexity for applications, and sometimes limits the expressiveness of the data models you can use. On the other hand, it can be very powerful. The next few chapters go into details of the issues that arise when data is distributed.

Replication vs. partitioning

There are two common ways how data is distributed across multiple nodes:

Replication

Keeping a copy of the same data on several different nodes, potentially in different locations. Replication provides redundancy: if some nodes are unavailable, the data can still be served from the remaining nodes. Replication can also help improve performance.

Partitioning

Splitting a big database into smaller subsets called *partitions*, so that different partitions can be assigned to different nodes (also known as *sharding*).

These are separate mechanisms, but they often go hand in hand, as illustrated in [Figure 4-1](#).

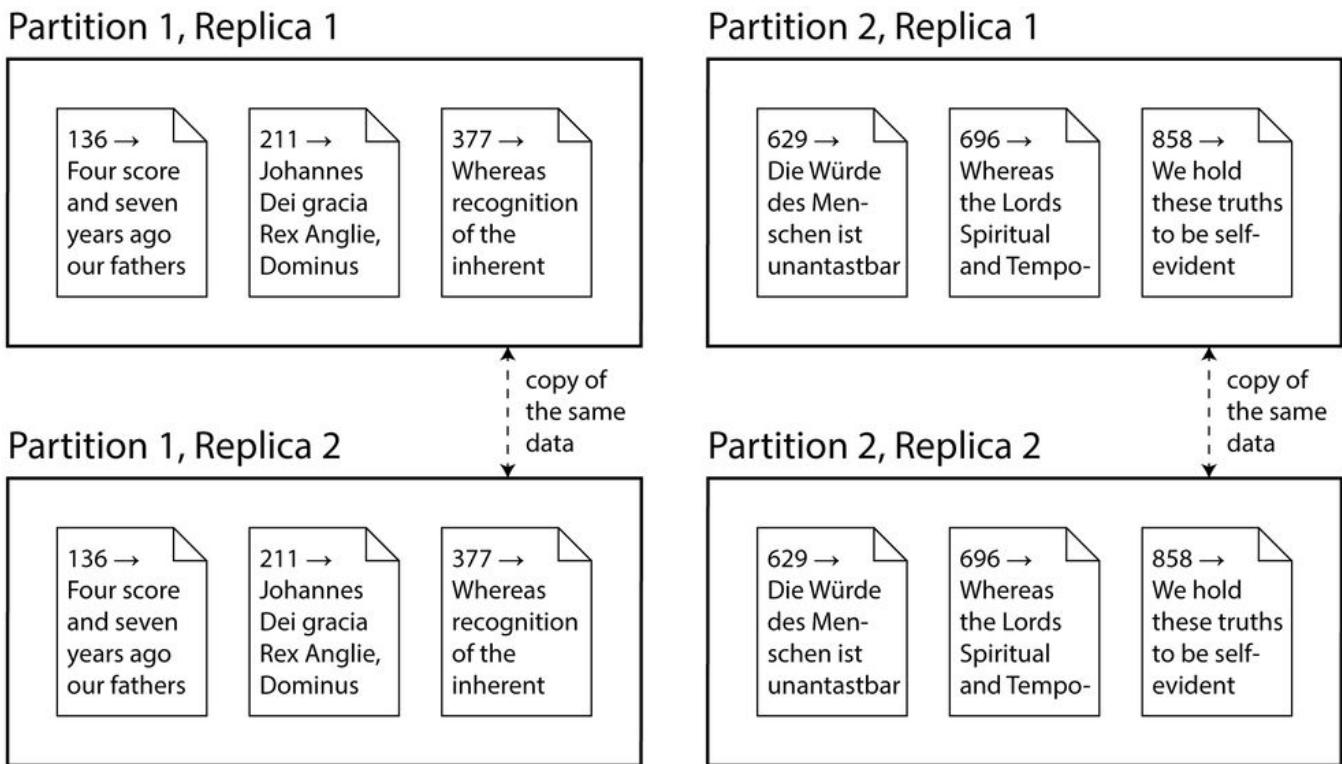


Figure 4-1. A database split into two partitions, with two replicas per partition.

In this chapter we will only discuss replication, and assume that your dataset is small enough that each node can hold a copy of the entire dataset. We will return to partitioning in [Link to Come].

Replication of databases is an old topic—the principles haven’t changed much since they were studied in the 1970s [[\[127\]](#)], because the fundamental constraints of networks have remained the same. However, outside of research, many developers continued to assume for a long time that a database consisted of just one node. Mainstream use of distributed databases is more recent. Since many application developers are new to this area, there has been a lot of misunderstanding around issues such as *eventual consistency* (discussed in [Problems With Replication Lag](#)).

In this chapter, we will look at a few different techniques for replication. Later, in (to come), we will discuss various kinds of fault that can occur in a replicated data system, and how to deal with them.

Leaders and Followers

Each node that stores a copy of the database is called a *replica*. With multiple replicas, a question inevitably arises: how do we ensure that all the data ends up on all the replicas?

Every write to the database needs to be processed by every replica, otherwise the replicas would no longer contain the same data. The most common solution for this is called *leader-based replication* (also known as *active/passive* or *master-slave replication*) and is illustrated in [Figure 4-2](#). It works as follows:

1. One of the replicas is designated the *leader* (also known as *master* or *primary*). When clients want to write to the database, they must send their query to the leader, which first writes the new data to its local storage.
2. The other replicas are known as *followers* (*read replicas*, *slaves*, or *hot standbys*^[128]). Whenever the leader writes new data to its local storage, it also sends the data change to all of its followers. Each follower takes the stream of changes from the leader and updates its local copy of the database accordingly.
3. When a client wants to read from the database, it can query either the leader or any of the followers. However, writes are only accepted on the leader (the followers are read-only from the client's point of view).

This mode of replication is a built-in feature of many relational databases, such as PostgreSQL (since version 9.0), MySQL, Oracle Data Guard [\[129\]](#), and SQL Server's AlwaysOn Availability Groups [\[130\]](#). It is also used in some non-relational databases, including MongoDB, RethinkDB and Espresso [\[131\]](#). Finally, leader-based replication is not restricted to only databases: distributed message brokers such as Kafka [\[132\]](#) and RabbitMQ highly available queues [\[133\]](#) also use it. Some network file systems and replicated block devices such as DRBD are similar.

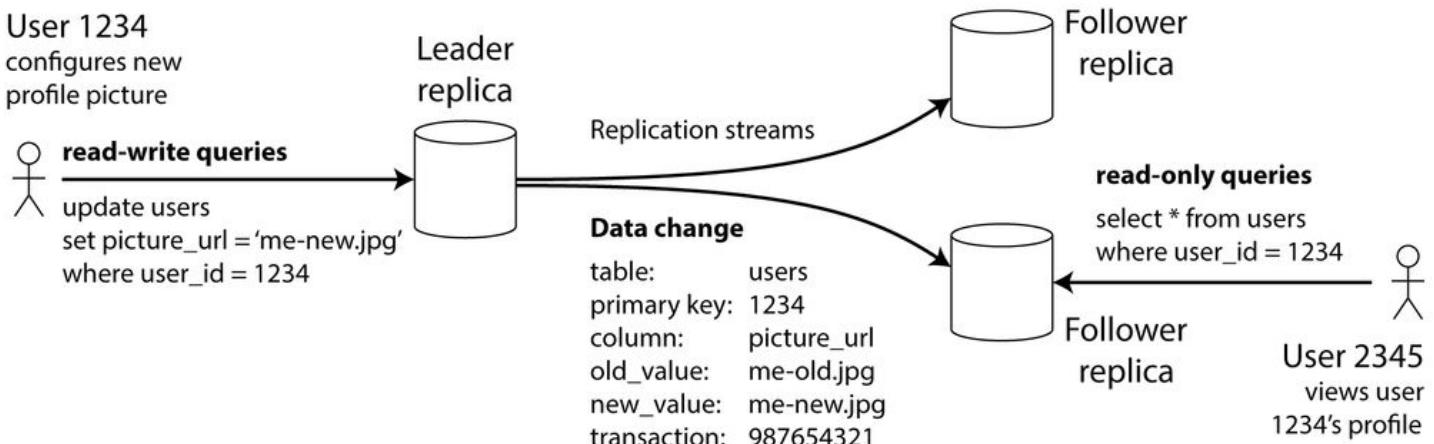


Figure 4-2. Leader-based (master-slave) replication.

Synchronous vs. asynchronous replication

An important detail of a replicated system is whether the replication happens *synchronously* or *asynchronously*. (In relational databases, this is often a configurable option; other systems are often hard-coded to be either one or the other.)

Think about what happens in [Figure 4-2](#), where the user of a website updates their profile image. At some point in time, the client sends the update query to the leader; shortly afterwards, it is received by the leader. At some point, the leader forwards the data change to the followers. Eventually, the leader notifies the client that the update was successful.

[Figure 4-3](#) shows the communication between various components of the system: the user's client, the leader, and two followers. Time flows from left to right. A request or response message is shown as a thick arrow.

In the example of [Figure 4-3](#), the replication to follower 1 is *synchronous*: the leader waits until follower 1 has confirmed that it received the write before reporting success to the user. The replication to follower 2 is *asynchronous*: the leader sends the message, but doesn't wait for a response from the follower.

