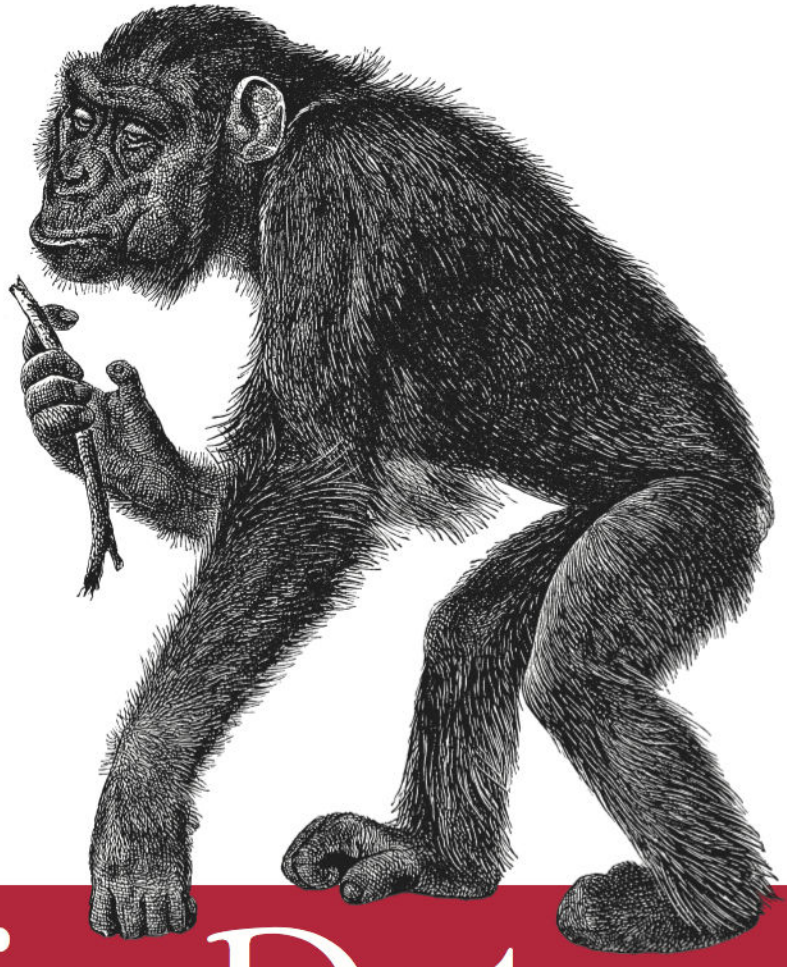

Big Data for Chimps

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Philip Kromer

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CHAPTER 1

Insight comes from Data in Context

Data is worthless. Actually, it's worse than worthless: it requires money and effort to collect, store, transport and organize. Nobody wants data.

What's valuable is *insight* — summaries, patterns and connections that lead to deeper understanding and better decisions. And insight comes from synthesizing data in context. We can predict air flight delays by placing commercial flight arrival times in context with hourly global weather data (as we do in Chapter (REF)). Take the mountain of events in a large website's log files, and regroup using context defined by the paths users take through the site, and you'll illuminate articles of similar interest (see Chapter (REF)). In Chapter (REF), we'll dismantle the text of every article on Wikipedia, then reassemble the words from each article about a physical place into context groups defined by the topic's location — and produce insights into human language not otherwise quantifiable.

Within each of those examples are two competing forces that move them out of the domain of traditional data analysis and into the topic of this book: "big data" analytics and simple analytics. Due to the volume of data, it is far too large to comfortably analyze on a single machine; and due to the comprehensiveness of the data, simple methods are able to extract patterns not visible in the small.

Big Data: Tools to Solve the Crisis of Comprehensive Data

Let's take an extremely basic analytic operation: counting. To count the votes for a bill in the state legislature, or for what type of pizza to order, we gather the relevant parties into the same room at a fixed time and take a census of opintions. The logistics here are straightforward.

It is impossible, however, to count votes for the President of the United States this way. No conference hall is big enough to hold 300 million people; if there were, no roads are

wide enough to get people to that conference hall; and even still the processing rate would not greatly exceed the rate at which voters come of age or die.

Once the volume of data required for synthesis exceeds some key limit of available computation — limited memory, limited network bandwith, limited time to prepare a relevant answer, or such — you're forced to fundamentally rework how you synthesize insight from data.

We conduct a presidential election by sending people to local polling places, distributed so that the participants to not need to travel far, and sized so that the logistics of voting remain straightforward. At the end of day the vote totals from each polling place are summed and sent to the state Elections Division. The folks in the Elections Division office add the results from each polling place to prepare the final result. This new approach doesn't completely discard the straightforward method (gathering people to the same physical location) that worked so well in the small. Instead, it applies another local method (summing a table of numbers). The orchestration of a gathering stage, an efficient data transfer stage, and a final tabulation stage arrives at a correct result, and the volume of people and data never exceeds what can be efficiently processed.

So our first definition of Big Data is a response to a crisis: "A collection of practical data analysis tools and processes that continue to scale even as the volume of data for justified synthesis exceeds some limit of available computation".

Big Data: Algorithms to Capitalize on the Opportunity of Comprehensive Data

The excitement around Big Data is more than you could explain as "like databases, but bigger". Those tools don't just unlock a new region of scalability, they enable transformative new capabilities.

The data that's powering this revolution isn't just comprehensive, it's *connected*. When your one-in-a-thousand events manifest in sample of ten thousand records, it's noise. When they manifest in ten million records, tiny coincidences reinforce each other to produce patterns. The website etsy.com (an open marketplace for handcrafted goods) has millions of records showing which handcrafted goods people browse and buy. And thanks to their Facebook app they have access to millions of people who have shown interest in those handcrafted goods. Thanks to Facebook's data, they have as well the overlapping interests of those potential customers: "surfing", "big data", "barbeque". Now work backwards. From each interest, find the customers, and from the customers find the purchases, and from the purchase find the categories. What comes forth are unmistakeable patterns such as "People who like the band Lynrd Skynrd are overwhelmingly more likely to purchase Taxidermy". Etsy can better connect people with the things they love, their sellers can better connect with a their fans, and southern-fried rockers can accessorize their living room with that elk's head they always wanted.

Here's what's surprising and important: the algorithms to expose these patterns are not specific to e-commerce, and don't require coming in with guesses about the associations to draw. The work proceeds in three broad steps: (a) provide comprehensive data, identifying its features and connectivity; (b) apply generic methods that use only those features and connectivity (and not a domain-specific model), to expose patterns in the data; (c) interpret those patterns back into the original domain.

This does *not* follow the accepted path to truth, namely the Scientific Method. Roughly speaking, the scientific method has you (a) use a simplified model of the universe to make falsifiable predictions; (b) test those predictions in controlled circumstances; (c) use established truths to bound any discrepancies [1]. Under this paradigm, data is non-comprehensive: scientific practice demands you carefully control experimental conditions, and the whole point of the model is to strip out all but the reductionistically necessary parameter. A large part of the analytic machinery acts to account for discrepancies from sampling (too little comprehensiveness) or discrepancies from "extraneous" effects (too much comprehensiveness). If those discrepancies are modest, the model is judged to be valid.

This new path to truth is what Peter Norvig (Google's Director of Research) calls "The unreasonable effectiveness of data". You don't have to start with a model and you don't necessarily end up with a model. There's no simplification of the universe down to a smaller explanation you can carry forward. Sure, we can apply domain knowledge and say that the correspondence of Lynrd Skynrd with Taxidermy means the robots have captured the notion of "Southern-ness". But for applying the result in practice, there's no reason to do so. The algorithms have replaced a uselessly complicated thing (the trillions of associations possible from interest to product category) with an *actionably* complicated thing (a scoring of what categories to probabilistically present based on interest). You haven't confirmed a falsifiable hypothesis. But you can win at the track.

The proposition that the Unreasonaly-Effective Method is a worthwhile rival to the Scientific Method is sure to cause barroom brawls at scientific conferences for years to come. This book will not go deeply into advanced algorithms, but we will repeatedly see examples of Unreasonable Effectiveness, as the data comes forth with patterns of its own.

The Answer to the Crisis

One solution to the big data crisis is high-performance supercomputing (HPC): push back the limits of computation with brute force. We could conduct our election by gathering supporters of one candidate on a set of cornfields in Iowa, supporters of the other on cornfields in Iowa, and using satellite imaging to tally the result. HPC solutions

1. plus (d) a secret dose of our sense of the model's elegance

are exceptionally expensive, require the kind of technology seen only when military and industrial get complex, and though the traditional "all data is local" methods continue to work, they lose their essential straightforward flavor. A supercomputer is not one giant connected room, it's a series of largish rooms connected by very wide multidimensional hallways; HPC programmers have to constantly think about the motion of data among caches, processors, and backing store.

The most important alternative to the HPC approach is the big data tool Hadoop which effectively takes the opposite approach. Instead of full control over all aspects of computation and the illusion of data locality, Hadoop revokes almost all control over the motion of data. Furthermore, unlike the HPC solutions of yore, Hadoop runs on commodity hardware and addresses a wide range of problem domains (finance, medicine, marketing; images, logfiles, mathmatical computation). This power comes at a cost, though. Hadoop understands only a limited vocabulary known as Map/Reduce, and you'll need to learn that vocabulary if Hadoop is to do any work for you.

To get a taste of Map/Reduce, imagine a publisher that banned all literary forms except the haiku:

> data flutters by
> elephants make sturdy piles
> context yields insight
>
> — The Map/Reduce Haiku

Our Map/Reduce haiku illustrates Hadoop's template:

1. The Mapper portion of your script processes records, attaching a label to each.
2. Hadoop assembles those records into context groups according to their label.
3. The Reducer portion of your script processes those context groups and writes them to a data store or external system.

While it would be unworkable to have every novel, critical essay, or sonnet be composed of haikus, map/reduce is surprisingly more powerful. From this single primitive, we can construct the familiar relational operations (such as GROUPs and ROLLUPs) of traditional databases, many machine-learning algorithms, matrix and graph transformations and the rest of the advanced data analytics toolkit.

In the coming chapters, we'll walk you through Map/Reduce in its pure form. We recognize that raw Map/Reduce can be intimidating and inefficient to develop, so we'll also spend a fair amount of time on Map/Reduce abstractions such as Wukong and Pig.

Wukong is a thin layer atop Hadoop using the Ruby programming language. It's the most easily-readable way for us to demonstrate the patterns of data analysis, and you

will be able to lift its content into the programming language of your choice [2]. It's also a powerful tool you won't grow out of.

