Chapter 1. Meet Hadoop

In pioneer days they used oxen for heavy pulling, and when one ox couldn't budge a log, they didn't try to grow a larger ox. We shouldn't be trying for bigger computers, but for more systems of computers.

—Grace Hopper

Data!

We live in the data age. It's not easy to measure the total volume of data stored electronically, but an IDC estimate put the size of the "digital universe" at 4.4 zettabytes in 2013 and is forecasting a tenfold growth by 2020 to 44 zettabytes.[3] A zettabyte is 10^{21} bytes, or equivalently one thousand exabytes, one million petabytes, or one billion terabytes. That's more than one disk drive for every person in the world.

This flood of data is coming from many sources. Consider the following:[4]

- The New York Stock Exchange generates about 4–5 terabytes of data per day.
- Facebook hosts more than 240 billion photos, growing at 7 petabytes per month.
- Ancestry.com, the genealogy site, stores around 10 petabytes of data.
- The Internet Archive stores around 18.5 petabytes of data.
- The Large Hadron Collider near Geneva, Switzerland, produces about 30 petabytes of data per year.

So there's a lot of data out there. But you are probably wondering how it affects you. Most of the data is locked up in the largest web properties (like search engines) or in scientific or financial institutions, isn't it? Does the advent of big data affect smaller organizations or individuals?

I argue that it does. Take photos, for example. My wife's grandfather was an avid photographer and took photographs throughout his adult life. His entire corpus of medium-format, slide, and 35mm film, when scanned in at high resolution, occupies around 10 gigabytes. Compare this to the digital photos my family took in 2008, which take up about 5 gigabytes of space. My family is producing photographic data at 35 times the rate my wife's grandfather's did, and the rate is increasing every year as it becomes easier to take more and more photos.

More generally, the digital streams that individuals are producing are growing apace. Microsoft Research's MyLifeBits project gives a glimpse of the archiving of personal

information that may become commonplace in the near future. MyLifeBits was an experiment where an individual's interactions—phone calls, emails, documents—were captured electronically and stored for later access. The data gathered included a photo taken every minute, which resulted in an overall data volume of 1 gigabyte per month. When storage costs come down enough to make it feasible to store continuous audio and video, the data volume for a future MyLifeBits service will be many times that.

The trend is for every individual's data footprint to grow, but perhaps more significantly, the amount of data generated by machines as a part of the Internet of Things will be even greater than that generated by people. Machine logs, RFID readers, sensor networks, vehicle GPS traces, retail transactions—all of these contribute to the growing mountain of data.

The volume of data being made publicly available increases every year, too. Organizations no longer have to merely manage their own data; success in the future will be dictated to a large extent by their ability to extract value from other organizations' data.

Initiatives such as Public Data Sets on Amazon Web Services and Infochimps.org exist to foster the "information commons," where data can be freely (or for a modest price) shared for anyone to download and analyze. Mashups between different information sources make for unexpected and hitherto unimaginable applications.

Take, for example, the Astrometry.net project, which watches the Astrometry group on Flickr for new photos of the night sky. It analyzes each image and identifies which part of the sky it is from, as well as any interesting celestial bodies, such as stars or galaxies. This project shows the kinds of things that are possible when data (in this case, tagged photographic images) is made available and used for something (image analysis) that was not anticipated by the creator.

It has been said that "more data usually beats better algorithms," which is to say that for some problems (such as recommending movies or music based on past preferences), however fiendish your algorithms, often they can be beaten simply by having more data (and a less sophisticated algorithm).[5]

The good news is that big data is here. The bad news is that we are struggling to store and analyze it.

Data Storage and Analysis

The problem is simple: although the storage capacities of hard drives have increased massively over the years, access speeds—the rate at which data can be read from drives—have not kept up. One typical drive from 1990 could store 1,370 MB of data and had a transfer speed of 4.4 MB/s,[6] so you could read all the data from a full drive in around five minutes. Over 20 years later, 1-terabyte drives are the norm, but the transfer speed is

around 100 MB/s, so it takes more than two and a half hours to read all the data off the disk.