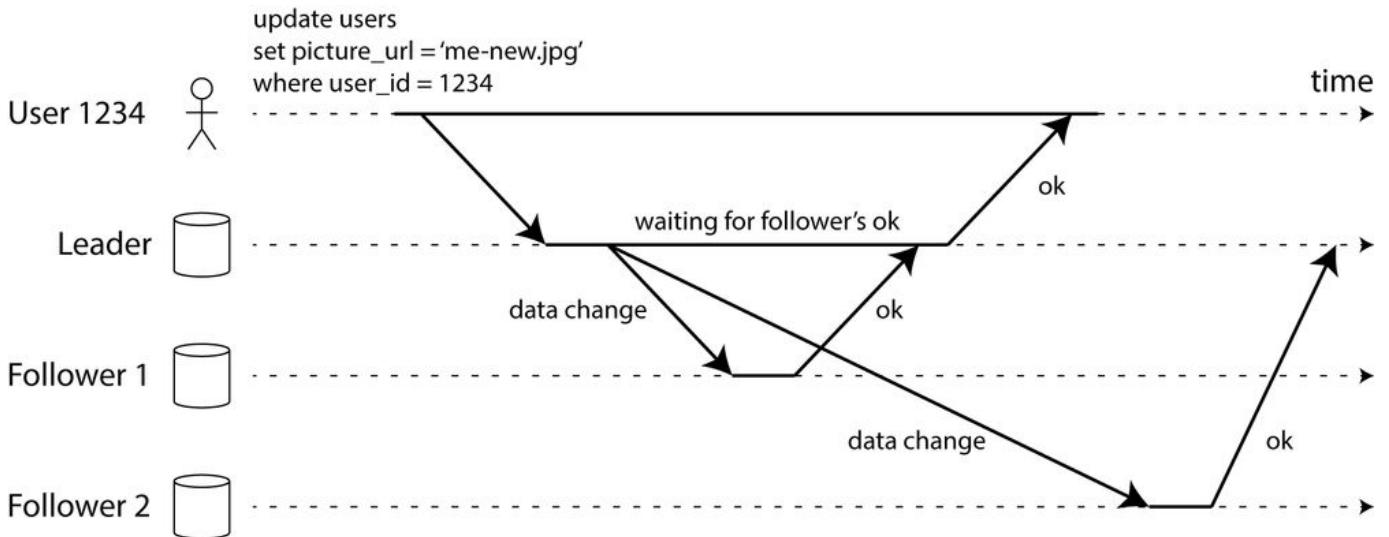


Figure 4-3. Leader-based replication with one synchronous and one asynchronous follower.

The diagram shows that there is a substantial delay before follower 2 processes the message. Normally, replication is quite fast: most database systems apply changes to followers in less than a second. However, there is no guarantee for how long it might take. There are circumstances when followers might fall behind the leader by several minutes or more, for example if a follower is recovering from a failure, if the system is operating near maximum capacity, or if there are network problems between the nodes.

The advantage of synchronous replication is that the follower is guaranteed to have an up-to-date copy of the data that is consistent with the leader. If the leader suddenly fails, we can be sure that the data is still available on the follower. The disadvantage is that if the synchronous follower doesn't respond (because it has crashed, or there is a network fault, or for any other reason), the write cannot be processed. The leader must block all writes and wait until the synchronous replica is available again.

For that reason, it is impractical for all followers to be synchronous: any one node outage would cause the whole system to grind to a halt. In practice, if you enable synchronous replication on a database, it usually means that *one* of the followers is synchronous, and the others are asynchronous. If the synchronous follower becomes unavailable or goes slow, one of the asynchronous followers is made synchronous. This guarantees that you have an up-to-date copy of the data on at least two nodes: the leader and one synchronous follower. This configuration is sometimes also called *semi-synchronous*.

Often, leader-based replication is configured to be completely asynchronous. In this case, if the leader fails and is not recoverable, any writes that have not yet been replicated to followers are lost. This means that a write is not guaranteed to be durable, even if it has been confirmed to the client. However, a fully asynchronous configuration has the advantage that the leader can continue processing writes, even if all of its followers have fallen behind.

Weakening durability may sound like a bad trade-off, but asynchronous replication is almost inevitable if there are many followers, or if they are geographically distributed. We will return to this in [Problems With Replication Lag](#).

Setting up new followers

From time to time, you need to set up new followers—perhaps to increase the number of replicas, or to replace failed nodes. How do you ensure that the new follower has an accurate copy of the leader’s data?

Simply copying data files from one node to another is typically not sufficient: clients are constantly writing to the database, and the data is always in flux, so a standard file copy would see different parts of the database at different points in time. The result might not make any sense.

You could make the files on disk consistent by locking the database (making it unavailable for writes), but that would go against our goal of high availability. Fortunately, setting up a follower can usually be done without downtime. Conceptually, the process looks like this:

1. Take a consistent snapshot of the leader’s database at some point in time—if possible, without taking a lock on the entire database. Most databases have this feature, as it is also required for backups. In some cases, third-party tools are needed, such as `innobackupex` for MySQL [[\[134\]](#)].
2. Copy the snapshot to the new follower node.
3. The follower connects to the leader, and requests all data changes that happened since the snapshot was taken. This requires that the snapshot is associated with an exact position in the leader’s change stream. That position has various different names: for example, PostgreSQL calls it *log sequence number*, and MySQL calls it *binlog coordinates*.
4. When the follower has processed the backlog of data changes since the snapshot, we say it has *caught up*. It can now continue to process data changes from the leader as they happen.

The practical steps of setting up a follower vary significantly by database. In some systems, the process is fully automated, whereas in others, it can be a somewhat arcane multi-step workflow that needs to be manually performed by an administrator.

Handling node outages: failover

Any node in the system can go down, and our goal is to keep the system as a whole running nevertheless. How do you achieve high availability with leader-based replication?

Follower failure

On its local disk, each follower keeps a log of the data changes it has received from the leader. If a follower crashes and is restarted, or if the network between the leader and the follower is temporarily interrupted, the follower can recover quite easily: from its log, it knows the last transaction that was processed before the fault occurred. Thus the follower can connect to the leader, and request all data changes that occurred during the time when the follower was disconnected. When it has applied these changes, it has caught up to the leader, and can continue receiving a stream of data changes as before.

Leader failure

Handling a failure of the leader is trickier: one of the followers needs to be promoted to be the new leader, clients need to be reconfigured to send their writes to the new leader, and the other followers need to start consuming data changes from the new leader. This process is called *failover*.

Failover can happen manually (an administrator is notified that the leader has failed, and takes the necessary steps to make a new leader), or automatically. An automatic failover process usually consists of the following steps:

1. *Determining that the leader has failed.* There are many things that could potentially go wrong: crashes, power outages, network issues and many more. There is no foolproof way of detecting what has gone wrong, so most systems simply use a timeout: nodes frequently bounce messages back and forth between each other, and if a node doesn't respond for some period of time—say, 30 seconds—it is assumed to be dead.
2. *Choosing a new leader.* This could either be an election process (where the leader is chosen by a majority of the remaining replicas), or a new leader could be appointed by a previously-elected *controller node*. The best candidate for leadership is usually the replica with the most up-to-date data changes from the old leader (to minimize any data loss). Getting all the nodes to agree on a new leader is a difficult algorithmic problem, discussed in detail in (to come).
3. *Reconfiguring the system to use the new leader.* Clients now need to send their write requests to the new leader (we discuss this in (to come)). If the old leader comes back, it might still believe that it is leader, not realizing that the other replicas have forced it to step down. The system needs to ensure that the old leader becomes a follower and recognizes the new leader.

Failover is fraught with things that can go wrong:

- If asynchronous replication is used, the new leader may not have received all writes from the old leader before it failed. If the former leader rejoins the cluster after a new leader has been chosen, what should happen to those writes? The new leader may have received conflicting writes in the meantime. The most common solution is for the old leader's unreplicated writes to simply be discarded, which may violate clients' durability expectations.
- Discarding writes is especially dangerous if other storage systems outside of the database need to be coordinated with the database contents. For example, in one incident at GitHub [135], an out-of-date MySQL follower was promoted to leader. The database used an auto-incrementing counter to assign primary keys to new rows, but because the new leader's counter lagged behind the old leader, it re-used some primary keys that were previously assigned by the old leader. These primary keys were also used in a Redis store, so the reuse of primary keys resulted in inconsistency between MySQL and Redis, which caused some private data to be disclosed to the wrong users.
- In certain network faults, it could happen that two nodes both believe that they are the leader. This is a dangerous situation, as it may result in corrupted data. As a safety catch, some systems have a mechanism to shut down one node if two leaders are detected.[136] However, if you're unlucky, you can end up with both nodes being shut down. [137]
- What is the right timeout before the leader is declared dead? A longer timeout means a longer time to recovery in the case where the leader fails. However, if the timeout is too short, there could be unnecessary failovers. For example, a temporary load spike could cause a node's response time to increase above the timeout, or a network glitch could cause delayed packets. And if the system is already struggling with high load or network problems, an unnecessary failover is likely to make the situation worse, not better.

There are no easy solutions to these problems. For this reason, some operations teams prefer to perform failover manually, even if the software supports automatic failover.

Implementation of replication streams

How does leader-based replication work under the hood? Several different replication methods are used in practice, so let's look at each one briefly.

Statement-based replication

In the simplest case, the leader logs every write query that it executes, and sends that query log to its followers. For a relational database, this means that every *insert*, *update* or *delete* statement is forwarded to followers, and each follower parses and executes that SQL statement as if it had been received from a client.

Although this may sound reasonable, there are various ways in which this approach to replication can break down:

- Any query that calls a non-deterministic function, for example `NOW()` to get the current date and time, or `RAND()` to get a random number, is likely to generate a different value on each replica.
- If queries use an auto-incrementing column, or if they depend on the existing data in the database (e.g. `UPDATE ... WHERE <some condition>`), they must be executed in exactly the same order on each replica, otherwise they may have a different effect. This can be limiting when there are multiple concurrently executing transactions.
- Queries that cause non-SQL functionality to be invoked (e.g. triggers, stored procedures, user-defined functions) may have side-effects, and those effects may be different on each replica.