The high-level Pig programming language has you describe the kind of full-table transformations familiar to database programmers (selecting filtered data, groups and aggregations, joining records from multiple tables). Pig carries out those transformations using efficient map/reduce scripts in Hadoop, based on optimized algorithms you'd otherwise have to reimplement or do without. To hit the sweet spot of "common things are simple, complex things remain possible", you can extend Pig with User-Defined Functions (UDFs), covered in chapter (REF).

This book's code will be roughly 30% Wukong, 60% Pig, and 10% using Java to extend Pig.

Let's take a quick look at some code to compare the two tools.

First, here's a Wukong script. Don't worry about understanding it in full; just try to get a feel for the flow.

```
# CODE validate script, column number, file naming
cat ufo_sightings.tsv                     | \
  egrep "\w+\tUnited States of America\t" | \
  cut -f 11                               | \
  sort                                    | \
  uniq -c > /tmp/state_sightings_ct_sh.tsv
```

```
SELECT COUNT(*), `state`
  FROM `ufo_sightings`.sightings ufos
  WHERE (`country` = 'United States of America') AND (`state` != '')
  GROUP BY `ufos`.`state`
  INTO OUTFILE '/tmp/state_sightings_ct_sql.tsv';
```

```
outfile = File.open('/tmp/state_sightings_ct_rb.tsv', "w");
File.open('ufo_sightings.tsv').
  select{|line| line =~ /\w+\tUnited States of America\t/ }.
  map{|line| line.split("\t")[10] }.
  sort.chunk(&:to_s).
  map{|key,grp| [grp.count, key] }.
  each{|ct,key| outfile << [ct, key].join("\t") << "\n" }
outfile.close
```

We simply *load* a table, *project* one field from its contents, *sort* the values (and in so doing, group each state name's occurrences in a contiguous run), *aggregate* each group into value and count, and *store* them into an output file.

```
mapper(:tsv) do |_,_,_,_,_,_,_,_,_,state,country,*_|
  yield state if country = "United States of America"
```

2. In the spirit of this book's open-source license, if an eager reader submits a "translation" of the example programs into the programming language of their choice we would love to fold it into in the example code repository and acknowledge the contribution in future printings.

```
end

reducer do |state, grp|
  yield [state, grp.count]
end
```

Here's a similar operation using Pig:

```
sightings          = load_sightings();
sightings_us       = FILTER sightings BY (country == 'United States of America') AND (state !=
states             = FOREACH sightings_us GENERATE state;
state_sightings_ct = FOREACH (GROUP states BY state)
  GENERATE COUNT_STAR(states), group;
STORE state_sightings_ct INTO '$out_dir/state_sightings_ct_pig';
```

The triad: batch, stream, scale

Earlier, we defined insight as deeper understanding and better decisions. Hadoop's ability to process data of arbitrary scale, combined with our increasing ability to comprehensively instrument every aspect of an enterprise, represent a fundamental improvement in how we expose patterns and the range of human endeavors available for pattern mining.

But a funny thing happens as an organization's Hadoop investigations start to pay off: they realize they don't just want a deeper understanding of the patterns, they want to act on those patterns and make prompt decisions. The factory owner will want to stop the manufacturing line when signals predict later defects; the hospital will want to have a social worker follow up with patients unlikely to fill their postoperative medications. Just in time, a remarkable new capability has entered the core Big Data toolset: Streaming Analytics.

Streaming Analytics gets you *fast relevant insight* to go with Hadoop's *deep global insight*. Storm+Trident (the clear frontrunner toolkit) can process data with low latency and exceptional throughput (we've benchmarked it at half a million events per second); it can perform complex processing in Java, Ruby and more; it can hit remote APIs or databases with high concurrency.

This triad — Batch Analytics, Stream Analytics, and Scalable Datastores — are the three legs of the Big Data toolset. Together they let you analyze data at terabytes and petabytes, data at milliseconds, and data from ponderously many sources.

Grouping and Sorting: Analyzing UFO Sightings with Pig

While those embarassingly parallel, Map-only jobs are useful, Hadoop also shines when it comes to filtering, grouping, and counting items in a dataset. We can apply these techniques to build a travel guide of UFO sightings across the continental US.

Whereas our last example used the wukong framework, this time around we'll use another Hadoop abstraction, called Pig. [3] Pig's claim to fame is that it gives you full Hadoop power, using a syntax that lets you think in terms of data flow instead of pure Map and Reduce operations.

The example data included with the book includes a data set from the National UFO Reporting Center, containing more than 60,000 documented UFO sightings [4]. Now it's sad to say, but many of the sighting reports are likely to be bogus, and we'd like to eliminate them. How will we define bogus? As a first guess, let's reject descriptions that are fewer than 12 characters (too short), or contain the word *lol* (by an internet troll).

```
sightings     = load_sightings();
-- Significant sightings: >= 12 characters, no lulz
sig_sightings = FILTER sightings BY
  ((SIZE(description) >= 12) AND NOT (description MATCHES '(^|.*\W)lol(\W.*|$)'));
```

A key activity in a Big Data exploration is summarizing big datasets into a comprehensible smaller ones. Each sighting has a field giving the shape of the flying object: cigar, disk, etc. This script will tell us how many sightings there are for each craft type:

```
sightings = load_sightings();
craft_sightings = GROUP sightings BY craft;
craft_cts       = FOREACH cf_sightings GENERATE COUNT_STAR(sightings)
STORE craft_cts INTO '$out_dir/craft_cts';
```

We can make a little travel guide for the sightings by amending each sighting with the Wikipedia article about its place. The JOIN operator matches records from different tables based on a common key:

```
DEFINE Wikipedify  pigsy.text.Wikipedify;
articled_sightings = JOIN
  articles  BY (wikipedia_id),
  sightings BY (Wikipedify(CONCAT(city, ', ', state))
  USING replicated;
```

Here's the part that was easy: searching through 4+ million articles to find matches. Here's the part that was hard: *preparing* that common key. Pig doesn't have that capability built in, but it does let you extend its language with User-Defined Functions (UDFs). We have enabled such a UDF — a function to prepare a string in Wikipedia's article id format — using the `DEFINE` statement. On the fourth line, we combine the city and state into a single value and apply our `Wikipedify` function, giving a common basis for matching records. Here's the part that is clever: knowing when to attach `USING replicated`, and which order to place `articles` and `sightings` in the statement. The correct choice can mean a multiple times speedup in how fast this query executes. This book

3. *http://pig.apache.org*

4. For our purposes, although sixty thousand records are too small to justify Hadoop on their own, it's the perfect size to learn with.

will equip you to trust the framework for the easy part, push past the hard part, and know when and why to attach the clever part.

```
TODO: sample output
```

This travel guide is a bit of a gimmick so far, but hey, we're only at the end of the first chapter. We can come up with all sorts of ways to improve it. For instance, a proper guide would hold not just the one article about the general location, but a set of nearby places of interest. Later in the book we'll show you how to do a nearby-ness query (in the Geodata chapter (REF)), which is fiendishly hard until you know how. You'll immediately find that an undifferentiated listing of points of interest is almost worse than only listing one. Later in the book, we'll show you how to attach a notion of "prominence" (in the event log chapter (REF)).

To get us started, we're going to meet Chimpanzee & Elephant, some new friends whose adventures seem to curiously correspond to ours…

PART I

Mechanics: How Hadoop and Map/Reduce Work

CHAPTER 2
Hadoop Basics

Chimpanzee and Elephant Start a Business

A few years back, two friends — JT, a gruff silverback chimpanzee, and Nanette, a meticulous matriarch elephant — decided to start a business. As you know, Chimpanzees love nothing more than sitting at keyboards processing and generating text. Elephants have a prodigious ability to store and recall information, and will carry huge amounts of cargo with great determination. This combination of skills impressed a local publishing company enough to earn their first contract, so Chimpanzee and Elephant Corporation (C&E Corp for short) was born.

The publishing firm's project was to translate the works of Shakespeare into every language known to man, so JT and Nanette devised the following scheme. Their crew set up a large number of cubicles, each with one elephant-sized desk and one or more chimp-sized desks, and a command center where JT and Nanette can coordinate the action.

As with any high-scale system, each member of the team has a single responsibility to perform. The task of each chimpanzee is simply to read a set of passages and type out the corresponding text in a new language. JT, their foreman, efficiently assigns passages to chimpanzees, deals with absentee workers and sick days, and reports progress back to the customer. The task of each librarian elephant is to maintain a neat set of scrolls, holding either a passage to translate or some passage's translated result. Nanette serves as chief librarian. She keeps a card catalog listing, for every book, the location and essential characteristics of the various scrolls that maintain its contents.

When workers clock in for the day, they check with JT, who hands off the day's translation manual and the name of a passage to translate. Throughout the day the chimps radio progress reports in to JT; if their assigned passage is complete, JT will specify the next passage to translate.

If you were to walk by a cubicle mid-workday, you would see a highly-efficient interplay between chimpanzee and elephant, ensuring the expert translators rarely had a wasted moment. As soon as JT radios back what passage to translate next, the elephant hands it across. The chimpanzee types up the translation on a new scroll, hands it back to its librarian partner and radios for the next passage. The librarian runs the scroll through a fax machine to send it to two of its counterparts at other cubicles, producing the redundant copies Nanette's scheme requires.

The fact that each chimpanzee's work is independent of any other's — no interoffice memos, no meetings, no requests for documents from other departments — made this the perfect first contract for the Chimpanzee & Elephant, Inc. crew. JT and Nanette, however, were cooking up a new way to put their million-chimp army to work, one that could radically streamline the processes of any modern paperful office [1]. JT and Nanette would soon have the chance of a lifetime to try it out for a customer in the far north with a big, big problem.

Introduction

Hadoop is a large and complex beast. There's a lot to learn before one can even begin to use the system, much less become meaningfully adept at doing so. While Hadoop has stellar documentation, not everyone is comfortable diving right in to the menagerie of Mappers, Reducers, Shuffles, and so on. For that crowd, we've taken a different route, in the form of a story.

Map-only Jobs: Process Records Individually

Having read that short allegory, you've just learned a lot about how Hadoop operates under the hood. We can now use it to walk you through some examples. This first example uses only the *Map* phase of MapReduce, to take advantage of what some people call an "embarrassingly parallel" problem.

We may not be as clever as JT's multilingual chimpanzees, but even we can translate text into a language we'll call *Igpay Atinlay* [2]. For the unfamiliar, here's how to translate standard English into Igpay Atinlay:

1. Some chimpanzee philosophers have put forth the fanciful conceit of a "paper-less" office, requiring impossibilities like a sea of electrons that do the work of a chimpanzee, and disks of magnetized iron that would serve as scrolls. These ideas are, of course, pure lunacy!