This is a long time to read all data on a single drive—and writing is even slower. The obvious way to reduce the time is to read from multiple disks at once. Imagine if we had 100 drives, each holding one hundredth of the data. Working in parallel, we could read the data in under two minutes.

Using only one hundredth of a disk may seem wasteful. But we can store 100 datasets, each of which is 1 terabyte, and provide shared access to them. We can imagine that the users of such a system would be happy to share access in return for shorter analysis times, and statistically, that their analysis jobs would be likely to be spread over time, so they wouldn't interfere with each other too much.

There's more to being able to read and write data in parallel to or from multiple disks, though.

The first problem to solve is hardware failure: as soon as you start using many pieces of hardware, the chance that one will fail is fairly high. A common way of avoiding data loss is through replication: redundant copies of the data are kept by the system so that in the event of failure, there is another copy available. This is how RAID works, for instance, although Hadoop's filesystem, the Hadoop Distributed Filesystem (HDFS), takes a slightly different approach, as you shall see later.

The second problem is that most analysis tasks need to be able to combine the data in some way, and data read from one disk may need to be combined with data from any of the other 99 disks. Various distributed systems allow data to be combined from multiple sources, but doing this correctly is notoriously challenging. MapReduce provides a programming model that abstracts the problem from disk reads and writes, transforming it into a computation over sets of keys and values. We look at the details of this model in later chapters, but the important point for the present discussion is that there are two parts to the computation—the map and the reduce—and it's the interface between the two where the "mixing" occurs. Like HDFS, MapReduce has built-in reliability.

In a nutshell, this is what Hadoop provides: a reliable, scalable platform for storage and analysis. What's more, because it runs on commodity hardware and is open source, Hadoop is affordable.

Querying All Your Data

The approach taken by MapReduce may seem like a brute-force approach. The premise is that the entire dataset—or at least a good portion of it—can be processed for each query. But this is its power. MapReduce is a *batch* query processor, and the ability to run an ad hoc query against your whole dataset and get the results in a reasonable time is transformative.

It changes the way you think about data and unlocks data that was previously archived on tape or disk. It gives people the opportunity to innovate with data. Questions that took too long to get answered before can now be answered, which in turn leads to new questions and new insights.

For example, Mailtrust, Rackspace's mail division, used Hadoop for processing email logs. One ad hoc query they wrote was to find the geographic distribution of their users. In their words:

This data was so useful that we've scheduled the MapReduce job to run monthly and we will be using this data to help us decide which Rackspace data centers to place new mail servers in as we grow.

By bringing several hundred gigabytes of data together and having the tools to analyze it, the Rackspace engineers were able to gain an understanding of the data that they otherwise would never have had, and furthermore, they were able to use what they had learned to improve the service for their customers.

Beyond Batch

For all its strengths, MapReduce is fundamentally a batch processing system, and is not suitable for interactive analysis. You can't run a query and get results back in a few seconds or less. Queries typically take minutes or more, so it's best for offline use, where there isn't a human sitting in the processing loop waiting for results.

However, since its original incarnation, Hadoop has evolved beyond batch processing. Indeed, the term "Hadoop" is sometimes used to refer to a larger ecosystem of projects, not just HDFS and MapReduce, that fall under the umbrella of infrastructure for distributed computing and large-scale data processing. Many of these are hosted by the Apache Software Foundation, which provides support for a community of open source software projects, including the original HTTP Server from which it gets its name.

The first component to provide online access was HBase, a key-value store that uses HDFS for its underlying storage. HBase provides both online read/write access of individual rows and batch operations for reading and writing data in bulk, making it a good solution for building applications on.

The real enabler for new processing models in Hadoop was the introduction of YARN (which stands for *Yet Another Resource Negotiator*) in Hadoop 2. YARN is a cluster resource management system, which allows any distributed program (not just MapReduce) to run on data in a Hadoop cluster.

In the last few years, there has been a flowering of different processing patterns that work with Hadoop. Here is a sample:

Interactive SQL

By dispensing with MapReduce and using a distributed query engine that uses dedicated "always on" daemons (like Impala) or container reuse (like Hive on Tez), it's possible to achieve low-latency responses for SQL queries on Hadoop while still scaling up to large dataset sizes.