It is possible to work around those issues—for example, the leader can replace any non-deterministic function calls with a fixed return value when the statement is logged, so that the followers all get the same value. However, because there are so many edge cases, other replication methods are now generally preferred.

Statement-based replication was used in MySQL before version 5.1. It is still sometimes used today, as it is quite compact, but by default MySQL now switches to row-based replication (see below) if there is any nondeterminism in a query.

Write-ahead log (WAL) shipping

In [Chapter 3](#) we discussed how storage engines represent data on disk, and we found that usually every write is appended to a log:

- In the case of a log-structured storage engine, this log is the main place for storage. Log segments are compacted and garbage-collected in the background.
- In the case of a B-tree, which overwrites individual disk blocks, every modification is first written to a write-ahead log (WAL) so that the index can be restored to a consistent state after a crash.

See [Update-in-place vs. append-only logging](#) for details. In either case, the log is an append-only sequence of bytes containing all writes to the database. We can use the exact same log to build a replica on another node: besides writing the log to disk, the leader also sends it across the network to its followers. When the follower processes this log, it builds a copy of the exact same data structures as found on the leader.

This method of replication works well, and is used in PostgreSQL and Oracle, among others. [\[138\]](#) The main disadvantage is that the log describes the data on a very low level: a WAL contains details of which bytes were changed in which disk block. This makes replication closely

coupled to the storage engine. If the database changes its storage format from one version to another, it is typically not possible to run different versions of the database software on the leader and the followers.

Logical log replication

An alternative is to use different log formats for replication and for the storage engine. This allows the replication log to be decoupled from the storage engine internals. This is sometimes called a *logical log*, to distinguish it from the storage engine's (*physical*) data representation.

A logical log for a relational database is usually a sequence of records describing writes to database tables at the granularity of a row:

- For an inserted row, the new values of all columns;
- For an updated row, the old and new values of all columns;
- For a deleted row, the old values of all columns.

A transaction that modifies several rows generates several such log records, followed by a record indicating that the transaction was committed.

MySQL's binlog (when configured to use row-based replication) uses this approach. [\[139\]](#) Backwards compatibility allows the follower to use a newer database software version or different storage engine to the leader. This allows for software upgrades without downtime: the node with the new software version can start as a follower, then be promoted to leader, and finally the node with the old software version can be shut down. Zero-downtime upgrades can be a big operational advantage.

A logical log format is also easier for external applications to parse. This is useful if you want to send the contents of a database to an external system, such as a data warehouse for offline analysis, or for building custom indexes and caches. [\[140\]](#) This is called *change capture*, and we will return to it in (to come).

Trigger-based replication

The replication approaches described so far are implemented by the database system, without involving any application code. In many cases, that's what you want—but there are some circumstances when more flexibility is needed. For example, if you want to only replicate a subset of the data, or want to replicate from one kind of database to another, or if you need

conflict resolution logic (see [Beyond leader-based replication](#)), then you may need to move replication up to the application layer.

Some tools, such as Oracle GoldenGate [[\[141\]](#)], can do this by reading the database log. An alternative is to use features that are available in many relational databases: *triggers* and *stored procedures*.

A trigger lets you register custom application code in a database system so that it is automatically executed when a data change (write query) occurs. The trigger has the opportunity to log this change into a separate table, from where it can be read by an external process. That external process can then apply any necessary application logic, and replicate the data change to another system. Databus for Oracle [[\[142\]](#)] and Bucardo for Postgres [[\[143\]](#)] work like this.

Trigger-based replication typically has greater overheads than other replication methods, but it can nevertheless be useful due to its flexibility.

Problems With Replication Lag

Being able to tolerate node failures is just one reason for wanting replication. As mentioned before, other reasons are scalability (processing more requests than a single machine can handle) and latency (placing replicas geographically closer to users).

Leader-based replication requires all writes to go through a single node, but read-only queries can go to any replica. For workloads that consist mostly of reads, and only a small percentage of writes (a common pattern on the web), there is an attractive option: create many followers, and distribute the read requests across those followers. This removes load from the leader, and allows reads to be served by a nearby replica.

In this *read-scaling* architecture, you can increase the capacity for serving read-only requests simply by adding more followers. However, this approach only realistically works with asynchronous replication—if you tried to synchronously replicate to all followers, a single node failure or network outage would make the entire system unavailable for writing. And the more nodes you have, the likelier that one is down, so a fully synchronous configuration would be a very unreliable.

Unfortunately, if an application reads from *asynchronous* followers, it may see outdated information if the follower has fallen behind. This leads to apparent *inconsistencies* in the database: if you run the same query on the leader and a follower at the same time, you may get different results, because not all writes have been reflected in the follower. This inconsistency is just a temporary state—if you stop writing to the database and wait a while, the followers will

eventually catch up and become consistent with the leader. For that reason, this effect is known as *eventual consistency*.^[144] ^[145], ^[146]

The term *eventually* is deliberately vague: in general, there is no limit how far a replica can fall behind. In normal operation, the delay between a write happening on the leader and being reflected on a follower—the *replication lag*—may be only a fraction of a second, and not noticeable in practice. However, if the system is operating near capacity or if there is a problem in the network, the lag can easily increase to several seconds or minutes.

When the lag is so large, the inconsistencies it introduces are not just a theoretical issue, but a real problem for applications. In this section we will highlight three examples of problems that are likely to occur when there is replication lag, and outline some approaches to solving them.

Reading your own writes

Many applications let the user submit some data, and then view what they have submitted. This might be a record in a customer database, or a comment on a discussion thread, or something of that sort. When new data is submitted, it must be sent to the leader, but when the user views the data, it can be read from a follower. This is especially appropriate if data is frequently viewed, but only occasionally written.

With asynchronous replication, there is a problem, illustrated in [Figure 4-4](#): if the user views the data shortly after making a write, the new data may have not yet reached the replica. To the user, it looks as though the data they submitted was lost, so they will be understandably unhappy.

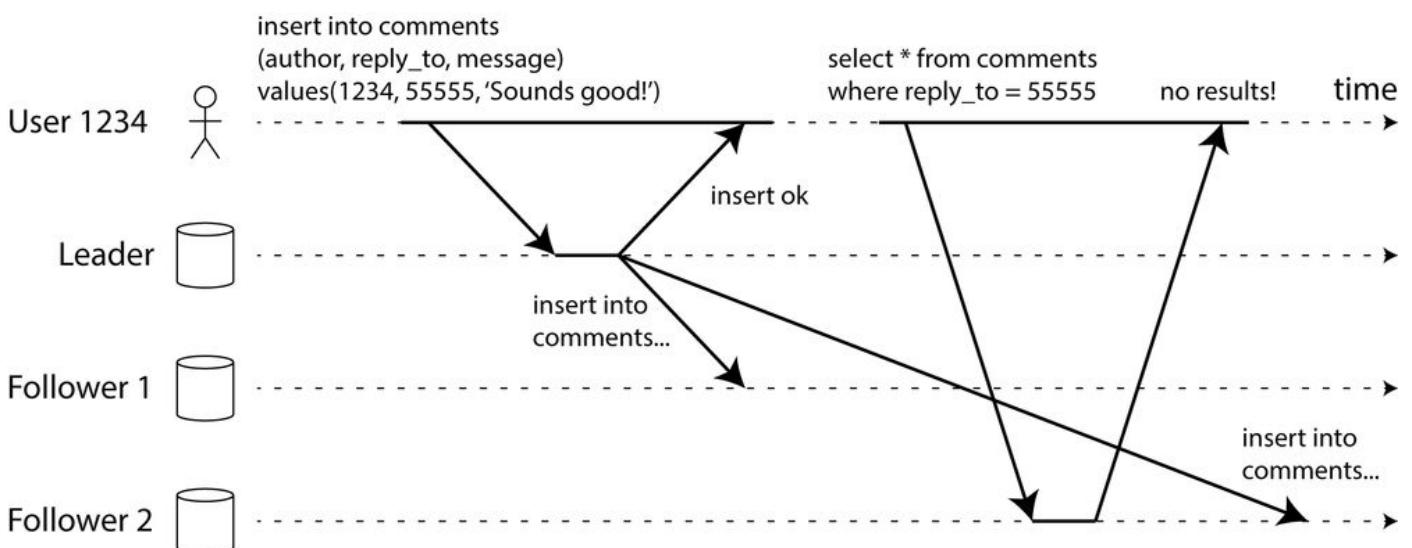


Figure 4-4. A user makes a write, followed by a read from a stale replica. To prevent this anomaly, we need **read-after-write consistency**.

In this situation, we need *read-after-write consistency*, also known as *read-your-writes consistency*. [147] This is a guarantee that if the user reloads the page, they will always see any updates they submitted themselves. It makes no promises about other users: other users' updates may not be visible until some later time. However, it reassures the user that their own input has been saved correctly.

How can we implement read-after-write consistency in a system with leader-based replication? There are various possible techniques, to mention a few:

- When reading something that the user may have modified, read it from the leader, otherwise read it from a follower. This requires that you have some way of knowing whether something might have been modified, without actually querying it. For example, user profile information on a social network is normally only editable by the only owner of the profile, not by anybody else. Thus, a simple rule is: **always read the user's own profile from the leader, and any other users' profiles from a follower.**
- If most things in the application are potentially editable by the user, that approach won't be effective, as most things would have to be read from the leader (negating the benefit of read scaling). In that case, other criteria may be used to decide whether to read from the leader. For example, you could track the time of the last update; for one minute after the last update, all reads are made from the leader. You could also monitor the replication lag on followers, and prevent queries on any follower that is more than one minute behind the leader.
- Another approach: the client can remember the **timestamp of its most recent write**—then the system can ensure that the replica serving any reads for that user reflects updates at least until that timestamp. If a replica is not sufficiently up-to-date, the read can either be handled by another replica, or the query can wait until the replica has caught up. The timestamp could be a *logical timestamp* (something that indicates ordering of writes, such as the log sequence number), or the actual system clock (in which case clock synchronization becomes critical). [148]
- If your replicas are distributed across multiple datacenters (for geographical proximity to users or for availability), there is additional complexity. Any request that needs to be served by the leader must be routed to the datacenter that contains the leader.