2. Sharp-eyed readers will note that this language is really called *Pig Latin*. That term has another name in the Hadoop universe, though, so we've chosen to call it Igpay Atinlay — Pig Latin for "Pig Latin".

- If the word begins with a consonant-sounding letter or letters, move them to the end of the word adding "ay": "happy" becomes "appy-hay", "chimp" becomes "imp-chay" and "yes" becomes "es-yay".
- In words that begin with a vowel, just append the syllable "way": "another" becomes "another-way", "elephant" becomes "elephant-way".

Igpay Atinlay translator, actual version is our first Hadoop job, a program that translates plain text files into Igpay Atinlay. It's written in Wukong, a simple library to rapidly develop big data analyses. Like the chimpanzees, it is single-concern: there's nothing in there about loading files, parallelism, network sockets or anything else. Yet you can run it over a text file from the commandline — or run it over petabytes on a cluster (should you for whatever reason have a petabyte of text crying out for pig-latinizing).

Igpay Atinlay translator, actual version.

```
CONSONANTS   = "bcdfghjklmnpqrstvwxz"
UPPERCASE_RE = /[A-Z]/
PIG_LATIN_RE = %r{
  \b                    # word boundary
  ([#{CONSONANTS}]*)    # all initial consonants
  ([\w\']+)             # remaining wordlike characters
}xi

each_line do |line|
  latinized = line.gsub(PIG_LATIN_RE) do
    head, tail = [$1, $2]
    head        = 'w' if head.blank?
    tail.capitalize! if head =~ UPPERCASE_RE
    "#{tail}-#{head.downcase}ay"
  end
  yield(latinized)
end
```

Igpay Atinlay translator, pseudocode.

```
for each line,
  recognize each word in the line
  and change it as follows:
    separate the head consonants (if any) from the tail of the word
    if there were no initial consonants, use 'w' as the head
    give the tail the same capitalization as the word
    thus changing the word to "{tail}-#{head}ay"
  end
  having changed all the words, emit the latinized version of the line
end
```

Ruby helper

- The first few lines define "regular expressions" selecting the initial characters (if any) to move. Writing their names in ALL CAPS makes them be constants.
- Wukong calls the `each_line do ... end` block with each line; the `|line|` part puts it in the `line` variable.
- the `gsub` ("globally substitute") statement calls its `do ... end` block with each matched word, and replaces that word with the last line of the block.
- `yield(latinized)` hands off the `latinized` string for wukong to output

It's best to begin developing jobs locally on a subset of data. Run your Wukong script directly from your terminal's commandline:

```
wu-local examples/text/pig_latin.rb data/magi.txt -
```

The - at the end tells wukong to send its results to standard out (STDOUT) rather than a file — you can pipe its output into other unix commands or Wukong scripts. In this case, there is no consumer and so the output should appear on your terminal screen. The last line should read:

```
Everywhere-way ey-thay are-way isest-way. Ey-thay are-way e-thay agi-may.
```

That's what it looks like when a `cat` is feeding the program data; let's see how it works when an elephant sets the pace.

Are you running on a cluster?

If you've skimmed Hadoop's documentation already, you've probaby seen the terms *fully-distributed, pseudo-distributed,* and *local,* bandied about. Those describe different ways to setup your Hadoop cluster, and they're relevant to how you'll run the examples in this chapter.

In short: if you're running the examples on your laptop, during a long-haul flight, you're likely running in local mode. That means all of the computation work takes place on your machine, and all of your data sits on your local filesystem.

On the other hand, if you have access to a cluster, your jobs run in fully-distributed mode. All the work is farmed out to the cluster machines. In this case, your data will sit in the cluster's filesystem called HDFS.

Run the following commands to copy your data to HDFS:

```
hadoop fs -mkdir ./data
hadoop fs -put   wukong_example_data/text ./data/
```

These commands understand `./data/text` to be a path on the HDFS, not your local disk; the dot `.` is treated as your HDFS home directory (use it as you would ~ in Unix.). The `wu-put` command, which takes a list of local paths and copies them to the HDFS, treats its final argument as an HDFS path by default, and all the preceding paths as being local.

(Note: if you don't have access to a Hadoop cluster, Appendix 1 (REF) lists resources for acquiring one.)

Run the Job

First, let's test on the same tiny little file we used at the commandline.

```
wukong launch examples/text/pig_latin.rb ./data/text/magi.txt ./output/latinized_magi
```

While the script outputs a bunch of happy robot-ese to your screen, open up the jobtracker in your browser window (see the sidebar REF). The job should appear on the jobtracker window within a few seconds — likely in more time than the whole job took to complete.

The Jobtracker Console

When you are running on a distributed Hadoop cluster, the jobtracker offers a built-in console for monitoring and diagnosing jobs. You typically access it by pointing your web browser at *http://hostname.of.jobtracker:50030* (replace "hostname.of.jobtracker" with, you know, the hostname of your jobtracker and if that jobtracker is running on your local machine, you can use *http://hostname.of.jobtracker:50030*`). At the top, the

cluster summary shows how many jobs are running and how many worker slots exist. Clicking on the hyperlinked value under "nodes" will take you to a screen summarizing all the task trackers in the cluster. Keep an eye out for other such hyperlinked values within the jobtracker console — they lead to screens describing those elements in details.

Further down the page, you will see sections for running, completed and failed jobs. The last part of each job's name is an index showing the order it was received and appears in the flurry of messages when you launched your job.

Clicking on the job name will take you to a page summarizing that job. We will walk through the page from the bottom up because that is how to best understand the job's progress. The very bottom of the page contains a fun pair of bar charts showing the progress of each Map and Reduce task, from zero to 100-percent complete. A healthy job with many tasks should look like the screenshots below (CODE: Screenshot). During the Map phase, you should see a rolling wave of bars: completed tasks at 100 percent on the left, pending tasks at zero percent on the right and a wavefront of running tasks that smoothly advance from zero to 100 percent at a fairly uniform pace. During the Reduce phase, you should see the full set of bars advanced at nearly the same rate up the page. Each bar has three sections (we will learn later more about what they mean but it is enough for now to know how they should behave).

You should observe slow progress through the shuffle stage beginning part way through the Map phase of the job and steady progress at a slightly higher pace as soon as the Map phase concludes. Unless you are heavily burdening your Reducers, the graph should walk right through the Sort stage and begin making steady uniform progress through the final Reduce step. (CODE: Check that shuffle progress is displayed as non-0 during Map phase).

The job is not completely finished when the last Reducer hits 100 percent — there remains a Commit phase with minor bookkeeping chores, and replication of the output data — but the delay from end of Reduce to successful job completion should be small.

The main thing to watch for in the Reduce phase is rapid progress by most of your Reducers and painfully slow progress by a few of them — the "skewed reducer" problem. Because of either a simple mistake on your part or a deep challenge resulting from the structure of your data, Hadoop has sent nearly all the records to those few machines. Those simple mistakes are described in Chapter (REF); defense against highly-skewed data is, in a sense, the motivation for most of the methods presented in the middle section of the book.

Do not put too much faith in the "percent complete" numbers for the job as a whole and even for its individual tasks. These really only show the fraction of data processed, which is an imperfect indicator of progress and harder to determine than you might think. Among other pecadillos, some compressed input formats report no progress mid-task; they linger at zero then go straight to 100 percent.

Above the job progress bar graphs is a hot mess of a table showing all sorts of metrics about your job, such as how much data read and written at each phase. We will run down the important ones a bit later in the book (REF).

Above that section is a smaller table giving the count of pending, running, complete, killed and failed jobs. Most of the values in that table are hyperlinks that begin the annoyingly long trip required to see your logs. Clicking on the completed tasks number takes you to a screen listing all the tasks; clicking on a task ID takes you to a screen listing the machine or machines running it. Clicking on the attempt ID shows a page describing that machine's progress through the task; and all the way on the right side of the table on that page, you will find three sets of links reading "4KB," "8KB," "All." (TECH: check details). Those links lead, at long last, to the log files for that job on that machine. The "All" link shows you the full contents but if your job is so screwed up that the log file will flood your browser, the "8KB" link shows the truncated tale.

Lastly, near the top of a page is a long URL that ends with "job.xml". Do not go there now, but keep it in mind for when you have run out of ideas as to why a job is failing: it is a monstrous but useful file listing every single configuration value set by your job.

You can compare its output to the earlier by running

```
hadoop fs -cat ./output/latinized_magi/\*
```

That command, like the Unix 'cat' command, dumps the contents of a file to standard out, so you can pipe it into any other command line utility. It produces the full contents of the file, which is what you would like for use within scripts but if your file is hundreds of MB large, as HDFS files typically are, dumping its entire contents to your terminal screen is ill appreciated. We typically, instead, use the Unix 'head' command to limit its output (in this case, to the first ten lines).

```
hadoop fs -cat ./output/latinized_magi/\* | head -n 10
```

Since you wouldn't want to read a whole 10GB file just to see whether the right number of closing braces come at the end, there is also a `hadoop fs -tail` command that dumps the last one kilobyte of a file to the terminal.

Here's what the head and tail of your output should contain:

```
CODE screenshot of hadoop fs -cat ./output/latinized_magi/\* | head -n 10
CODE screenshot of hadoop fs -tail ./output/latinized_magi/\*
```

See Progress and Results

Till now, we've run small jobs so you could focus on learning. Hadoop is built for big jobs, though, and it's important to understand how work flows through the system.

So let's run it on a corpus large enough to show off the power of distributed computing. Shakespeare's combined works are too small — at (CODE find size) even the prolific

bard's lifetime of work won't make Hadoop break a sweat. Luckily, we've had a good slice of humanity typing thoughts into wikipedia for several years, and the corpus containing every single wikipedia article is enough to warrant Hadoop's power (and tsoris [3]).

```
wukong launch examples/text/pig_latin.rb ./data/text/wikipedia/wp_articles ./output/latinized_wiki
```

Visit the jobtracker console (see sidebar REF). The first thing you'll notice is how much slower this runs! That gives us a chance to demonstrate how to monitor its progress. (If your cluster is so burly the job finishes in under a minute or so, quit bragging and supply enough duplicate copies of the input to grant you time.) In the center of the Job Tracker's view of your job you will find a table that lists status of map and reduce tasks. The number of tasks pending (waiting to be run), running, complete, killed (terminated purposefully not by error) and failed (terminated due to failure).