Iterative processing

Many algorithms—such as those in machine learning—are iterative in nature, so it's much more efficient to hold each intermediate working set in memory, compared to loading from disk on each iteration. The architecture of MapReduce does not allow this, but it's straightforward with Spark, for example, and it enables a highly exploratory style of working with datasets.

Stream processing

Streaming systems like Storm, Spark Streaming, or Samza make it possible to run real-time, distributed computations on unbounded streams of data and emit results to Hadoop storage or external systems.

Search

The Solr search platform can run on a Hadoop cluster, indexing documents as they are added to HDFS, and serving search queries from indexes stored in HDFS.

Despite the emergence of different processing frameworks on Hadoop, MapReduce still has a place for batch processing, and it is useful to understand how it works since it introduces several concepts that apply more generally (like the idea of input formats, or how a dataset is split into pieces).

Comparison with Other Systems

Hadoop isn't the first distributed system for data storage and analysis, but it has some unique properties that set it apart from other systems that may seem similar. Here we look at some of them.

RELATIONAL DATABASE MANAGEMENT SYSTEMS

Why can't we use databases with lots of disks to do large-scale analysis? Why is Hadoop needed?

The answer to these questions comes from another trend in disk drives: seek time is improving more slowly than transfer rate. Seeking is the process of moving the disk's head to a particular place on the disk to read or write data. It characterizes the latency of a disk operation, whereas the transfer rate corresponds to a disk's bandwidth.

If the data access pattern is dominated by seeks, it will take longer to read or write large portions of the dataset than streaming through it, which operates at the transfer rate. On the other hand, for updating a small proportion of records in a database, a traditional B-Tree (the data structure used in relational databases, which is limited by the rate at which it can perform seeks) works well. For updating the majority of a database, a B-Tree is less efficient than MapReduce, which uses Sort/Merge to rebuild the database.

In many ways, MapReduce can be seen as a complement to a Relational Database Management System (RDBMS). (The differences between the two systems are shown in Table 1-1.) MapReduce is a good fit for problems that need to analyze the whole dataset in a batch fashion, particularly for ad hoc analysis. An RDBMS is good for point queries or updates, where the dataset has been indexed to deliver low-latency retrieval and update times of a relatively small amount of data. MapReduce suits applications where the data is written once and read many times, whereas a relational database is good for datasets that are continually updated.[7]

Table 1-1. RDBMS compared to MapReduce

	Traditional RDBMS	MapReduce
Data size	Gigabytes	Petabytes
Access	Interactive and batch	Batch
Updates	Read and write many times	Write once, read many times
Transactions	ACID	None
Structure	Schema-on-write	Schema-on-read
Integrity	High	Low
Scaling	Nonlinear	Linear

However, the differences between relational databases and Hadoop systems are blurring. Relational databases have started incorporating some of the ideas from Hadoop, and from the other direction, Hadoop systems such as Hive are becoming more interactive (by moving away from MapReduce) and adding features like indexes and transactions that make them look more and more like traditional RDBMSs.

Another difference between Hadoop and an RDBMS is the amount of structure in the datasets on which they operate. *Structured data* is organized into entities that have a defined format, such as XML documents or database tables that conform to a particular predefined schema. This is the realm of the RDBMS. *Semi-structured data*, on the other hand, is looser, and though there may be a schema, it is often ignored, so it may be used only as a guide to the structure of the data: for example, a spreadsheet, in which the

structure is the grid of cells, although the cells themselves may hold any form of data. *Unstructured data* does not have any particular internal structure: for example, plain text or image data. Hadoop works well on unstructured or semi-structured data because it is designed to interpret the data at processing time (so called *schema-on-read*). This provides flexibility and avoids the costly data loading phase of an RDBMS, since in Hadoop it is just a file copy.

Relational data is often *normalized* to retain its integrity and remove redundancy. Normalization poses problems for Hadoop processing because it makes reading a record a nonlocal operation, and one of the central assumptions that Hadoop makes is that it is possible to perform (high-speed) streaming reads and writes.