Another complication arises when the same user is accessing your service from multiple devices, for example a desktop web browser and a mobile app. In this case you may want to provide *cross-device read-after-write consistency*: if the user enters some information on one device, and then views it on another device, they should see the information they just entered.

In this case, there are some additional issues to consider:

- Approaches which require remembering a timestamp of the user's last update become more difficult, because the code running on one device doesn't know what updates have happened on the other device. This metadata would need to be centralized.

- If your replicas are distributed across different datacenters, there is no guarantee that connections from different devices are routed to the same datacenter. (For example, if the desktop computer uses the home broadband connection and the mobile device uses the cellular data network, their network routes may be completely different.) If your approach requires reading from the leader, you may first need to route requests from all of a user's devices to the same datacenter.

Monotonic reads

Our second example of an anomaly that can occur when reading from asynchronous followers: it's possible for a user to see things *moving backwards in time*.

This can happen if a user makes several reads from different replicas. For example, [Figure 4-5](#) shows user 2345 making the same query twice, first to a follower with little lag, then to a follower with greater lag. (This scenario is quite likely if the user refreshes a web page, and each request is routed to a random server.) The first query returns a comment that was recently added by user 1234, but the second query doesn't return anything, because the lagging follower has not yet picked up that write.

In effect, the second query is observing the system at an earlier point in time than the first query. It wouldn't be so bad if the first query hadn't returned anything, because user 2345 probably wouldn't know that user 1234 has recently added a comment. However, it's very confusing for user 2345 if they first see user 1234's comment appear, and then see it disappear again.

Monotonic reads [[146](#)] is a guarantee that this kind of anomaly does not happen. It's a lesser guarantee than strong consistency, but a stronger guarantee than eventual consistency. When you read data, you may see an old value; monotonic reads only means that if one user makes several reads in sequence, they will not see time go backwards, i.e. they will not read older data after having previously read newer data.

One way of achieving monotonic reads is to make sure that each user always makes their reads from the same replica (different users can read from different replicas). For example, the replica can be chosen based on a hash of their user ID, rather than randomly.

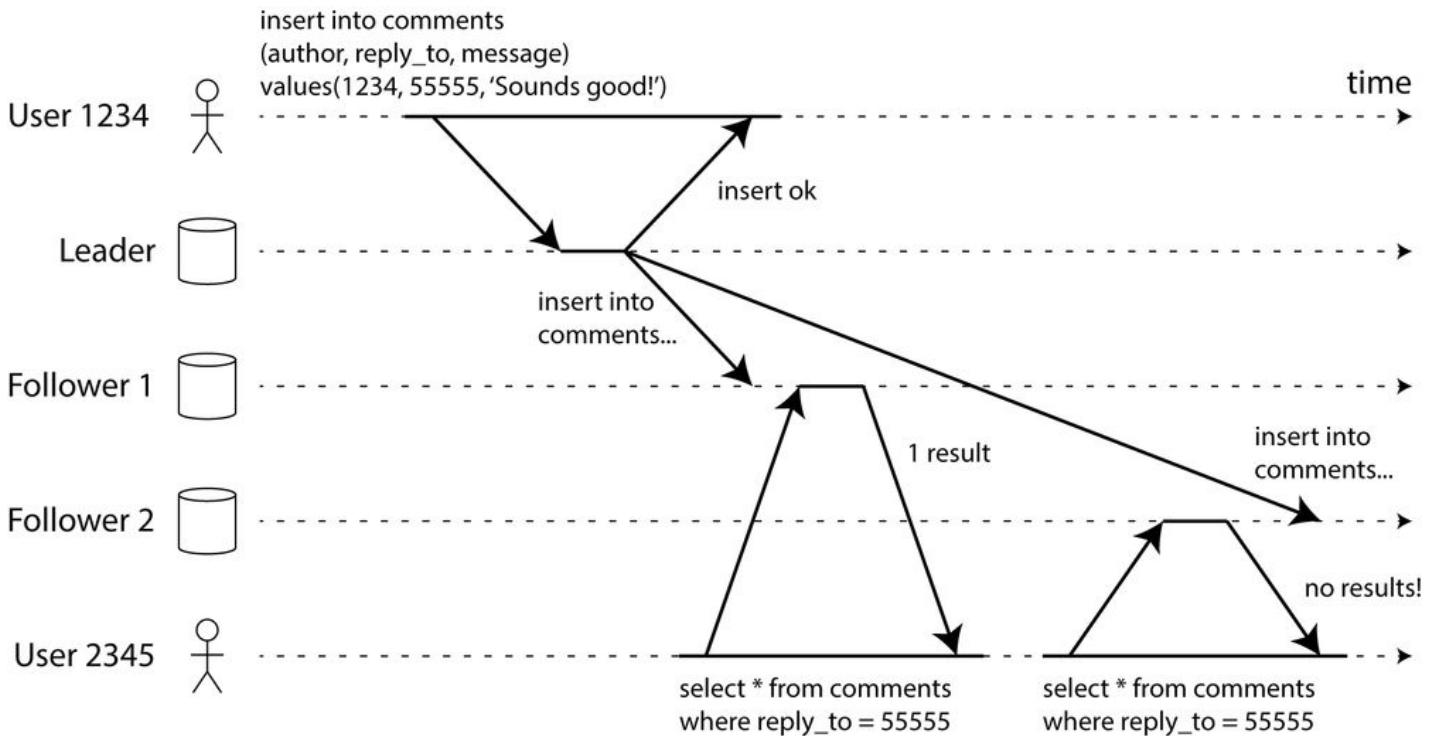


Figure 4-5. A user first reads from a fresh replica, then from a stale replica. Time appears to go backwards. To prevent this anomaly, we need monotonic reads.

Consistent prefix reads

Our third example of replication lag anomalies concerns violation of causality. Imagine the following short dialog between Mr Poons and Mrs Cake:

Mr Poons

How far into the future can you see, Mrs Cake?

Mrs Cake

About ten seconds usually, Mr Poons.

There is a causal relationship between those two sentences: Mrs Cake heard Mr Poons' question, and answered it.

Now, imagine a third person is listening to this conversation through followers. The things said by Mrs Cake go through a follower with little lag, but the things said by Mr Poons have a longer replication lag (see [Figure 4-6](#)). This observer would hear the following:

Mrs Cake

About ten seconds usually, Mr Poons.

Mr Poons

How far into the future can you see, Mrs Cake?

To the observer it looks as though Mrs Cake is answering the question before Mr Poons has even asked it. Such psychic powers are impressive, but also very confusing. [[149]]

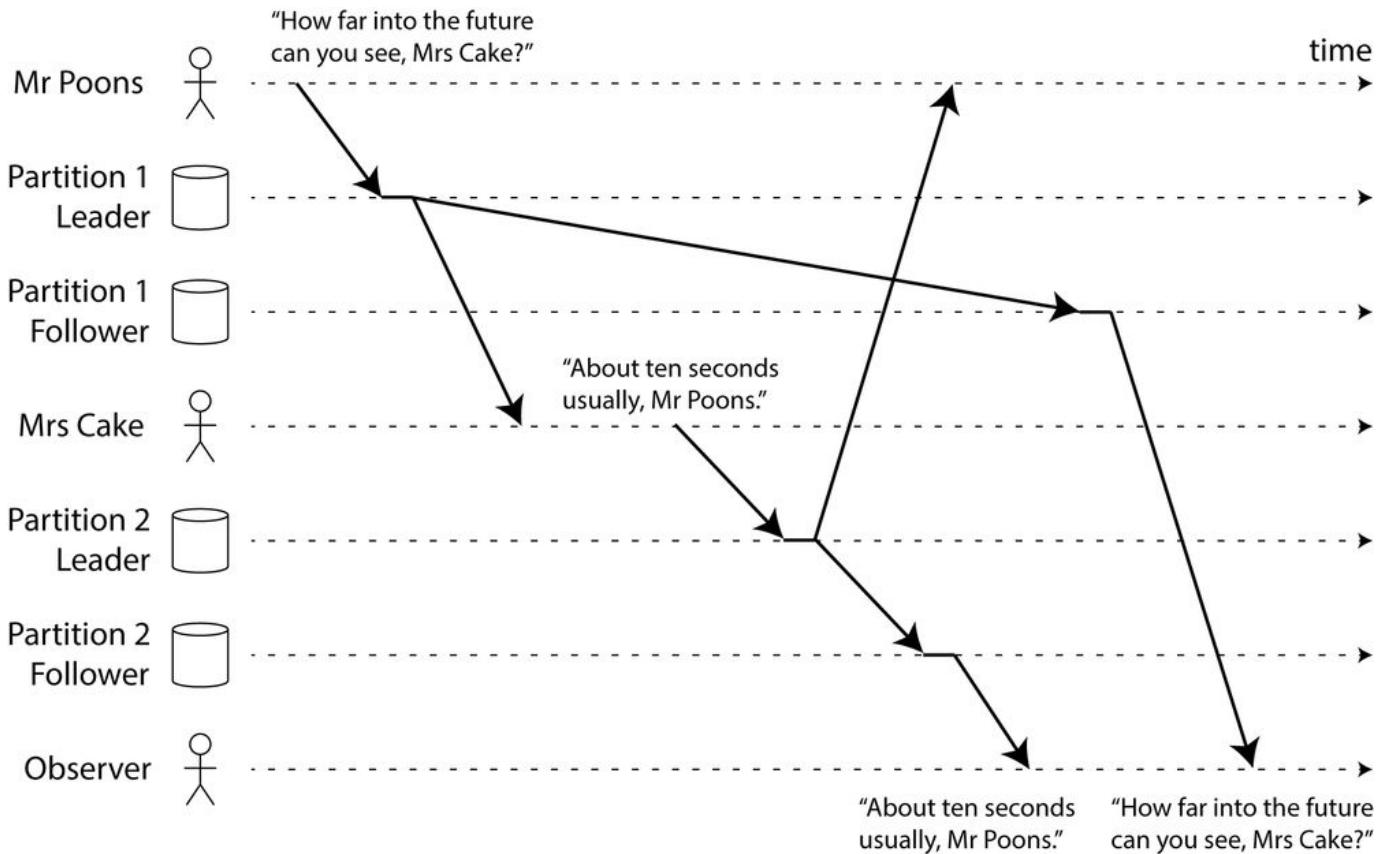


Figure 4-6. If some partitions are replicated slower than others, an observer may see the answer before they see the question.