The most important numbers to note are the number of running tasks (there should be some unless your job is finished or the cluster is congested) and the number of failed tasks (for a healthy job on a healthy cluster, there should never be any). Don't worry about killed tasks; for reasons we'll explain later on, it's OK if a few appear late in a job. We will describe what to do when there are failing attempts later in the section on debugging Hadoop jobs (REF), but in this case, there shouldn't be any. Clicking on the number of running Map tasks will take you to a window that lists all running attempts (and similarly for the other categories). On the completed tasks listing, note how long each attempt took; for the Amazon M3.xlarge machines we used, each attempt took about x seconds (CODE: correct time and machine size). There is a lot of information here, so we will pick this back up in chapter (REF), but the most important indicator is that your attempts complete in a uniform and reasonable length of time. There could be good justification for why task 00001 is still running after five minutes while all other attempts finished in ten seconds, but if that's not what you thought would happen you should dig deeper [4].

You should get in the habit of sanity-checking the number of tasks and the input and output sizes at each job phase for the jobs you write. In this case, the job should ultimately require x Map tasks, no Reduce tasks and on our x machine cluster, it completed in x minutes. For this input, there should be one Map task per HDFS block, x GB of input with the typical one-eighth GB block size, means there should be 8x Map tasks. Sanity checking the figure will help you flag cases where you ran on all the data rather than the one little slice you intended or vice versa; to cases where the data is organized inefficiently; or to deeper reasons that will require you to flip ahead to chapter (REF).

3. trouble and suffering

4. A good justification is that task 00001's input file was compressed in a non-splittable format and is 40 times larger than the rest of the files. It's reasonable to understand how this unfortunate situation unfairly burdened a single mapper task. A bad justification is that task 00001 is trying to read from a failing-but-not-failed datanode, or has a corrupted record that is sending the XML parser into recursive hell. The good reasons you can always predict from the data itself; otherwise assume it's a bad reason

Annoyingly, the Job view does not directly display the Mapper input data, only the cumulative quantity of data per source, which is not always an exact match. Still, the figure for HDFS bytes read should closely match the size given by 'Hadoop fs -du' (CODE: add paths to command).

You can also estimate how large the output should be, using the "Gift of the Magi" sample we ran earlier (one of the benefits of first running in local mode). That job had an input size of x bytes and an output size of y bytes, for an expansion factor of z, and there is no reason to think the expansion factor on the whole Wikipedia corpus should be much different. In fact, dividing the HDFS bytes written by the HDFS bytes read line shows an expansion factor of q.

We cannot stress enough how important it is to validate that your scripts are doing what you think they are. The whole problem of Big Data is that it is impossible to see your data in its totality. You can spot-check your data, and you should, but without independent validations like these you're vulnerable to a whole class of common defects. This habit — of validating your prediction of the job's execution — is not a crutch offered to the beginner, unsure of what will occur; it is a best practice, observed most diligently by the expert, and one every practitioner should adopt.

How a job is born, the thumbnail version

Apart from one important detail, the mechanics of how a job is born should never become interesting to a Hadoop user. But since some people's brains won't really believe that the thing actually works unless we dispel some of the mystery, here's a brief synopsis.

When you run `wukong ...` or `pig ...` or otherwise launch a Hadoop job, your local program contacts the jobtracker to transfer information about the job and the Java `.jar` file each worker should execute. If the input comes from an HDFS, the jobtracker (TECH: ?job client?) consults its namenode for details about the input blocks, figures out a job ID and any other remaining configuration settings, and accepts the job. It replies to your job client with the job ID and other information, leading to the happy mess of log messages your program emits. (TECH: check the details on this) Your local program continues to run during the full course of the job so that you can see its progress, but is now irrelevant — logging out or killing the local program has no impact on the job's success.

As you have gathered, each Hadoop worker runs a tasktracker daemon to coordinate the tasks run by that machine. Like JT's chimpanzees, those tasktrackers periodically report progress to the jobtracker, requesting new work whenever there is an idle slot. The jobtracker never makes outward contact with a task tracker — this ensures work is only distributed to healthy machines at a rate they can handle. Just as JT strives to ensure that chimpanzees are only assigned passages held by their cubicle mates, the jobtracker schedules strives to assign each map attempt to a machine that holds its input blocks (known as "mapper-local" task). But if too many blocks of a file hotspot on a small

number of datanodes, mapper slots with no remaining mapper-local blocks to handle still receive task attempts, and simply pull in their input data over the network.

The one important detail to learn in all this is that *task trackers do not run your job, they only launch it*. Your job executes in a completely independent child process with its own Java settings and library dependencies. In fact, if you are using Hadoop streaming programs like Wukong, your job runs in even yet its own process, spawned by the Java child process. We've seen people increase the tasktracker memory sizes thinking it will improve cluster performance — the only impact of doing so is to increase the likelihood of out-of-memory errors.

Outro

In the next chapter, you'll learn about map/reduce jobs — the full power of Hadoop's processing paradigm.. Let's start by joining JT and Nannette with their next client.

CHAPTER 3
Map/Reduce

Chimpanzee and Elephant Save Christmas

It was holiday time at the North Pole, and letters from little boys and little girls all over the world flooded in as they always do. But one year several years ago, the world had grown just a bit too much. The elves just could not keep up with the scale of requests — Christmas was in danger! Luckily, their friends at the Elephant & Chimpanzee Corporation were available to help. Packing their typewriters and good winter coats, JT, Nanette and the crew headed to the Santaplex, the headquarters for toy manufacture at the North Pole. Here's what they found.

Trouble in Toyland

As you know, each year children from every corner of the earth write to Santa to request toys, and Santa — knowing who's been naughty and who's been nice — strives to meet the wishes of every good little boy and girl who writes him. He employs a regular army of toymaker elves, each of whom specializes in certain kinds of toy: some elves make Action Figures and Dolls, others make Xylophones and Yo-Yos.

Under the elves' old system, as bags of mail arrived they were examined by an elven postal clerk and then hung from the branches of the Big Tree at the center of the Santaplex. Letters were organized on the tree according to the child's town, as the shipping department has a critical need to organize toys by their final delivery schedule. But the toymaker elves must know what toys to make as well, and so for each letter a postal clerk recorded its Big Tree coordinates in a ledger that was organized by type of toy.

So to retrieve a letter, a doll-making elf would look under "Doll" in the ledger to find the next letter's coordinates, then wait as teamster elves swung a big claw arm to retrieve it from the Big Tree. As JT readily observed, the mail couldn't be organized both by toy type and also by delivery location, and so this ledger system was a necessary evil. "The next request for Lego is as likely to be from Cucamonga as from Novosibirsk, and letters can't be pulled from the tree any faster than the crane arm can move!"

What's worse, the size of Santa's operation meant that the workbenches were very far from where letters came in. The hallways were clogged with frazzled elves running from Big Tree to workbench and back, spending as much effort requesting and retrieving letters as they did making toys. "Throughput, not Latency!" trumpeted Nanette. "For hauling heavy loads, you need a stately elephant parade, not a swarm of frazzled elves!"

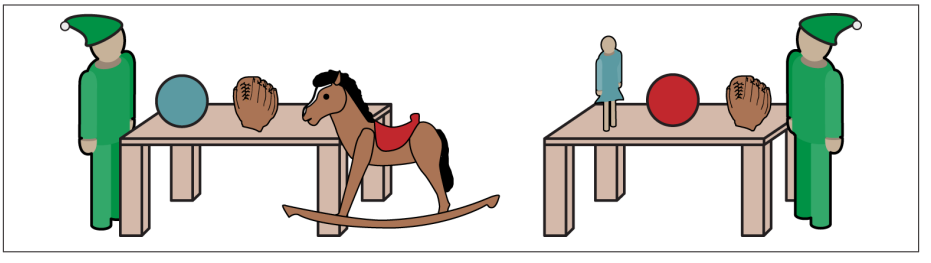


Figure 3-1. The elves' workbenches are meticulous and neat.

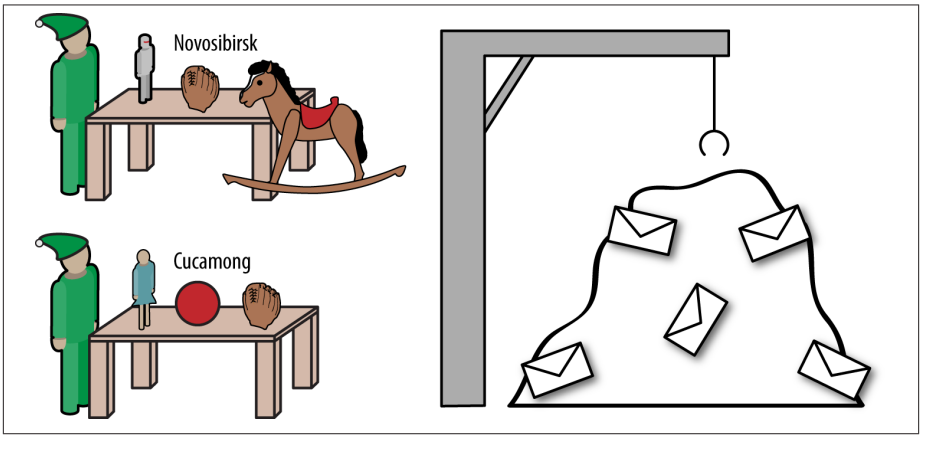


Figure 3-2. Little boys and girls' mail is less so.

Chimpanzees Process Letters into Labelled Toy Forms

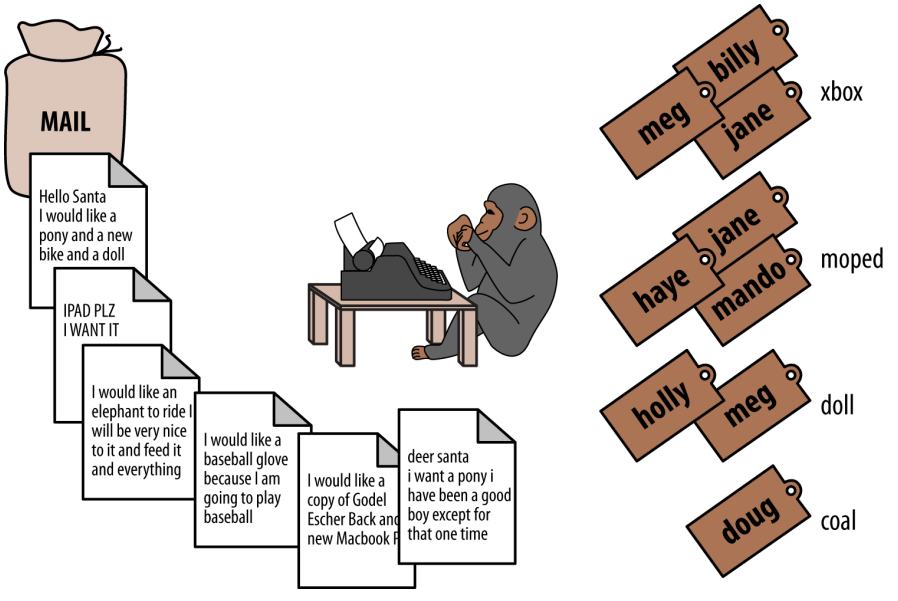
In marched Chimpanzee and Elephant, Inc, and set up a finite number of chimpanzees at a finite number of typewriters, each with an elephant desk-mate.