A web server log is a good example of a set of records that is not normalized (for example, the client hostnames are specified in full each time, even though the same client may appear many times), and this is one reason that logfiles of all kinds are particularly well suited to analysis with Hadoop. Note that Hadoop can perform joins; it's just that they are not used as much as in the relational world.

MapReduce—and the other processing models in Hadoop—scales linearly with the size of the data. Data is partitioned, and the functional primitives (like map and reduce) can work in parallel on separate partitions. This means that if you double the size of the input data, a job will run twice as slowly. But if you also double the size of the cluster, a job will run as fast as the original one. This is not generally true of SQL queries.

GRID COMPUTING

The high-performance computing (HPC) and grid computing communities have been doing large-scale data processing for years, using such application program interfaces (APIs) as the Message Passing Interface (MPI). Broadly, the approach in HPC is to distribute the work across a cluster of machines, which access a shared filesystem, hosted by a storage area network (SAN). This works well for predominantly compute-intensive jobs, but it becomes a problem when nodes need to access larger data volumes (hundreds of gigabytes, the point at which Hadoop really starts to shine), since the network bandwidth is the bottleneck and compute nodes become idle.

Hadoop tries to co-locate the data with the compute nodes, so data access is fast because it is local.[8] This feature, known as *data locality*, is at the heart of data processing in Hadoop and is the reason for its good performance. Recognizing that network bandwidth is the most precious resource in a data center environment (it is easy to saturate network links by copying data around), Hadoop goes to great lengths to conserve it by explicitly modeling network topology. Notice that this arrangement does not preclude high-CPU analyses in Hadoop.

MPI gives great control to programmers, but it requires that they explicitly handle the mechanics of the data flow, exposed via low-level C routines and constructs such as sockets, as well as the higher-level algorithms for the analyses. Processing in Hadoop operates only

at the higher level: the programmer thinks in terms of the data model (such as key-value pairs for MapReduce), while the data flow remains implicit.

Coordinating the processes in a large-scale distributed computation is a challenge. The hardest aspect is gracefully handling partial failure—when you don't know whether or not a remote process has failed—and still making progress with the overall computation. Distributed processing frameworks like MapReduce spare the programmer from having to think about failure, since the implementation detects failed tasks and reschedules replacements on machines that are healthy. MapReduce is able to do this because it is a *shared-nothing* architecture, meaning that tasks have no dependence on one other. (This is a slight oversimplification, since the output from mappers is fed to the reducers, but this is under the control of the MapReduce system; in this case, it needs to take more care rerunning a failed reducer than rerunning a failed map, because it has to make sure it can retrieve the necessary map outputs and, if not, regenerate them by running the relevant maps again.) So from the programmer's point of view, the order in which the tasks run doesn't matter. By contrast, MPI programs have to explicitly manage their own checkpointing and recovery, which gives more control to the programmer but makes them more difficult to write.

VOLUNTEER COMPUTING

When people first hear about Hadoop and MapReduce they often ask, "How is it different from SETI@home?" SETI, the Search for Extra-Terrestrial Intelligence, runs a project called SETI@homein which volunteers donate CPU time from their otherwise idle computers to analyze radio telescope data for signs of intelligent life outside Earth. SETI@home is the most well known of many *volunteer computing* projects; others include the Great Internet Mersenne Prime Search (to search for large prime numbers) and Folding@home (to understand protein folding and how it relates to disease).

Volunteer computing projects work by breaking the problems they are trying to solve into chunks called *work units*, which are sent to computers around the world to be analyzed. For example, a SETI@home work unit is about 0.35 MB of radio telescope data, and takes hours or days to analyze on a typical home computer. When the analysis is completed, the results are sent back to the server, and the client gets another work unit. As a precaution to combat cheating, each work unit is sent to three different machines and needs at least two results to agree to be accepted.