Preventing this kind of anomaly requires another type of guarantee: *consistent prefix reads*. [[146]] This guarantee says that if a sequence of writes happens in a certain order, then anyone reading those writes will see them appear in the same order.

Consistent prefix reads are easy to achieve in a single partition (leader-based replication normally applies writes in the same order to each follower), but are difficult if there are multiple independent partitions (shards). This guarantee is similar to *snapshot isolation*, which we will discuss in [Link to Come].

Solutions for replication lag

When working with an eventually consistent system, it is worth thinking about how the application behaves if the replication lag increases to several minutes or even hours. If the answer is “no problem”, that’s great. However, if the result is a bad experience for users, it’s important to design the system to provide a stronger guarantee, such as read-after-write.

Pretending that replication is synchronous, when in fact it is asynchronous, is a recipe for problems down the line.

As discussed above, there are ways in which an application can provide a stronger guarantee than the underlying database, for example by performing certain kinds of reads on the leader. However, this adds complexity to the application, and is easy to get wrong.

It would be better if application developers didn't have to worry about subtle replication issues, and could just trust their database to "do the right thing". This is why *transactions* exist: they are a way for a database to provide stronger guarantees, so that the application can be simpler.

Single-node transactions have existed for a long time. However, in the move to distributed (replicated and partitioned) databases, many systems have abandoned them, claiming that transactions are too expensive in terms of performance and availability, and asserting that eventual consistency is inevitable in a scalable system. That is not necessarily true. We will return to the topic of transactions in [Link to Come].

Beyond leader-based replication

So far in this chapter we have only considered leader-based replication. Although that is a common replication model, there are interesting alternatives as well.

Leader-based replication has one major downside: there is only one leader, and all writes must go through it.^[150] If you can't connect to the leader for any reason, for example due to a network interruption between you and the leader, you can't write to the database.

In this section we will look at two alternatives which try to get around this limitation. They can help achieve higher availability for writes, but there is no free lunch: as we shall see, their downside is greater complexity.

Multi-leader replication

A natural extension of the leader-based replication model is to allow more than one node to accept writes. Replication still happens in the same way: each node that processes a write query must forward that data change to all the other nodes. We call this a *multi-leader* configuration (also known as *master-master replication* or *active/active*). In this setup, each leader simultaneously acts as a follower to the other leaders.

It rarely makes sense to use a multi-leader setup within a single datacenter, because the benefits rarely outweigh the added complexity. However, there are some situations in which this is a reasonable configuration.

Use case: multi-datacenter operation

Imagine you have a database with replicas in several different datacenters (perhaps so that you can tolerate failure of an entire datacenter, or perhaps in order to be closer to your users). With a normal leader-based replication setup, the leader has to be in *one* of the datacenters, and all writes must go through that datacenter.

In a multi-leader configuration, you can have a leader in *each* datacenter. [Figure 4-7](#) shows what this architecture might look like. Within each datacenter, regular leader-follower replication is used; between datacenters, each datacenter's leader replicates its changes to the leaders in other datacenters.

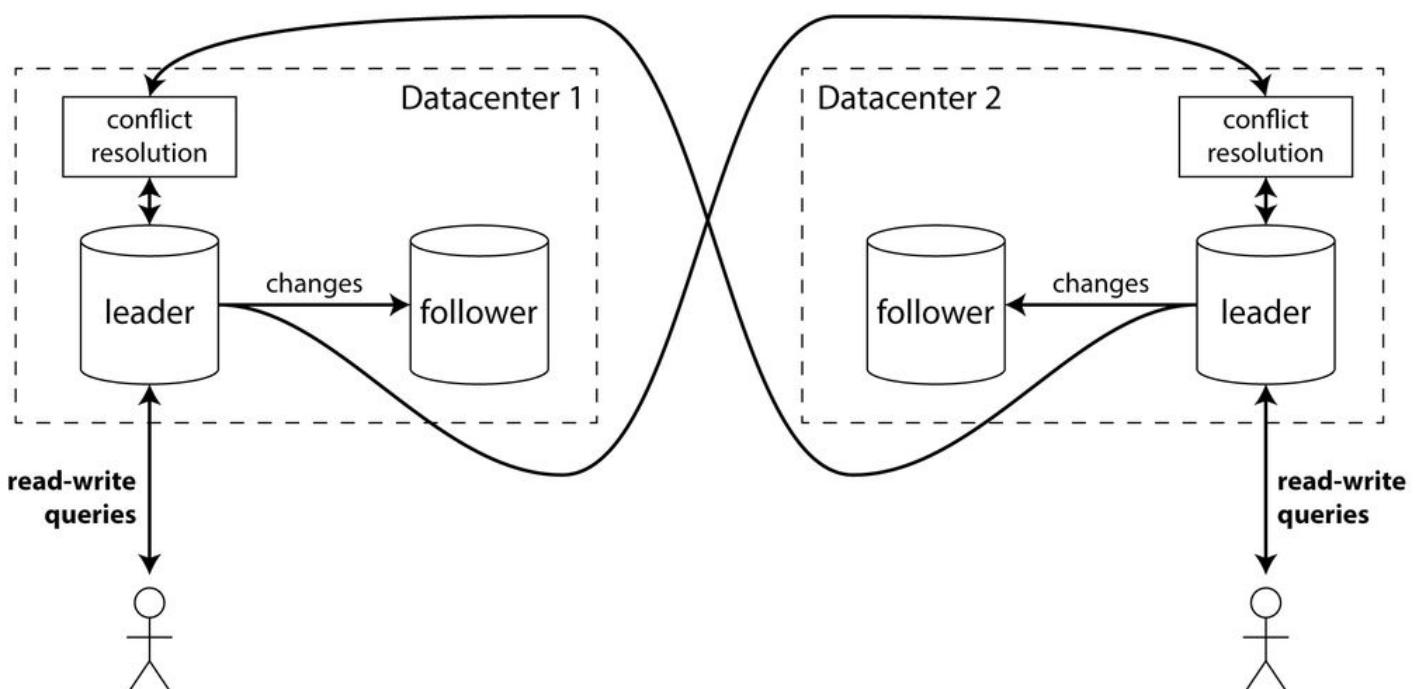


Figure 4-7. Multi-leader replication across multiple datacenters.

Let's compare how the single-leader and multi-leader configurations fare in a multi-datacenter deployment:

Performance

In a single-leader configuration, every write must go over the internet to the datacenter with the leader. This can add significant latency to writes, and might contravene the purpose of having multiple datacenters in the first place. In a multi-leader configuration, every write can be processed in the local

datacenter, and is replicated asynchronously to the other datacenters. Thus the inter-datacenter latency is hidden from users, which means the perceived performance may be better.

Tolerance of datacenter outages

In a single-leader configuration, if the datacenter with the leader fails, failover can promote a follower in another datacenter to be leader. In a multi-leader configuration, each datacenter can continue operating independently of the others, and replication catches up when the failed datacenter comes back online.

Tolerance of network problems

Traffic between datacenters usually goes over the public internet, which may be less reliable than the local network within a datacenter. A single-leader configuration is very sensitive to problems in this inter-datacenter link, because write queries are made synchronously over this link. A multi-leader configuration with asynchronous replication can usually tolerate network problems better: a temporary network interruption does not prevent writes being processed.

Database systems typically implement this kind of multi-leader configuration by using external tools, such as Tungsten Replicator for MySQL [[\[151\]](#)], Bucardo for PostgreSQL [[\[143\]](#)] and GoldenGate for Oracle [[\[141\]](#)].

Although multi-leader replication has advantages, it also has a big downside: the same data may be concurrently modified in two different datacenters, and those write conflicts must be resolved (indicated as “conflict resolution” in [Figure 4-7](#)). We will discuss this in [Handling write conflicts](#).

As multi-leader replication is a somewhat retrofitted feature in many databases, there are often subtle configuration pitfalls and surprising interactions with other database features. For this reason, it is often considered dangerous territory that should be avoided if possible. [[\[152\]](#)]

Use case: clients with offline operation

Another situation in which multi-leader replication is appropriate is if you have an application that needs to continue to work while it is disconnected from the internet.

For example, consider the calendar apps on your mobile phone, your laptop, and other devices. You need to be able to see your meetings (make read requests) and create new meetings (make write requests) at any time, regardless of whether your device currently has an internet connection. If you make any changes while you are offline, they need to be synced with a server and your other devices when the device is next online.

In this case, every device has a local database that acts as a leader (it accepts write requests), and there is an asynchronous multi-leader replication process (sync) between the replicas of

your calendar on all of your devices. The replication lag may be hours or even days, depending on when you have internet access available.

From an architectural point of view, this is essentially the same as multi-leader replication between datacenters, taken to the extreme: each device is a ‘datacenter’, and the network connection between them is extremely unreliable. As the rich history of broken calendar sync implementations demonstrates, multi-master replication is a tricky thing to get right.