Postal clerks still stored each letter on the Big Tree (allowing the legacy shipping system to continue unchanged), but now also handed off bags holding copies of the mail. As she did with the translation passages, Nanette distributed these mailbags across the desks just as they arrived. The overhead of recording each letter in the much-hated ledger was no more, and the hallways were no longer clogged with elves racing to and fro.

The chimps' job was to take letters one after another from a mailbag, and fill out a toyform for each request. A toyform has a prominent label showing the type of toy, and

a body with all the information you'd expect: Name, Nice/Naughty Status, Location, and so forth. You can see some examples here:

```
Deer SANTA

I wood like a doll for me and
and an optimus prime robot for my
brother joe

I have been good this year

love julia

# Good kids, generates a toy for Julia and a toy for her brother
# Toy Forms:
#   doll  | type="green hair"  recipient="Joe's sister Julia"
#   robot | type="optimus prime" recipient="Joe"

Greetings to you Mr Claus, I came to know of you in my search for a reliable and
reputable person to handle a very confidential business transaction, which involves
the transfer of a large sum of money...

# Spam
# (no toy forms)

HEY SANTA I WANT A YANKEES HAT AND NOT
ANY DUMB BOOKS THIS YEAR

FRANK

# Frank is a jerk. He will get a lump of coal.
# Toy Forms:
#   coal  | type="anthracite" recipient="Frank" reason="doesn't like to read"
```

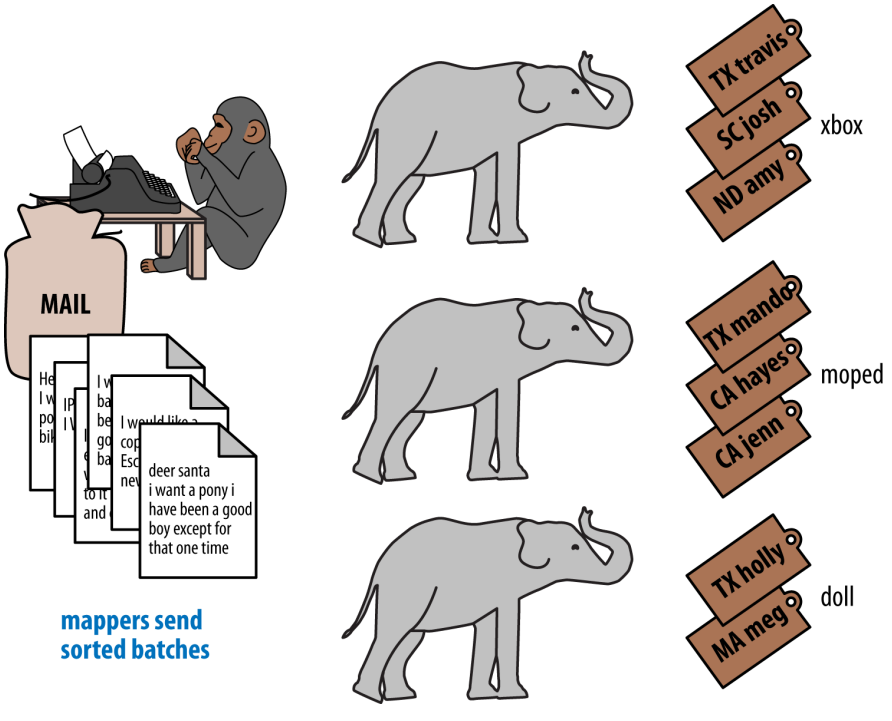


The first note, from a very good girl who is thoughtful for her brother, creates two toyforms: one for Joe's robot and one for Julia's doll. The second note is spam, so it creates no toyforms. The third one yields a toyform directing Santa to put coal in Frank's stocking.

Pygmy Elephants Carry Each Toyform to the Appropriate Workbench

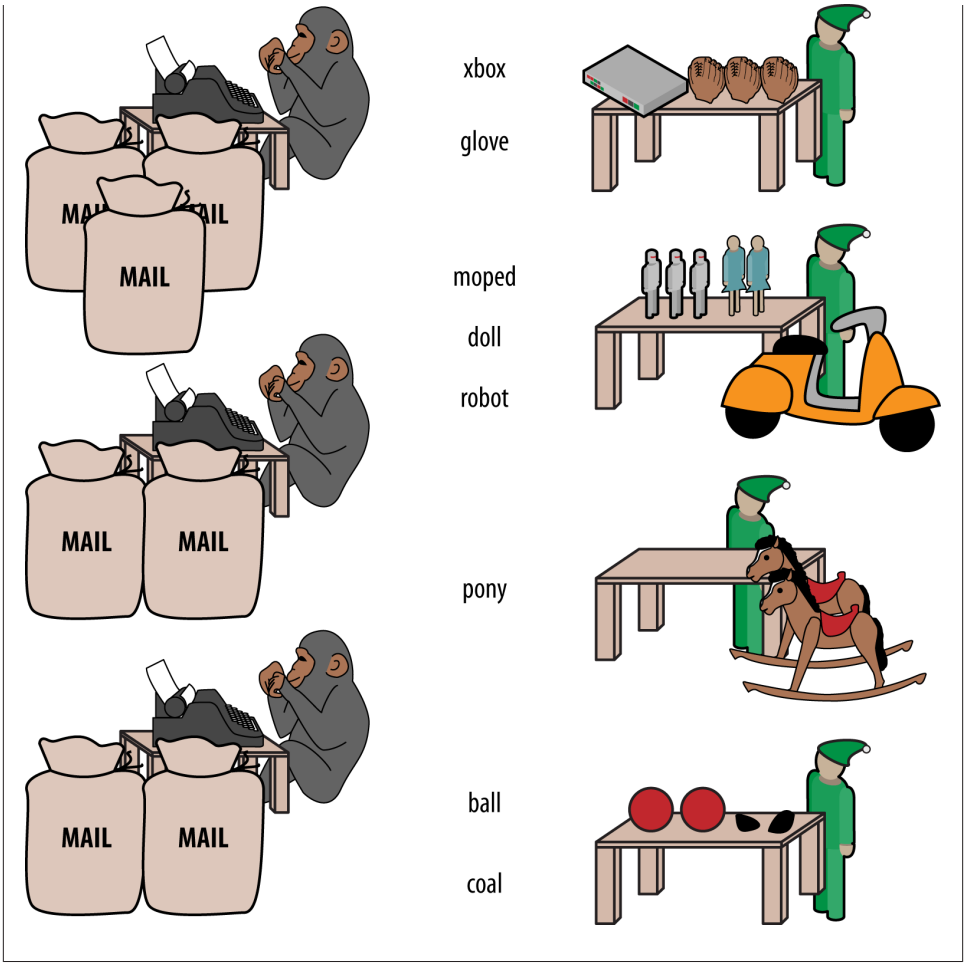
Here's the new wrinkle on top of the system used in the translation project. Next to every desk now stood a line of pygmy elephants, each dressed in a capes that listed the types of toy it would deliver. Each desk had a pygmy elephant for Archery Kits and Dolls, another one for Xylophones and Yo-Yos, and so forth — matching the different specialties of toymaker elves.

As the chimpanzees would work through a mail bag, they'd place each toyform into the basket on the back of the pygmy elephant that matched its type. At the completion of a bag, the current line of elephants would march off to the workbenches, and behind them a new line of elephants would trundle into place. What fun!



Finally, the pygmy elephants would march through the now-quiet hallways to the toy shop floor, each reporting to the workbench that matched its toy types. So the Archery Kit/Doll workbench had a line of pygmy elephants, one for every Chimpanzee&Elephant desk; similarly the Xylophone/Yo-Yo workbench, and all the rest.

Toymaker elves now began producing a steady stream of toys, no longer constrained by the overhead of walking the hallway and waiting for Big-Tree retrieval on every toy.



Introduction

In the previous chapter, you worked with the simple-as-possible Pig Latin script, which let you learn the mechanics of running Hadoop jobs, understand the essentials of the HDFS, and appreciate its scalability. It is an example of an "embarrassingly parallel" problem: each record could be processed individually, just as they were organized in the source files.

Hadoop's real power comes from the ability to process data in context, using what's known as the Map/Reduce paradigm. Every map/reduce job is a program with the same three phases: map, group-sort, and reduce. In the map phase, your program processes its input in any way you see fit, emitting labelled output records. In the group-sort phase, Hadoop groups and sorts those records according to their labels. Finally, in the reduce

phase, your program processes each sorted group and Hadoop stores its output. That grouping-by-label part is where the magic lies: it ensures that no matter where the relevant records started, they arrive at the same place in a predictable manner, ready to be synthesized.

If Map/Reduce is the core of Hadoop's operation, then getting to *think* in Map/Reduce terms is the key to effectively using Hadoop. In turn, thinking in Map/Reduce requires that you develop an innate, physical sense of how Hadoop moves data around. You can't understand the fundamental patterns of data analysis in Hadoop — grouping, filtering, joining records, and so forth — without knowing the basics. [1]

It can take some time to wrap one's head around Map/Reduce, though, so we're going to move slowly in this chapter. We'll open with a straightforward example map/reduce program: aggregating records from a dataset of Unidentified Flying Object sightings to find out when UFOs are most likely to appear. Next, we'll revisit our friends at Elephant and Chimpanzee, Inc, to explore how a Map/Reduce dataflow works. We'll round out the chapter with a deeper, more technical look into map/reduce from a Hadoop perspective.

The one thing we won't be doing too much of yet is actually writing lots of Hadoop programs. That will come in Chapter 5 (REF), which has example after example demonstrating core map/reduce programming patterns — those patterns are difficult to master without a grounding in this chapter's material. But if you're the type of reader who learns best by seeing multiple examples in practice and then seeing its internal mechanics, skim that chapter and then come back.

Example: Reindeer Games

Santa Claus and his elves are busy year-round, but outside the holiday season Santa's flying reindeer do not have many responsibilities. As flying objects themselves, they spend a good part of their multi-month break pursuing their favorite hobby: UFOlogy (the study of Unidentified Flying Objects and the search for extraterrestrial civilization). So you can imagine how excited they were to learn about the data set of more than 60,000 documented UFO sightings we worked with in the first chapter.

Sixty thousand sightings is much higher than a reindeer can count (only four hooves!), so JT and Nanette occasionally earn a little good favor from Santa Claus by helping the reindeer answer questions about the UFO data. We can do our part by helping our reindeer friends understand when, during the day, UFOs are most likely to be sighted.