Although SETI@home may be superficially similar to MapReduce (breaking a problem into independent pieces to be worked on in parallel), there are some significant differences. The SETI@home problem is very CPU-intensive, which makes it suitable for running on hundreds of thousands of computers across the world[9] because the time to transfer the work unit is dwarfed by the time to run the computation on it. Volunteers are donating CPU cycles, not bandwidth.

MapReduce is designed to run jobs that last minutes or hours on trusted, dedicated hardware running in a single data center with very high aggregate bandwidth

interconnects. By contrast, SETI@home runs a perpetual computation on untrusted machines on the Internet with highly variable connection speeds and no data locality.

A Brief History of Apache Hadoop

Hadoop was created by Doug Cutting, the creator of Apache Lucene, the widely used text search library. Hadoop has its origins in Apache Nutch, an open source web search engine, itself a part of the Lucene project.

THE ORIGIN OF THE NAME "HADOOP"

The name Hadoop is not an acronym; it's a made-up name. The project's creator, Doug Cutting, explains how the name came about:

The name my kid gave a stuffed yellow elephant. Short, relatively easy to spell and pronounce, meaningless, and not used elsewhere: those are my naming criteria. Kids are good at generating such. Googol is a kid's term.

Projects in the Hadoop ecosystem also tend to have names that are unrelated to their function, often with an elephant or other animal theme ("Pig," for example). Smaller components are given more descriptive (and therefore more mundane) names. This is a good principle, as it means you can generally work out what something does from its name. For example, the namenode[10] manages the filesystem namespace.

Building a web search engine from scratch was an ambitious goal, for not only is the software required to crawl and index websites complex to write, but it is also a challenge to run without a dedicated operations team, since there are so many moving parts. It's expensive, too: Mike Cafarella and Doug Cutting estimated a system supporting a one-billion-page index would cost around $500,000 in hardware, with a monthly running cost of $30,000.[11] Nevertheless, they believed it was a worthy goal, as it would open up and ultimately democratize search engine algorithms.

Nutch was started in 2002, and a working crawler and search system quickly emerged. However, its creators realized that their architecture wouldn't scale to the billions of pages on the Web. Help was at hand with the publication of a paper in 2003 that described the architecture of Google's distributed filesystem, called GFS, which was being used in production at Google.[12] GFS, or something like it, would solve their storage needs for the very large files generated as a part of the web crawl and indexing process. In particular, GFS would free up time being spent on administrative tasks such as managing storage nodes. In 2004, Nutch's developers set about writing an open source implementation, theNutch Distributed Filesystem (NDFS).

In 2004, Google published the paper that introduced MapReduce to the world.[13] Early in 2005, the Nutch developers had a working MapReduce implementation in Nutch, and by the middle of that year all the major Nutch algorithms had been ported to run using MapReduce and NDFS.

NDFS and the MapReduce implementation in Nutch were applicable beyond the realm of search, and in February 2006 they moved out of Nutch to form an independent subproject of Lucene called Hadoop. At around the same time, Doug Cutting joined Yahoo!, which provided a dedicated team and the resources to turn Hadoop into a system that ran at web scale (see the following sidebar). This was demonstrated in February 2008 when Yahoo! announced that its production search index was being generated by a 10,000-core Hadoop cluster.[14]

HADOOP AT YAHOO!

Building Internet-scale search engines requires huge amounts of data and therefore large numbers of machines to process it. Yahoo! Search consists of four primary components: the *Crawler*, which downloads pages from web servers; the *WebMap*, which builds a graph of the known Web; the *Indexer*, which builds a reverse index to the best pages; and the *Runtime*, which answers users' queries. The WebMap is a graph that consists of roughly 1 trillion (10^{12}) edges, each representing a web link, and 100 billion (10^{11}) nodes, each representing distinct URLs. Creating and analyzing such a large graph requires a large number of computers running for many days. In early 2005, the infrastructure for the WebMap, named *Dreadnaught*, needed to be redesigned to scale up to more nodes. Dreadnaught had successfully scaled from 20 to 600 nodes, but required a complete redesign to scale out further. Dreadnaught is similar to MapReduce in many ways, but provides more flexibility and less structure. In particular, each fragment in a Dreadnaught job could send output to each of the fragments in the next stage of the job, but the sort was all done in library code. In practice, most of the WebMap phases were pairs that corresponded to MapReduce. Therefore, the WebMap applications would not require extensive refactoring to fit into MapReduce.