There are tools which aim to make this kind of multi-leader configuration easier. For example, CouchDB is designed for this mode of operation. [[\[153\]](#)]

Use case: collaborative editing

Real-time collaborative editing applications allow several people to edit a document simultaneously. For example, Google Docs allows several people to concurrently edit a text document or spreadsheet.

We don’t usually think of collaborative editing as a database replication problem, but it has a lot in common with the previously mentioned offline editing use case. When one user edits a document, the changes are instantly applied to their local replica (the state of the document in their web browser or client application), and asynchronously replicated to the server and any other users who are editing the same document.

If you want to guarantee that there will be no editing conflicts, the application must obtain a lock on the document before a user can edit it. If another user wants to edit the same document, they first have to wait until the first user has committed their changes and released the lock. This collaboration model is equivalent to single-leader replication with transactions on the leader.

However, for faster collaboration, you may want to make the unit of change very small (e.g. a single keystroke), and avoid locking. This allows multiple users to edit simultaneously, but it also brings all the challenges of multi-leader replication.

Handling write conflicts

The biggest problem with multi-leader replication is that write conflicts can occur, which means that conflict resolution is required.

For example, consider a wiki page that is simultaneously being edited by two users, as shown in [Figure 4-8](#). User 1 changes the title of the page from A to B, and user 2 changes the title from A

to C at the same time. Each user's change is successfully applied to their local leader. However, when the changes are asynchronously replicated, a conflict is detected. This problem does not occur in a single-leader database.

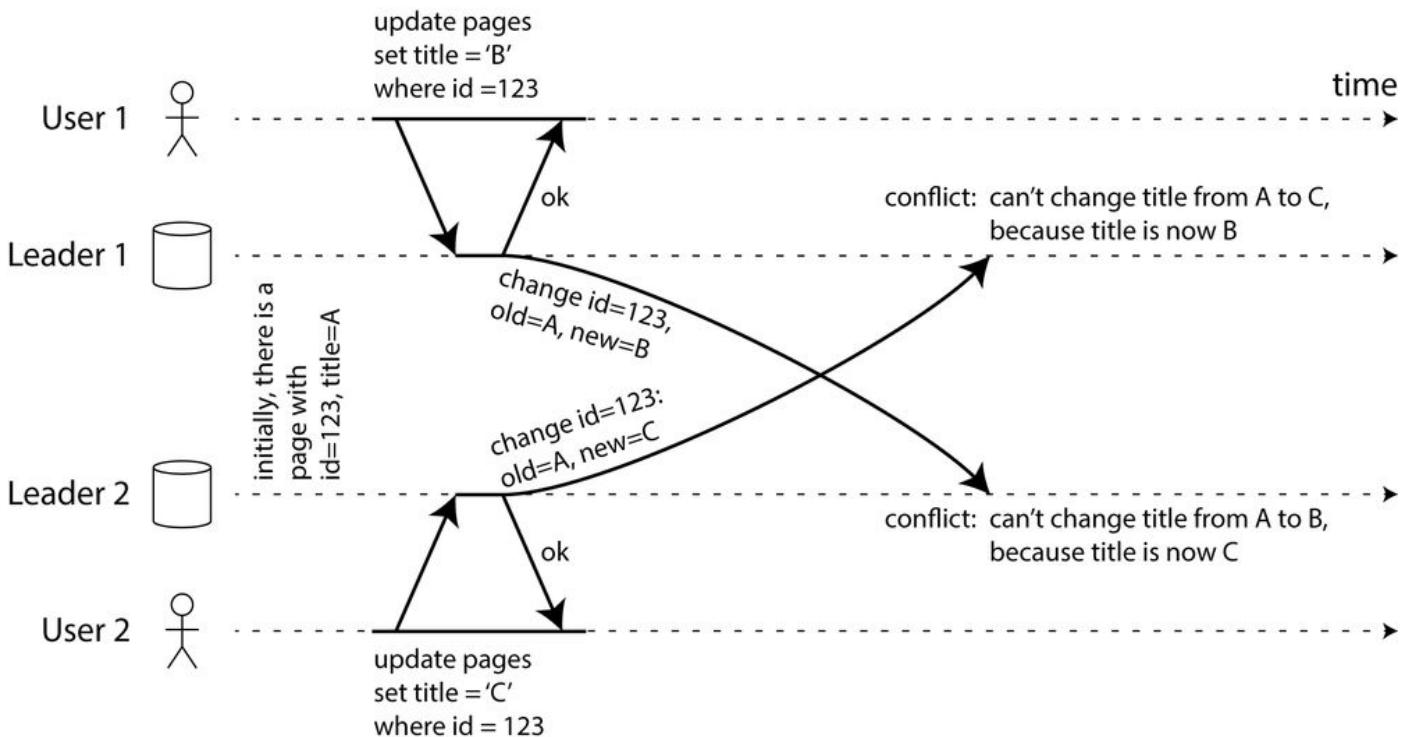


Figure 4-8. A write conflict caused by two leaders concurrently updating the same record.

Synchronous vs. asynchronous conflict detection

In a single-leader database, the second writer will either block and wait for the first write to complete, or abort the second write transaction, forcing the user to retry the write.

On the other hand, in a multi-leader setup, both writes are successful, and the conflict is only detected asynchronously at some later point in time. At that time, it may be too late to ask the user to resolve the conflict.

In principle, you could make the conflict detection synchronous, i.e. wait for the write to be replicated to all replicas before telling the user that the write was successful. However, by doing so, you would lose the main advantage of multi-leader replication: allowing each replica to accept writes independently. If you want synchronous conflict detection, you might as well just use single-leader replication.

Determining a consistent outcome

A single-leader database applies writes in a sequential order: if there are several updates to the same field, the last write determines the final value of the field.

In a multi-leader configuration, there is no defined ordering of writes, so it's not clear what the final value should be. In [Figure 4-8](#) at leader 1, the title is first updated to B and then to C; at leader 2, it is first updated to C and then to B.

If each replica simply applied writes in the order that it saw the writes, the database would end up in an inconsistent state: the final value would be C at leader 1, and B at leader 2. That is not acceptable—every replication scheme must ensure that the data is eventually the same in all replicas. Thus, the database must resolve the conflict *consistently*, which means that all replicas must agree on the same final value.

There are many possible ways of achieving consistent conflict resolution:

- Give each *write* a unique ID (e.g. a timestamp, a long random number or UUID), sort conflicting writes by this ID, and give precedence to the write with the highest ID. The write with the highest ID is called the *winner*. If a timestamp is used, this technique is known as *last-write-wins* (however, note that clocks may not be exactly in sync, so the definition of which write is more recent may be approximate).
- Give each *replica* a unique ID, and let writes that originated at a higher-numbered replica always take precedence over writes that originated at a lower-numbered replica.
- Somehow merge the values together, e.g. order them alphabetically and then concatenate them (in [Figure 4-8](#), the merged title may be something like “B/C”).
- Record the conflict in an explicit data structure that preserves all information, and write application code which prompts a user to resolve the conflict manually at some later time.

Implementing conflict resolution

The simplest strategy for dealing with conflicts is to avoid them in the first place: if the application can ensure that all writes for a particular item go through the same leader, then conflicts cannot occur. However, that is essentially equivalent to a single-leader configuration. If you can guarantee at an application level that no conflicts will occur, that probably means you don't really need multi-leader replication in the first place.

As there are so many possible ways of resolving conflicts, most multi-leader replication tools let you write conflict resolution logic using application code. That code may be executed on write or on read:

On write

As soon as the database system detects a conflict in the stream of replicated changes, it calls the conflict handler. For example, Bucardo allows you to write a snippet of Perl for this purpose. This handler typically cannot prompt a user—it runs in a background process and it must execute quickly.

On read

When a conflict is detected, all the conflicting writes are stored. The next time the data is read, these multiple versions of the data are returned to the application. The application may prompt the user or automatically resolve the conflict, and write the result back to the database. CouchDB works this way, for example.

Automatic conflict resolution

Conflict resolution rules can quickly become complicated, and custom code can be error-prone. Amazon is a frequently cited example of surprising effects due to a conflict resolution handler: for some time, the conflict resolution logic on the shopping cart would preserve items added to the cart, but not items removed from the cart. Thus, customers would sometimes see items re-appearing in their cart even though they had previously been removed. [\[\[154\]\]](#)

There has been some interesting research into automatically resolving conflicts caused by concurrent data modifications. In particular, two lines of research are worth mentioning:

- *Conflict-free replicated data types* (CRDTs) [\[\[155\]\]](#) are a family of data structures for sets, maps, ordered lists, counters etc. which can be concurrently edited by multiple users, and which automatically resolve conflicts in sensible ways. Some CRDTs have been implemented in Riak 2.0. [\[\[156\]\]](#)
- *Operational transformation* [\[\[157\]\]](#) is the conflict resolution algorithm behind collaborative editing applications such as Google Docs. It is designed particularly for concurrent editing of an ordered list of items, such as the list of characters that constitute a text document.

Implementations of these algorithms are still young, but it's likely that they will be integrated into more replicated data systems in future: automatic conflict resolution could make multi-leader data synchronization much simpler for applications to deal with.

What is a conflict?

Some kinds of conflict are obvious. In the example in [Figure 4-8](#), two writes concurrently modified the same field in the same record, setting it to two different values. There is little doubt that this is a conflict.

Other kinds of conflict can be more subtle to detect. For example, consider a meeting room booking system: it tracks which room is booked by which group of people at one time. This application needs to ensure that each room is only booked by one group of people at any one time (i.e. there must not be any overlapping bookings for the same room).

In this case, a conflict may arise if two different bookings are created for the same room at the same time. Even if the application checks availability before allowing a user to make a booking, there can be a conflict if the two bookings are made on two different leaders.