1. When he lectures on Hadoop, Q often gets questions to the effect of, "Can I do *X* in Hadoop?" and the answer is always, "If you can express that problem or algorithm in Map/Reduce terms, then, yes."

UFO Sighting Data Model

The data model for a UFO sighting has fields for: date of sighting and of report; human-entered location; duration; shape of craft; and eye-witness description.

```
class SimpleUfoSighting
include Wu::Model
  field :sighted_at,   Time
  field :reported_at,  Time
  field :shape,        Symbol
  field :city,         String
  field :state,        String
  field :country,      String
  field :duration_str, String
  field :location_str, String
  field :description,  String
end
```

Group the UFO Sightings by Time Bucket

The first request from the reindeer team is to organize the sightings into groups by the shape of craft, and to record how many sightings there are for each shape.

Mapper

In the Chimpanzee & Elephant world, a chimp had the following role:

1. read and understand each letter
2. create a new intermediate item having a label (the type of toy) and information about the toy (the work order)
3. hand it to the elephant which delivers to that toy's workbench

We're going to write a Hadoop *mapper* which performs a similar purpose:

1. reads the raw data and parses it into a structured record
2. creates a new intermediate item having a label (the shape of craft) and information about the sighting (the original record).
3. hands it to Hadoop for delivery to that group's reducer

The program looks like this:

```
mapper(:count_ufo_shapes) do
  consumes UfoSighting, from: json
  #
  process do |ufo_sighting|     # for each record
    record = 1                  # create a dummy payload,
    label  = ufo_sighting.shape # label with the shape,
    yield [label, record]       # and send it downstream for processing
```

```
  end
end
```

You can test the mapper on the commandline:

```
$ cat ./data/geo/ufo_sightings/ufo_sightings-sample.json   |
./examples/geo/ufo_sightings/count_ufo_shapes.rb --map |
head -n25 | wu-lign
disk      1972-06-16T05:00:00Z  1999-03-02T06:00:00Z    Provo (south of), UT      disk      severa
sphere    1999-03-02T06:00:00Z  1999-03-02T06:00:00Z    Dallas, TX                sphere    60 sec
triangle  1997-07-03T05:00:00Z  1999-03-09T06:00:00Z    Bochum (Germany),         triangle  ca. 2m
light     1998-11-19T06:00:00Z  1998-11-19T06:00:00Z    Phoenix (west valley), AZ light     15mim
triangle  1999-02-27T06:00:00Z  1999-02-27T06:00:00Z    San Diego, CA             triangle  10 min
triangle  1997-09-15T05:00:00Z  1999-02-17T06:00:00Z    Wedgefield, SC            triangle  15 min
...
```

The intermediate output is simply the partitioning label (UFO shape), followed by the attributes of the sighting, separated by tabs. The framework uses the first field to group by default; the rest is cargo.

Reducer

Just as the pygmy elephants transported work orders to elves' workbenches, Hadoop delivers each record to the *reducer*, the second stage of our job.

```
reducer(:count_sightings) do
  def process_group(label, group)
    count = 0
    group.each do |record|      # on each record,
      count += 1                #   increment the count
      yield record              #   re-output the record
    end                         #
    yield ['    %%%% end of group %%%%     ct:', count, label] # at end of group, summarize
  end
end
```

The elf at each workbench saw a series of work orders, with the guarantee that a) work orders for each toy type are delivered together and in order; and b) this was the only workbench to receive work orders for that toy type.

Similarly, the reducer receives a series of records, grouped by label, with a guarantee that it is the unique processor for such records. All we have to do here is re-emit records as they come in, then add a line following each group with its count. We've put a # at the start of the summary lines, which lets you easily filter them.

Test the full map/reduce stack from the commandline:

```
$ ./examples/geo/ufo_sightings/count_ufo_shapes.rb --run \
    ./data/geo/ufo_sightings/ufo_sightings-sample.json - | wu-lign

1985-06-01T05:00:00Z    1999-01-14T06:00:00Z    North Tonawanda, NY chevron  1 hr       7 lights i
1999-01-20T06:00:00Z    1999-01-31T06:00:00Z    Olney, IL           chevron  10 seconds Stargazing
```

```
1998-12-16T06:00:00Z    1998-12-16T06:00:00Z    Lubbock, TX         chevron  3 minutes  Object sou
    %%%% end of group %%%%      ct:  3  chevron
1999-01-16T06:00:00Z    1999-01-16T06:00:00Z    Deptford, NJ        cigar    2 Hours    An aircraf
    %%%% end of group %%%%      ct:  1  cigar
1947-10-15T06:00:00Z    1999-02-25T06:00:00Z    Palmira,            circle   1 hour     After a co
1999-01-10T06:00:00Z    1999-01-11T06:00:00Z    Tyson's Corner, VA  circle   1 to 2 sec Bright gre
...
```

Plot the Data

When people work with data, their end goal is to uncover some answer or pattern. They most often employ Hadoop to turn Big Data into small data, then use traditional analytics techniques to turn small data into insight. One such technique is to *plot* the information. If a picture is worth a thousand words, then even a basic data plot is worth reams of statistical analysis. (TODO-qem: I think that line is original, but it sounds familiar. Must check around to make sure I didn't just pinch someone's quote.) That's because the human eye often gets a rough idea of a pattern faster than people can write code to divine the proper mathematical result. Here, we've used the free, open-source R programming language to see how UFO sightings are distributed around the country.[2]

The Map-Reduce Haiku

As you recall, the bargain that Map/Reduce proposes is that you agree to only write programs fitting this Haiku:

> data flutters by
> elephants make sturdy piles
> context yields insight
>
> — The Map/Reduce Haiku

More prosaically,

description	phase	explanation
process and label	map	turn each input record into any number of labelled records
sorted context groups	group-sort	Hadoop groups those records uniquely under each label, in a sorted order. (You'll see this also called the shuffle/sort phase)
synthesize (process context groups)	reduce	for each group, process its records in order; emit anything you want.

The trick lies in the *group-sort* phase: assigning the same label to two records in the map phase ensures that they will become local in the reduce step.

2. That said, people sometimes want to run R *inside* Hadoop, to analyze large-scale datasets. If you're interested in using R and Hadoop together, please check out Q's other book, *Parallel R* (O'Reilly) *http://shop.oreilly.com/product/0636920021421.do*

The records in stage 1 (*label*) are out of context. The mappers see each record exactly once, but with no promises as to order, and no promises as to which mapper sees which record. We've *moved the compute to the data*, allowing each process to work quietly on the data in its work space. Over at C&E, letters and translation passages aren't pre-organized and they don't have to be; J.T. and Nanette care about keeping all the chimps working steadily and keeping the hallways clear of inter-office document requests.

Once the map attempt finishes, each *partition* (the collection of records destined for a common reducer) is dispatched to the corresponding machine, and the mapper is free to start a new task. If you notice, the only time data moves from one machine to another is when the intermediate piles of data get shipped. Instead of monkeys flinging poo, we now have a dignified elephant parade, conducted in concert with the efforts of our diligent workers.

Map Phase, in Light Detail

Digging a little deeper into the mechanics of it all, a mapper receives one record at a time. By default, Hadoop works on text files, and a record is one line of text. (Hadoop supports other file formats and other types of storage beside files, but for the most part the examples in this book will focus on processing files on disk in a readable text format.) The whole point of the mapper is to "label" the record so that the group-sort phase can track records with the same label.

Hadoop feeds the mapper that one record, and in turn, the mapper spits out one or more *labelled records.* Usually the values in each record fields are some combination of the values in the input record and simple transformation of those values. But the output is allowed to be anything — the entire record, some subset of fields, the phase of the moon, the contents of a web page, nothing, … — and at times we'll solve important problems by pushing that point. The mapper can output those records in any order, at any time in its lifecyle, each with any label.

Group-Sort Phase, in Light Detail

In the group-sort phase, Hadoop transfers all the map output records in a partition to the corresponding reducer. That reducer merges the records it receives from all mappers, so that each group contains all records for its label regardless of what machine it came from. What's nice about the group-sort phase is that you don't have to do anything for it. Hadoop takes care of moving the data around for you. What's less nice about the group-sort phase is that it is typically the performance bottleneck. We'll learn how to take care of Hadoop so that it can move the data around smartly.

Reducers, in Light Detail

Whereas the mapper sees single records in isolation, a reducer receives one key (the label) and *all* records that match that key. In other words, a reducer operates on a group of related records. Just as with the mapper, as long as it keeps eating records and doesn't fail the reducer can do anything with those records it pleases and emit anything it wants. It can nothing, it can contact a remote database, it can emit nothing until the very end and then emit one or a ziillion records. The output can be text, it can be video files, it can be angry letters to the President. They don't have to be labelled, and they don't have to make sense. Having said all that, usually what a reducer emits are nice well-formed records resulting from sensible transformations of its input, like the count of records, the largest or smallest value from a field, or full records paired with other records. And though there's no explicit notion of a label attached to a reducer output record, it's pretty common that within the record's fields are values that future mappers will use to form labels.

Once you understand the label-group-process data flow we've just introduced, you understand enough about map/reduce to reason about the large-scale motion of data and thus your job's performance. But to understand how we can extend this one simple primitive to encompass the whole range of data analysis operations, we need to attach more nuance to the intermediate phase, and the importance of sorting to Hadoop's internal operation.

Elephant and Chimpanzee Save Christmas part 2: A Critical Bottleneck Emerges

After a day or two of the new toyform process, Mrs. Claus reported dismaying news. Even though productivity was much improved over the Big-Tree system, it wasn't going to be enough to hit the Christmas deadline.

The problem was plain to see. Repeatedly throughout the day, workbenches would run out of parts for the toys they were making. The dramatically-improved efficiency of order handling, and the large built-up backlog of orders, far outstripped what the toy parts warehouse could supply. Various workbenches were clogged with Jack-in-the-boxes awaiting springs, number blocks awaiting paint and the like. Tempers were running high, and the hallways became clogged again with overloaded parts carts careening off each other. JT and Nanette filled several whiteboards with proposed schemes, but none of them felt right.

To clear his mind, JT wandered over to the reindeer ready room, eager to join in the cutthroat games of poker Rudolph and his pals regularly ran. During a break in the action, JT found himself idly sorting out the deck of cards by number, to check that none of his Reindeer friends slipped an extra ace or three into the deck. As he did so, something in his mind flashed back to the unfinished toys on the assembly floor: mounds of number

blocks, stacks of Jack-in-the-boxes, rows of dolls. Sorting the cards by number had naturally organized them into groups by kind as well: he saw all the numbers in blocks in a run, followed by all the jacks, then the queens and the kings and the aces.