Eric Baldeschwieler (aka Eric14) created a small team, and we started designing and prototyping a new framework, written in C++ modeled and after GFS and MapReduce, to replace Dreadnaught. Although the immediate need was for a new framework for WebMap, it was clear that standardization of the batch platform across Yahoo! Search was critical and that by making the framework general enough to support other users, we could better leverage investment in the new platform.

At the same time, we were watching Hadoop, which was part of Nutch, and its progress. In January 2006, Yahoo! hired Doug Cutting, and a month later we decided to abandon our prototype and adopt Hadoop. The advantage of Hadoop over our prototype and design was that it was already working with a real application (Nutch) on 20 nodes. That allowed us to bring up a research cluster two months later and start helping real customers use the new framework much sooner than we could have otherwise. Another advantage, of course, was that since Hadoop was already open source, it was easier (although far from easy!) to get permission from Yahoo!'s legal department to work in open source. So, we set up a 200-node cluster for the researchers in early 2006 and put the WebMap conversion plans on hold while we supported and improved Hadoop for the research users.

—Owen O'Malley, 2009

In January 2008, Hadoop was made its own top-level project at Apache, confirming its success and its diverse, active community. By this time, Hadoop was being used by many other companies besides Yahoo!, such as Last.fm, Facebook, and the *New York Times*.

In one well-publicized feat, the *New York Times* used Amazon's EC2 compute cloud to crunch through 4 terabytes of scanned archives from the paper, converting them to PDFs for the Web.[15] The processing took less than 24 hours to run using 100 machines, and the project probably wouldn't have been embarked upon without the combination of Amazon's pay-by-the-hour model (which allowed the *NYT* to access a large number of machines for a short period) and Hadoop's easy-to-use parallel programming model.

In April 2008, Hadoop broke a world record to become the fastest system to sort an entire terabyte of data. Running on a 910-node cluster, Hadoop sorted 1 terabyte in 209 seconds (just under 3.5 minutes), beating the previous year's winner of 297 seconds.[16] In November of the same year, Google reported that its MapReduce implementation sorted 1 terabyte in 68 seconds.[17] Then, in April 2009, it was announced that a team at Yahoo! had used Hadoop to sort 1 terabyte in 62 seconds.[18]

The trend since then has been to sort even larger volumes of data at ever faster rates. In the 2014 competition, a team from Databricks were joint winners of the Gray Sort benchmark. They used a 207-node Spark cluster to sort 100 terabytes of data in 1,406 seconds, a rate of 4.27 terabytes per minute.[19]

Today, Hadoop is widely used in mainstream enterprises. Hadoop's role as a general-purpose storage and analysis platform for big data has been recognized by the industry, and this fact is reflected in the number of products that use or incorporate Hadoop in some way. Commercial Hadoop support is available from large, established enterprise vendors, including EMC, IBM, Microsoft, and Oracle, as well as from specialist Hadoop companies such as Cloudera, Hortonworks, and MapR.

What's in This Book?

The book is divided into five main parts: Parts I to III are about core Hadoop, Part IV covers related projects in the Hadoop ecosystem, and Part V contains Hadoop case studies. You can read the book from cover to cover, but there are alternative pathways through the book that allow you to skip chapters that aren't needed to read later ones. See Figure 1-1.

Part I is made up of five chapters that cover the fundamental components in Hadoop and should be read before tackling later chapters. Chapter 1 (this chapter) is a high-level introduction to Hadoop. Chapter 2 provides an introduction to MapReduce. Chapter 3 looks at Hadoop filesystems, and in particular HDFS, in depth. Chapter 4 discusses YARN, Hadoop's cluster resource management system. Chapter 5 covers the I/O building blocks in Hadoop: data integrity, compression, serialization, and file-based data structures.