Solutions to this problem have been proposed [\[158\]](#), but can be hard to implement in practice. For now, detecting conflicts is a question to think about when designing a replicated system, but there isn't a quick ready-made answer.

Infinite replication loops

We should briefly mention another issue that occurs in multi-leader replication: if the system is misconfigured, it's possible to create infinite replication loops. The stream of data changes produced by a node contains two kinds of records:

1. data changes that originated on this node (i.e. a client sent a write query to this node),
2. data changes that originated on another node and were replicated to this one.

If the stream is replicated back to the other node where the write originated, a data change could keep going around in a circle.

Fortunately, there is a simple solution to this problem: each replica is given a unique identifier, and in the replication stream, each write is tagged with the identifiers of all the replicas it has passed through. [\[159\]](#) When a node receives a data change that is tagged with its own identifier, that data change is ignored, because the node knows that it has already been processed. [\[160\]](#)

Quorum-based replication

The replication approaches we have discussed so far in this chapter—single-leader and multi-leader replication—are based on the idea that a client sends a write request to one node (the leader), and the database system takes care of copying that write to the other replicas.

Some data storage systems take a different approach, by making the *client* responsible for copying data to multiple replicas. In this approach, the nodes do not actively copy data among each other:^[161] if a client writes some data to just one node, it will be stored only on that one node. If the client wants the data to be replicated on multiple nodes, it must connect to each node and separately write the data to each node.

This is more work for the client, so why would you want to do this? The reason is that this kind of system can take a different approach to tolerating faults, such as node outages.

We call this approach *quorum-based replication* (the word *quorum* will be explained shortly). It is a classic of distributed systems ^[162], but it only became a fashionable architecture for databases after Amazon used it for their in-house Dynamo system ^[154]. Riak, Cassandra and Voldemort are open source datastores with quorum-based replication models inspired by Dynamo.

Writing to the database when a node is down

Imagine you have a database with three replicas, and one of the replicas is currently unavailable—perhaps it is being rebooted to install a system update. In a leader-based configuration, if you want to continue processing writes, you may need to perform a failover (see [Handling node outages: failover](#)).

On the other hand, if the client writes to each replica individually, there is no such thing as failover. [Figure 4-9](#) shows what happens: the client (user 1234) sends the write to all three replicas in parallel, the two available replicas accept the write, but the unavailable replica misses the write. Let's say that it's sufficient for two out of three replicas to acknowledge the write: after user 1234 has received two *ok* responses, we consider the write to be successful. The client simply ignores the fact that one of the replicas missed the write.

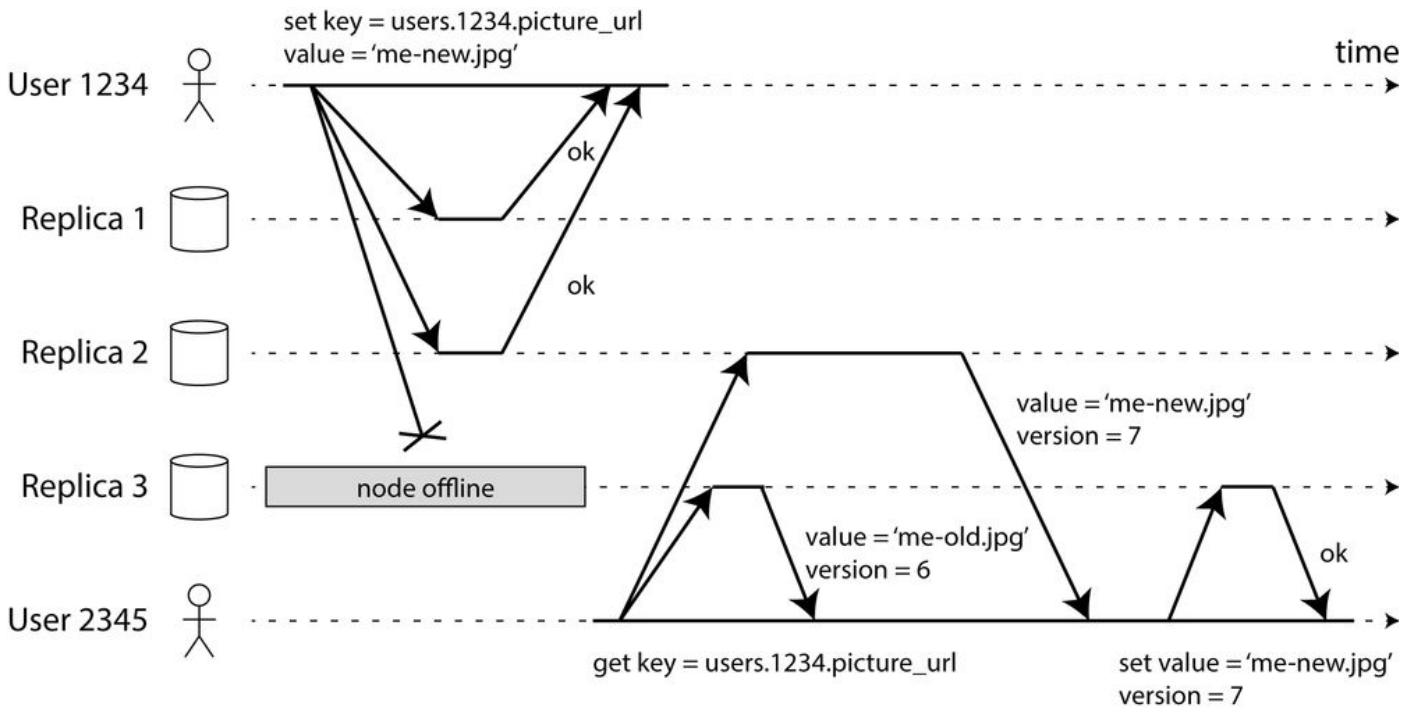


Figure 4-9. A quorum write, quorum read, and read repair after a node outage.

Now imagine that the unavailable node comes back online, and clients start reading from it. Any writes that happened while the node was down are missing from that node. Thus, if you read from that node, you may get outdated values as responses.

To solve that problem, when a client reads from the database, it doesn't just send its request to one replica: *read requests are also sent to several nodes in parallel*. The client may get different responses from different nodes, e.g. the up-to-date value from one node, and an outdated value from another. A version number is used to determine which value is newer.

Read repair and anti-entropy

The replication scheme should ensure that eventually all the data is copied to every replica. After an unavailable node comes back online, how does it catch up on the writes that it missed?

Two mechanisms are often used in Dynamo-style datastores:

Read repair

When a client makes a read from several nodes in parallel, it can detect any outdated responses. For example, in [Figure 4-9](#), user 2345 gets a version 6 value from replica 3, and a version 7 value from replica 2. The client sees that replica 3 has an outdated value, and writes the newer value back to that replica. This works well for values that are frequently read.

Anti-entropy process

In addition, some datastores have a background process which constantly looks for differences in the

data between replicas, and copies any missing data from one replica to another. Unlike the data change stream in leader-based replication, this *anti-entropy process* does not copy writes in any particular order, and there may be a significant delay before data is copied.

Not all systems implement both of these; for example, Voldemort currently does not have an anti-entropy process.

Quorums for reading and writing

In the example of [Figure 4-9](#), we considered it acceptable for the write to be processed on two out of three replicas, and we performed the read on two out of three replicas. Why those numbers?

If we know that every write is guaranteed to be present on at least two out of three replicas, that means at most one replica can be outdated. Thus, if we read from at least two replicas, we can be sure that at least one of the two is up-to-date.

More generally, if there are n replicas, every write must be confirmed by w nodes to be considered successful, and we must query at least r nodes for each read. (In our example, $n = 3$, $w = 2$, $r = 2$.) As long as $w + r > n$, we expect to get an up-to-date value on every read, because at least one of the r nodes we're reading from must be up-to-date. Reads and writes that obey these r and w values are called *quorum* reads and writes. You can think of r and w as the minimum number of votes required for the read or write to be valid.

The quorum allows the system to tolerate unavailable nodes as follows:

- If $w < n$, we can still process writes if a node is unavailable.
- If $r < n$, we can still process reads if a node is unavailable.
- With $n = 3$, $w = 2$, $r = 2$ we can tolerate one unavailable node.
- With $n = 5$, $w = 3$, $r = 3$ we can tolerate two unavailable nodes.

In Dynamo-style databases, these values n , r and w are typically configurable parameters, allowing you to tune the availability, consistency and performance properties of the database to the needs of your application. For example, if you don't mind reading outdated values, you can set r and w so that $w + r \leq n$.

However, unlike a leader-based replication system, it's typically not possible to monitor the replication lag in a quorum-based system. This makes it difficult to reason about correctness: if you allow outdated values to be read, you don't know *how* outdated they are (they might be recent, or they might be ancient).

Reconciling conflicts

Even if you always perform quorum reads and writes, conflicts are likely to occur:

- Two clients may write to the same key at the same time.
- If an error occurs during writing, or if a node is lost and needs to be rebuilt, a write may be present on fewer than w replicas.

The result is that replicas disagree about what a particular value in the database should be. Like in multi-leader replication (see [Handling write conflicts](#)), this calls for application logic to resolve the conflict.

Since Dynamo-style databases usually determine inconsistencies between replicas when performing a read, this conflict resolution usually also occurs at read time. Like in read repair, the application is given all the conflicting values for a particular key, and it's up to the application to write back the result of the conflict resolution to the datastore.

Replication and durability

Durability, i.e. ensuring that a fault does not cause data loss, is important for many datastores. Traditionally, databases provide durability by writing data to non-volatile storage (disk). However, replication is another way of increasing durability. Which is better?