"Sorting is equivalent to grouping!" he exclaimed to the reindeers' puzzlement. "Sorry, fellas, you'll have to deal me out," he said, as he ran off to find Nanette.

The next day, they made several changes to the toy-making workflow. First, they set up a delegation of elvish parts clerks at desks behind the letter-writing chimpanzees, directing the chimps to hand a carbon copy of each toy form to a parts clerk as well. On receipt of a toy form, each parts clerk would write out a set of tickets, one for each part in that toy, and note on the ticket the ID of its toyform. These tickets were then dispatched by pygmy elephant to the corresponding section of the parts warehouse to be retrieved from the shelves.

Now, here is the truly ingenious part that JT struck upon that night. Before, the chimpanzees placed their toy forms onto the back of each pygmy elephant in no particular order. JT replaced these baskets with standing file folders — the kind you might see on an organized person's desk. He directed the chimpanzees to insert each toy form into the file folder according to the alphabetical order of its ID. (Chimpanzees are exceedingly dextrous, so this did not appreciably impact their speed.) Meanwhile, at the parts warehouse Nanette directed a crew of elvish carpenters to add a clever set of movable set of frames to each of the part carts. She similarly prompted the parts pickers to put each cart's parts in the place properly preserving the alphabetical order of their toyform IDs.

After a double shift that night by the parts department and the chimpanzees, the toymakers arrived in the morning to find, next to each workbench, the pygmy elephants with their toy forms and a set of carts from each warehouse section holding the parts they'd need. As work proceeded, a sense of joy and relief soon spread across the shop.

The elves were now producing a steady stream of toys as fast as their hammers could fly, with an economy of motion they'd never experienced. Since both the parts and the toy forms were in the same order by toyform ID, as the toymakers would pull the next toy form from the file they would always find the parts for it first at hand. Get the toy form for a wooden toy train and you would find a train chassis next in the chassis cart, small wooden wheels next in the wheel cart, and magnetic bumpers next in the small parts cart. Get the toy form for a rolling duck on a string, and you would find instead,

a duck chassis, large wooden wheels and a length of string at the head of their respective carts.

Not only did work now proceed with an unbroken swing, but the previously cluttered workbenches were now clear — their only contents were the parts immediately required to assemble the next toy. This space efficiency let Santa pull in extra temporary workers from the elves' Rivendale branch, who were bored with fighting orcs and excited to help out.

Toys were soon coming off the line at a tremendous pace, far exceeding what the elves had ever been able to achieve. By the second day of the new system, Mrs. Claus excitedly reported the news everyone was hoping to hear: they were fully on track to hit the Christmas Eve deadline!

And that's the story of how Elephant and Chimpanzee saved Christmas.

Example: Close Encounters of the Reindeer Kind

In the last problem we solved for our Reindeer friends, we only cared that the data came to the reducer in groups. We had no concerns about which reducers handled which groups, and we had no concerns about how the data was organized within the group. The next example will draw on the full scope of the framework, equipping you to understand the complete contract that Hadoop provides the end user.

Since our reindeer friends want to spend their summer months visiting the locations of various UFO sighting, they would like more information to help plan their trip. The Geonames dataset (REF) provides more than seven million well-described points of interest, so we can extend each UFO sighting whose location matches a populated place name with its longitude, latitude, population and more.

Your authors have additionally run the free-text locations — "Merrimac, WI" or "Newark, NJ (South of Garden State Pkwy)" — through a geolocation service to (where possible) add structured geographic information: longitude, latitude and so forth.

Put UFO Sightings And Places In Context By Location Name

When you are writing a Map/Reduce job, the first critical question is how to group the records in context for the Reducer to synthesize. In this case, we want to match every UFO sighting against the corresponding Geonames record with the same city, state and country, so the Mapper labels each record with those three fields. This ensures records with the same location name all are received by a single Reducer in a single group, just as we saw with toys sent to the same workbench or visits "sent" to the same time bucket. The Reducer will also need to know which records are sightings and which records are places, so we have extended the label with an "A" for places and a "B" for sightings. (You

will see in a moment why we chose those letters.) While we are at it, we will also eliminate Geonames records that are not populated places.

```
class UfoSighting
  include Wu::Model
  field :sighted_at,   Time
  field :reported_at,  Time
  field :shape,        Symbol
  field :city,         String
  field :state,        String
  field :country,      String
  field :duration_str, String
  field :location_str, String
  #
  field :longitude,    Float
  field :latitude,     Float
  field :city,         String
  field :region,       String
  field :country,      String
  field :population,   Integer
  field :quadkey,      String
  #
  field :description,  String
end
```

Extend UFO Sighting Records With Location Data

An elf building a toy first selected the toy form, then selected each of the appropriate parts. To facilitate this, the elephants carrying toy forms stood at the head of the workbench next to all the parts carts. While the first part of the label (the partition key) defines how records are grouped, the remainder of the label (the sort key) describes how they are ordered within the group. Denoting places with an "A" and sightings with a "B" ensures our Reducer always first receives the place for a given location name followed by the sightings. For each group, the Reducer holds the place record in a temporary variable and appends the places fields to those of each sighting that follows. In the happy case where a group holds both place and sightings, the Reducer iterates over each sighting. There are many places that match no UFO sightings; these are discarded. There are some UFO sightings without reconcilable location data; we will hold onto those but leave the place fields blank. Even if these groups had been extremely large, this matching required no more memory overhead than the size of a place record.

Now that you've seen the partition, sort and secondary sort in action, it's time to attach more formal and technical detail to how it works.

Partition, Group and Secondary Sort

As we mentioned in the opening, the fundamental challenge of Big Data is how to put records into relevant context, even when it is distributed in a highly non-local fashion.

Traditional databases and high-performance computing approaches use a diverse set of methods and high-cost hardware to brute-force the problem but at some point, the joint laws of physics and economics win out. Hadoop, instead, gives you exactly and *only one* "locality" primitive — only one way to express which records should be grouped in context — namely, *partition-group-sort* -'ing the records by their label. The sidebar (REF) about the Hadoop contract describes the precise properties of this operation but here is a less formal explanation of its essential behavior.

Partition

The partition key portion of the label governs how records are assigned to Reducers; it is analogous to the tear-sheet that mapped which toy types went to which workbench. Just as there was only one workbench for dolls and one workbench for ponies, each partition maps to *exactly one* Reducer. Since there are generally a small number of Reducers and an arbitrary number of partitions, each Reducer will typically see many partitions.

The default partitioner (`HashPartitioner`) assigns partitions to Reducers arbitrarily, in order to give a reasonably uniform distribution of records to Reducers. It does not know anything specific about your data, though, so you could get unlucky and find that you have sent all the tweets by Justin Bieber and Lady Gaga to the same Reducer or all the census forms for New York, L.A. and Chicago to the same Reducer, leaving it with an unfairly large portion of the midstream data. If the partitions themselves would be manageable and you are simply unlucky as to which became neighbors, just try using one fewer Reduce slots — this will break up the mapping into a different set of neighbors.

For a given cluster with a given number of Reduce slots, the assignment of partitions by the hash Reducer will be stable from run to run, but you should not count on it any more than that.

The naive `HashPartitioner` would not work for the elves, we assume — you don't want the toyforms for ponies to be handled by the same workbench processing toyforms for pocketwatches. For us too, some operations require a specific partitioning scheme (as you will see when we describe the total sort operation (REF)), and so Hadoop allows you to specify your own partitioner. But this is rarely necessary, and in fact your authors have gone their whole careers without ever writing on. If you find yourself considering writing a custom partitioner, stop to consider whether you are going against the grain of Hadoop's framework. Hadoop knows what to do with your data and, typically, the fewer constraints you place on its operation, the better it can serve you.

Group

The group key governs, well, the actual groups your program sees. All the records within a group arrive together — once you see a record from one group, you will see all of them in a row and you will never again see a record from a preceding group.

Secondary Sort

Within the group, the records are sent in the order given by the sort key. When you are using the Hadoop streaming interface (the basis for Wukong, MrJobs and the like), the only datatype is text, and so records are sorted lexicographically by their UTF-8 characters. (TECHREVIEW: is it UTF-8 or binary strings?)

This means that:

- `Zoo` comes after `Apple`, because `A` comes before `Z`
- `Zoo` comes *before* `apple`, because upper-case characters precede lower-case characters
- `12345` comes before `42`, and both of them come before `Apple`, `Zoo` or `apple`
- `12345` comes after `` ` 42` `` because we used spaces to pad out the number 42 to five characters.
- `apple` and `zoo` come before `шимпанзе`, because the basic ASCII-like characters (like the ones on a US keyboard) precede extended unicode-like characters (like the russian characters in the word for "chimpanzee").
- `###` (hash marks) come before `Apple` and `zoo`; and `||||` (pipes) comes after all of them. Remember these characters — they are is useful for forcing a set of records to the top or bottom of your input, a trick we'll use in the geodata chapter (REF). The dot (`.`), hyphen (`-`), plus (`+`) hash (`#`) come near the start of the 7-bit ASCII alphanumeric set. The tilde (`~`), pipe (`|`) come at the end. All of them precede extended-character words like `шимпанзе`.

It's very important to recognize that *numbers are not sorted by their numeric value unless you have control over their Java type*. The simplest way to get numeric sorting of positive numbers is to pad numeric outputs a constant width by prepended spaces. In Ruby, the expression `%10d" % val` produces an ten-character wide string (wide enough for all positive thirty-two bit numbers). There's no good way in basic Hadoop Streaming to get negative numbers to sort properly — yes, this is very annoying. (TECHREVIEW: is there a good way?)

In the common case, the partition key, group key and sort key are the same, because all you care is that records are grouped. But of course it's also common to have the three keys not be the same. The prior example, (REF) a JOIN of two tables, demonstrated a common pattern for use of the secondary sort; and the roll-up aggregation example that follows illustrates both a secondary sort and a larger partition key than group key.

The set defined by the partition key must be identical or a superset of the sets defined by the group key, or your groups will be meaningless. Hadoop doesn't impose that constraint on you, so just be sure to think at least once. The easiest way to do this (and the way we almost always to this) is to have the partition key be the same as or an extension of the group key, and the sort key be the same as or an extension of the group key.

Playing with Partitions: How Partition, Group and Sort affect a Job

It is very important to get a good grasp of how the partition and group keys relate, so let's step through an exercise illustrating their influence on the distribution of records.

Here's another version of the script to total wikipedia pageviews. We've modified the mapper to emit separate fields for the century, year, month, day and hour (you wouldn't normally do this; we're trying to prove a point). The reducer intends to aggregate the total pageviews across all pages by year and month: a count for December 2010, for January 2011, and so forth. We've also directed it to use twenty reducers, enough to illustrate a balanced distribution of reducer data.