Part II has four chapters that cover MapReduce in depth. They provide useful understanding for later chapters (such as the data processing chapters in Part IV), but could be skipped on a first reading. Chapter 6 goes through the practical steps needed to develop a MapReduce application. Chapter 7looks at how MapReduce is implemented in

Hadoop, from the point of view of a user. Chapter 8 is about the MapReduce programming model and the various data formats that MapReduce can work with. Chapter 9 is on advanced MapReduce topics, including sorting and joining data.

Part III concerns the administration of Hadoop: Chapters 10 and 11 describe how to set up and maintain a Hadoop cluster running HDFS and MapReduce on YARN.

Part IV of the book is dedicated to projects that build on Hadoop or are closely related to it. Each chapter covers one project and is largely independent of the other chapters in this part, so they can be read in any order.

The first two chapters in this part are about data formats. Chapter 12 looks at Avro, a cross-language data serialization library for Hadoop, and Chapter 13 covers Parquet, an efficient columnar storage format for nested data.

The next two chapters look at data ingestion, or how to get your data into Hadoop. Chapter 14 is about Flume, for high-volume ingestion of streaming data. Chapter 15 is about Sqoop, for efficient bulk transfer of data between structured data stores (like relational databases) and HDFS.

The common theme of the next four chapters is data processing, and in particular using higher-level abstractions than MapReduce. Pig (Chapter 16) is a data flow language for exploring very large datasets. Hive (Chapter 17) is a data warehouse for managing data stored in HDFS and provides a query language based on SQL. Crunch (Chapter 18) is a high-level Java API for writing data processing pipelines that can run on MapReduce or Spark. Spark (Chapter 19) is a cluster computing framework for large-scale data processing; it provides a *directed acyclic graph* (DAG) engine, and APIs in Scala, Java, and Python.

Chapter 20 is an introduction to HBase, a distributed column-oriented real-time database that uses HDFS for its underlying storage. And Chapter 21 is about ZooKeeper, a distributed, highly available coordination service that provides useful primitives for building distributed applications.

Finally, Part V is a collection of case studies contributed by people using Hadoop in interesting ways.

Supplementary information about Hadoop, such as how to install it on your machine, can be found in the appendixes.