The truth is, neither is perfect:

- A correlated fault—a power failure or a bug that crashes every node on a particular input—can knock out all replicas at once (see [Reliability](#)).
- In an asynchronously replicated system, recent writes may be lost when a node becomes unavailable.
- When the power is suddenly cut, SSDs in particular have been shown to sometimes violate the guarantees they are supposed to provide: even `fsync` isn't guaranteed to work correctly. ^{[[163](#)]} Disk firmware can have bugs, just like any other kind of software.

In practice, there is no one technique that can provide absolute guarantees. There are only various risk-reduction techniques, including writing to disk, replicating to remote machines, and backups—and they can and should be used together. As always, it's wise to take any theoretical ‘guarantees’ with a healthy grain of salt.

Summary

In this chapter, we looked at the issue of replication, that is: keeping a copy of the same data on several machines. Replication can serve several purposes:

- *Scalability*: being able to handle a higher query throughput than a single machine could handle.
- *High availability*: keeping the system running, even when one machine (or several machines, or an entire datacenter) goes down.
- *Disconnected operation*: allowing an application to continue working when there is a network interruption.
- *Latency*: placing data geographically close to users, so that users can interact with it faster.

Despite having simple goal—a copy of the same data on several machines—replication turns out to be a remarkably tricky problem. It requires carefully thinking about all the things that can go wrong, and dealing with the consequences of those faults. At a minimum, we need to deal with unavailable nodes and network interruptions (and that's not even considering the more insidious kinds of fault, such as silent data corruption due to software bugs).

We discussed three main approaches to replication:

1. *Single-leader replication*: Clients send all writes to a single node (the leader), which sends a stream of data change events to the other replicas (followers). Reads can be performed on any replica.
2. *Multi-leader replication*: Clients send each write to one of several leader nodes which can accept writes. The leaders exchange streams of data change events among each other.
3. *Quorum-based replication*: Clients send each write to several nodes, and read from several nodes in parallel in order to detect and correct nodes with outdated data.

Replication can be synchronous or asynchronous, which has a profound effect on the system behavior when there is a fault. While replication is a built-in feature in many databases, it often comes with a very weak consistency guarantee such as *eventual consistency*.

Although asynchronous replication can be fast when the system is running smoothly, it's important to figure out what happens when replication lag increases. We looked at some strange effects that can be caused by replication lag, and we discussed a few consistency models which are helpful for deciding how an application should behave under replication lag:

- *Read-after-write consistency*: a user should always see data that they submitted themselves.
- *Monotonic reads*: after a user has seen the data at one point in time, they shouldn't later see the data from some earlier point in time.

- *Consistent prefix reads*: users should see the data in a state that makes causal sense, for example seeing a question and its reply in the correct order.

We also peeked under the hood of several popular data storage systems, and examined the trade-offs of how they implement replication.

In the next chapter we will continue looking at data that is distributed across multiple machines, through the counterpart of replication: splitting a large dataset into *partitions*.

^[123] In practice, although any CPU can access any part of memory, some banks of memory are closer to one CPU than to others (this is called *non-uniform memory access* or NUMA). To make efficient use of this architecture, the processing needs to be broken down so that each CPU mostly accesses memory that is nearby — which means that partitioning is still required, even when ostensibly running on one machine.

^[124] *Network Attached Storage* (NAS) or *Storage Area Network* (SAN).

^[125] Ben Stopford: “[Shared Nothing vs. Shared Disk Architectures: An Independent View](#),” benstopford.com, 24 November 2009.

^[126] Michael Stonebraker: “[The Case for Shared Nothing](#),” *IEEE Database Engineering Bulletin*, volume 9, number 1, pages 4–9, March 1986.

^[127] Bruce G Lindsay, Patricia Griffiths Selinger, C Galtieri, et al.: “[Notes on Distributed Databases](#),” IBM Research, Research Report RJ2571(33471), July 1979.

^[128] Different people have different definitions for *hot*, *warm* and *cold* standby servers. In PostgreSQL, for example, *hot standby* is used to refer to a replica which accepts reads from clients, whereas a *warm standby* processes changes from the leader but doesn’t process any queries from clients. For purposes of this book, the difference isn’t important.

^[129] “[Oracle Active Data Guard Real-Time Data Protection and Availability](#).” Oracle White Paper, June 2013.

^[130] “[AlwaysOn Availability Groups](#).” In *SQL Server Books Online*, Microsoft, 2012.

^[131] Lin Qiao, Kapil Surlaker, Shirshanka Das, et al.: “[On Brewing Fresh Espresso: LinkedIn’s Distributed Data Serving Platform](#),” at *ACM International Conference on Management of Data* (SIGMOD), June 2013.

[132] Jun Rao: “[Intra-cluster Replication for Apache Kafka](#),” at *ApacheCon North America*, February 2013.

[133] “[Highly Available Queues](#).” In *RabbitMQ Server Documentation*, Pivotal Software, Inc., 2014.

[134] “[Percona Xtrabackup - Documentation](#).” Percona LLC, 2014.

[135] Jesse Newland: “[GitHub availability this week](#),” github.com, 14 September 2012.

[136] This is known as *fencing* or, more emphatically, *Shoot The Other Node In The Head* (STONITH).

[137] Mark Imbriaco: “[Downtime last Saturday](#),” github.com, 26 December 2012.

[138] Amit Kapila: “[WAL Internals Of PostgreSQL](#),” at *PostgreSQL Conference* (PGCon), May 2012.

[139] [MySQL Internals Manual](#). Oracle, 2014.

[140] Laurent Demailly: “[Wormhole pub/sub system: Moving data through space and time](#),” code.facebook.com, 13 June 2013.

[141] “[Oracle GoldenGate 12c: Real-time access to real-time information](#).” Oracle White Paper, October 2013.

[142] Shirshanka Das, Chavdar Botev, Kapil Surlaker, et al.: “[All Aboard the Databus!](#),” at *ACM Symposium on Cloud Computing* (SoCC), October 2012.

[143] Greg Sabino Mullane: “[Version 5 of Bucardo database replication system](#),” blog.endpoint.com, 23 June 2014.

[144] The term *eventual consistency* was coined by Douglas Terry *et al.* [147], popularized by Werner Vogels [145], and became the battle cry of many NoSQL projects.

[145] Werner Vogels: “[Eventually Consistent](#),” *ACM Queue*, volume 6, number 6, pages 14–19, October 2008. [doi:10.1145/1466443.1466448](https://doi.org/10.1145/1466443.1466448)

[146] Douglas B Terry: “[Replicated Data Consistency Explained Through Baseball](#),” Microsoft Research, Technical Report MSR-TR-2011-137, October 2011.

[147] Douglas B Terry, Alan J Demers, Karin Petersen, et al.: “[Session Guarantees for Weakly Consistent Replicated Data](#),” at *3rd International Conference on Parallel and Distributed Information Systems* (PDIS), pages 140–149, September 1994. [doi:10.1109/PDIS.1994.331722](https://doi.org/10.1109/PDIS.1994.331722)

[148] Murat Demirbas: “[Spanner: Google’s Globally-Distributed Database](#),” muratbuffalo.blogspot.co.uk, 4 July 2013.

[149] Terry Pratchett: *Reaper Man: A Discworld Novel*. Victor Gollancz, 1991. ISBN: 0-575-04979-0

[150] If the database is partitioned ([Link to Come]), each partition has one leader. Different partitions may have their leaders on different nodes, but each partition must nevertheless have one leader node.

[151] “[Tungsten Replicator](#).” Continuent, Inc., 2014.

[152] Robert Hodges: “[If You *Must* Deploy Multi-Master Replication, Read This First](#),” scale-out-blog.blogspot.co.uk, 30 March 2012.

[153] J Chris Anderson, Jan Lehnardt, and Noah Slater: *CouchDB: The Definitive Guide*. O'Reilly Media, January 2010. ISBN: 978-0-596-15589-6

[154] Giuseppe DeCandia, Deniz Hastorun, Madan Jampani, et al.: “[Dynamo: Amazon’s Highly Available Key-Value Store](#),” at *21st ACM Symposium on Operating Systems Principles* (SOSP), October 2007.

[155] Marc Shapiro, Nuno Preguiça, Carlos Baquero, and Marek Zawirski: “[A comprehensive study of Convergent and Commutative Replicated Data Types](#),” INRIA Research Report no. 7506, January 2011.

[156] Sam Elliott: “[CRDTs: An UPDATE \(or maybe just a PUT\)](#),” at *RICON West* (RICON West), October 2013.

[157] Chengzheng Sun and Clarence Ellis: “[Operational Transformation in Real-Time Group Editors: Issues, Algorithms, and Achievements](#),” at *ACM Conference on Computer Supported Cooperative Work* (CSCW), November 1998.

[158] Douglas B Terry, Marvin M Theimer, Karin Petersen, et al.: “[Managing update conflicts in Bayou, a weakly connected replicated storage system](#),” at *15th ACM Symposium on Operating Systems Principles* (SOSP), pages 172–182, December 1995. [doi:10.1145/224056.224070](https://doi.org/10.1145/224056.224070)

^[159] Lars Hofhansl: “[HBASE-7709: Infinite loop possible in Master/Master replication](#),” issues.apache.org, 29 January 2013.

^[160] This is just like a graph traversal algorithm, which needs to prevent infinite looping in a cyclic graph.

^[161] With the exception of *anti-entropy processes*, discussed below.

^[162] David K Gifford: “[Weighted Voting for Replicated Data](#),” at *7th ACM Symposium on Operating Systems Principles* (SOSP), pages 150–162, December 1979. doi:[10.1145/800215.806583](https://doi.org/10.1145/800215.806583)

^[163] Mai Zheng, Joseph Tucek, Feng Qin, and Mark Lillibridge: “[Understanding the Robustness of SSDs under Power Fault](#),” at *11th USENIX Conference on File and Storage Technologies* (FAST), February 2013.