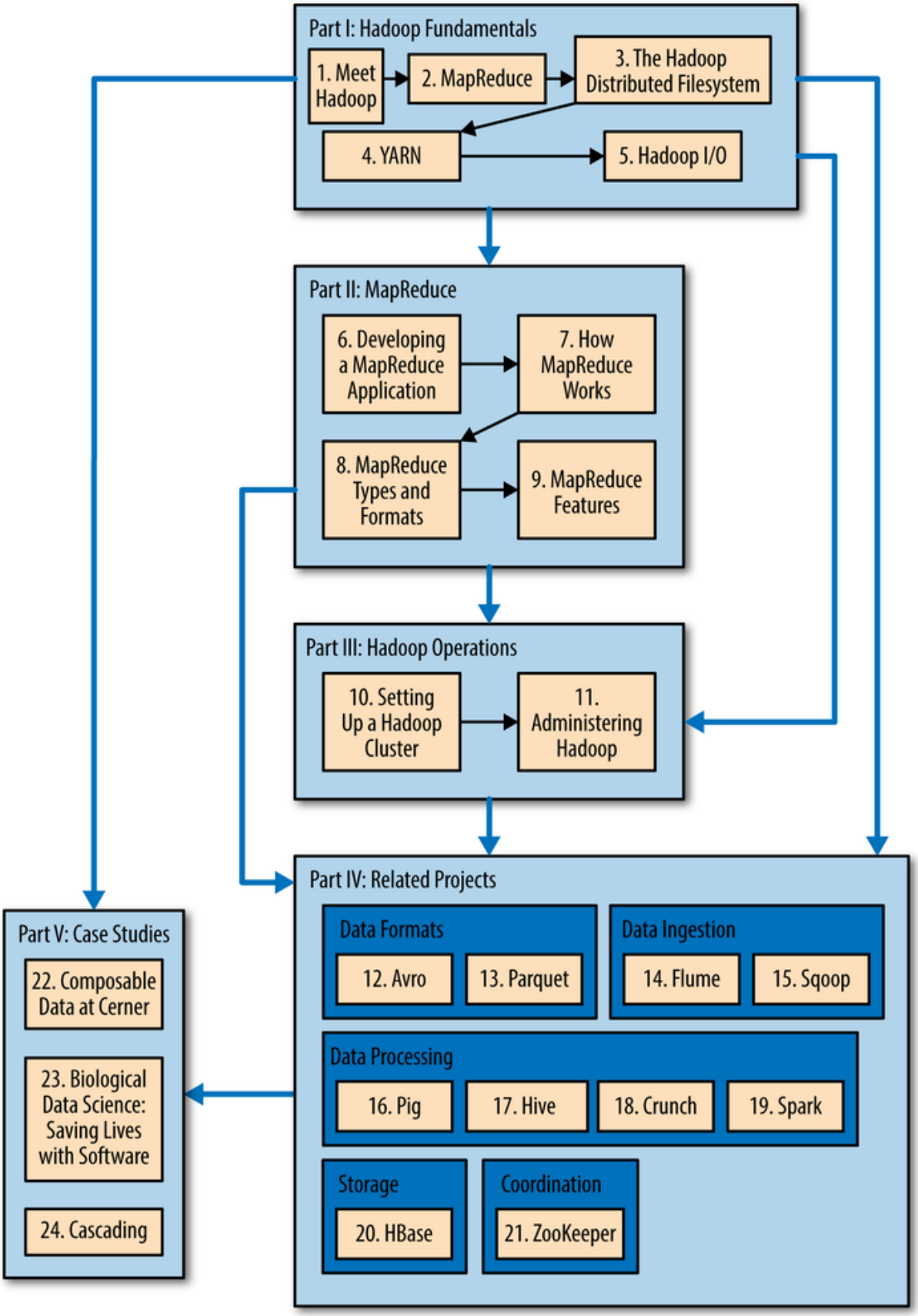
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Figure 1-1. Structure of the book: there are various pathways through the content

[3] These statistics were reported in a study entitled "The Digital Universe of Opportunities: Rich Data and the Increasing Value of the Internet of Things."

[4] All figures are from 2013 or 2014. For more information, see Tom Groenfeldt, "At NYSE, The Data Deluge Overwhelms Traditional Databases"; Rich Miller, "Facebook Builds Exabyte Data Centers for Cold Storage"; Ancestry.com's "Company Facts"; Archive.org's "Petabox"; and the Worldwide LHC Computing Grid project's welcome page.

[5] The quote is from Anand Rajaraman's blog post "More data usually beats better algorithms," in which he writes about the Netflix Challenge. Alon Halevy, Peter Norvig, and Fernando Pereira make the same point in "The Unreasonable Effectiveness of Data," *IEEE Intelligent Systems*, March/April 2009.

[6] These specifications are for the Seagate ST-41600n.

[7] In January 2007, David J. DeWitt and Michael Stonebraker caused a stir by publishing "MapReduce: A major step backwards," in which they criticized MapReduce for being a poor substitute for relational databases. Many commentators argued that it was a false comparison (see, for example, Mark C. Chu-Carroll's "Databases are hammers; MapReduce is a screwdriver"), and DeWitt and Stonebraker followed up with "MapReduce II," where they addressed the main topics brought up by others.

[8] Jim Gray was an early advocate of putting the computation near the data. See "Distributed Computing Economics," March 2003.

[9] In January 2008, SETI@home was reported to be processing 300 gigabytes a day, using 320,000 computers (most of which are not dedicated to SETI@home; they are used for other things, too).

[10] In this book, we use the lowercase form, "namenode," to denote the entity when it's being referred to generally, and the CamelCase form `NameNode` to denote the Java class that implements it.

[11] See Mike Cafarella and Doug Cutting, "Building Nutch: Open Source Search," *ACM Queue*, April 2004.

[12] Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung, "The Google File System," October 2003.

[13] Jeffrey Dean and Sanjay Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters," December 2004.

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