Run the script on the subuniverse pageview data with `--partition_keys=3 --sort_keys=3` (CODE check params), and you'll see it use the first three keys (century/year/month) as both partition keys and sort keys. Each reducer's output will tend to have months spread across all the years in the sample, and the data will be fairly evenly distributed across all the reducers. In our runs, the `-00000` file held the months of (CODE insert observed months), while the `-00001` file held the months of (CODE insert observed months); all the files were close to (CODE size) MB large. (CODE consider updating to "1,2,3" syntax, perhaps with a gratuitous randomizing field as well. If not, make sure wukong errors on a partition_keys larger than the sort_keys). Running with `--partition_keys=3 --sort_keys=4` doesn't change anything: the `get_key` method in this particular reducer only pays attention to the century/year/month, so the ordering within the month is irrelevant.

Running it instead with `--partition_keys=2 --sort_keys=3` tells Hadoop to *partition* on the century/year, but do a secondary sort on the month as well. All records that share a century and year now go to the same reducer, while the reducers still see months as continuous chunks. Now there are only six (or fewer) reducers that receive data — all of 2008 goes to one reducer, similarly 2009, 2010, and the rest of the years in the dataset. In our runs, we saw years X and Y (CODE adjust reducer count to let us prove

the point, insert numbers) land on the same reducer. This uneven distribution of data across the reducers should cause the job to take slightly longer than the first run. To push that point even farther, running with `--partition_keys=1 --sort_keys=3` now partitions on the century — which all the records share. You'll now see 19 reducers finish promptly following the last mapper, and the job should take nearly twenty times as long as with `--partition_keys=3`.

Finally, try running it with `--partition_keys=4 --sort_keys=4`, causing records to be partitioned by century/year/month/day. Now the days in a month will be spread across all the reducers: for December 2010, we saw `-00000` receive X, Y and `-00001` receive X, Y, Z; out of 20 reducers, X of them received records from that month (CODE insert numbers). Since our reducer class is coded to aggregate by century/year/month, each of those reducers prepared its own meaningless total pageview count for December 2010, each of them a fraction of the true value. You must always ensure that all the data you'll combine in an aggregate lands on the same reducer.

Hadoop's Contract

We will state very precisely what Hadoop guarantees, so that you can both attach a rigorous understanding to the haiku-level discussion and see how *small* the contract is. This formal understanding of the contract is very useful for reasoning about how Hadoop jobs work and perform.

Hadoop imposes a few seemingly-strict constraints and provides a very few number of guarantees in return. As you're starting to see, that simplicity provides great power and is not as confining as it seems. You can gain direct control over things like partitioning, input splits and input/output formats. We'll touch on a very few of those, but for the most part this book concentrates on using Hadoop from the outside — (REF) *Hadoop: The Definitive Guide* covers this stuff (definitively).

The Mapper's Input Guarantee

The contract Hadoop presents for a map task is simple, because there isn't much of one. Each mapper will get a continuous slice (or all) of some file, split at record boundaries, and in order within the file. You won't get lines from another input file, no matter how short any file is; you won't get partial records; and though you have no control over the processing order of chunks ("file splits"), within a file split all the records are in the same order as in the original file.

For a job with no reducer — a "mapper-only" job — you can then output anything you like; it is written straight to disk. For a Wukong job with a reducer, your output should be tab-delimited data, one record per line. You can designate the fields to use for the partition key, the sort key and the group key. (By default, the first field is used for all three.)

The typical job turns each input record into zero, one or many records in a predictable manner, but such decorum is not required by Hadoop. You can read in lines from Shakespeare and emit digits of *pi*; read in all input records, ignore them and emit nothing; or boot into an Atari 2600 emulator, publish the host and port and start playing Pac-Man. Less frivolously: you can accept URLs or filenames (local or HDFS) and emit their contents; accept a small number of simulation parameters and start a Monte Carlo simulation; or accept a database query, issue it against a datastore and emit each result.

The Reducer's Input Guarantee

When Hadoop does the group/sort, it establishes the following guarantee for the data that arrives at the reducer:

- each labelled record belongs to exactly one sorted group;
- each group is processed by exactly one reducer;
- groups are sorted lexically by the chosen group key;
- and records are further sorted lexically by the chosen sort key.

It's very important that you understand what that unlocks, so we're going to redundantly spell it out a few different ways:

- Each mapper-output record goes to exactly one reducer, solely determined by its key.
- If several records have the same key, they will all go to the same reducer.
- From the reducer's perspective, if it sees any element of a group it will see all elements of the group.

You should typically think in terms of groups and not about the whole reduce set: imagine each partition is sent to its own reducer. It's important to know, however, that each reducer typically sees multiple partitions. (Since it's more efficient to process large batches, a certain number of reducer processes are started on each machine. This is in contrast to the mappers, who run one task per input split.) Unless you take special measures, the partitions are distributed arbitrarily among the reducers [3]. They are fed to the reducer in order by key.

Similar to a mapper-only task, your reducer can output anything you like, in any format you like. It's typical to output structured records of the same or different shape, but you're free engage in any of the shenanigans listed above.

3. Using a "consistent hash"; see (REF) the chapter on Statistics

The traditional terms for the Hadoop phases are very unfortunately chosen. The name "map" isn't that bad, though it sure gets confusing when you're using a HashMap in the map phase of a job that maps locations to coordinates for a mapping application. Things get worse after that, though. Hadoop identifies two phases, called shuffle and sort, between the map and reduce. That division is irrelevant to you, the end user, and not even that essential internally. "Shuffling" is usually taken to mean "placing in random order", which is exactly not the case. And at every point of the intermediate phase, on both mapper and reducer, the data is being sorted (rather than only right at the end). This is horribly confusing, and we won't use those terms. Instead, we will refer to a single intermediate phase called the "group-sort phase". Last and worst is the phrase "Reducer". There is no obligation on a reducer that it eliminate data, that its output be smaller in size or fewer in count than its input, that its output combine records from its input or even pay attention to them at all. Reducers quite commonly emit more data than they receive, and if you're not careful explosively so. We're stuck with the name "Map/Reduce", and so we're also stuck calling this the "Reduce" phase, but put any concept of reduction out of your mind.

The Map Phase Processes Records Individually

The Map phase receives 0, 1 or many records individually, with no guarantees from Hadoop about their numbering, order or allocation. [4] Hadoop does guarantee that every record arrives in whole to exactly one Map task and that the job will only succeed if every record is processed without error.

The Mapper receives those records sequentially — it must fully process one before it receives the next — and can emit 0, 1 or many inputs of any shape or size. The chimpanzees working on the SantaCorp project received letters but dispatched toy forms. Julia's thoughtful note produced two toy forms, one for her doll and one for Joe's robot, while the spam letter produced no toy forms.

You can take this point to an arbitratry extreme. Now, the right way to bring in data from an external resource is by creating a custom loader or input format (see the chapter on Advanced Pig (REF)), which decouples loading data from processing data and allows Hadoop to intelligently manage tasks. There's also a poor-man's version of a custom loader, useful for one-offs, is to prepare a small number of file names, URLs, database queries or other external handles as input and emit the corresponding contents.

4. In special cases, you may know that your input bears additional guarantees — for example, the "Merge Join" described in Chapter (REF) requires its inputs to be in total sorted order. It is on you, however, to enforce and leverage those special properties.

Please be aware, however, that it is only appropriate to access external resources from within a Hadoop job in exceptionally rare cases. Hadoop processes data in batches, which means failure of a single record results in the retry of the entire batch. It also means that when the remote resource is unavailable or responding sluggishly, Hadoop will spend several minutes and unacceptably many retries before abandoning the effort. Lastly, Hadoop is designed to drive every system resource at its disposal to its performance limit. [5]

For another extreme example, Hadoop's *distcp* utility, used to copy data from cluster to cluster, moves around a large amount of data yet has only a trivial input and trivial output. In a distcp job, each mapper's input is a remote file to fetch; the action of the mapper is to write the file's contents directly to the HDFS as a datanode client; and the mapper's output is a summary of what was transferred.

While a haiku with only its first line is no longer a haiku, a Hadoop job with only a Mapper is a perfectly acceptable Hadoop job, as you saw in the Pig Latin translation example. In such cases, each Map Task's output is written directly to the HDFS, one file per Map Task, as you've seen. Such jobs are only suitable, however, for so-called "embarrassingly parallel problems" — where each record can be processed on its own with no additional context.

The Map stage in a Map/Reduce job has a few extra details. It is responsible for labeling the processed records for assembly into context groups. Hadoop files each record into the equivalent of the pigmy elephants' file folders: an in-memory buffer holding each record in sorted order. There are two additional wrinkles, however, beyond what the pigmy elephants provide. First, the Combiner feature lets you optimize certain special cases by preprocessing partial context groups on the Map side; we will describe these more in a later chapter (REF). Second, if the sort buffer reaches or exceeds a total count or size threshold, its contents are "spilled" to disk and subsequently merge-sorted to produce the Mapper's proper output.

The Hadoop Contract

Here in one place is a casually rigorous summation of the very few guarantees Hadoop provides your Map/Reduce program. Understanding these is a critical tool for helping you to create and reason about Hadoop workflows.

- Each record is processed in whole by *exactly one* Mapper.
- Each Mapper receives records from *exactly one* contiguous split of input data, in the same order as those records appear in the source.

5. We will drive this point home in the chapter on Event Log Processing (REF), where we will stress test a web server to its performance limit by replaying its request logs at full speed.

- There are no guarantees on how long a split is, how many there are, the order in which they are processed or the assignment of split to Mapper slot.
- In both Mapper and Reducer, there is no requirement on you to use any of the structure described here or even to use the records' contents at all. You do not have to do anything special when a partition or group begins or ends and your program can emit as much or as little data as you like before, during or after processing its input stream.
- In a Mapper-only job, each Mapper's output is placed in *exactly one* uniquely-named, immutable output file in the order the records were emitted. There are no further relevant guarantees for a Mapper-Only job.
- Each Mapper output record is processed in whole by *exactly one* Reducer.
- Your program must provide each output record with a label consisting of a partition key, group key and sort key; these expressly govern how Hadoop assigns records to Reducers.
- All records sharing a partition key are sent to the same Reducer; if a Reducer sees one record from a partition, it will see all records from that partition, and no other Reducer will see any record from that partition.
- Partitions are sent contiguously to the Reducer; if a Reducer receives one record from a partition, it will receive all of them in a stretch, and will never again see a record from a prior partition.
- Partitions themselves are ordered by partition key within the Reducer input.
- A custom partitioner can assign each partition to specific Reducer, but you should not depend on any pairing provided by the default partitioner (the `HashPartitioner`) .
- Within each partition, records are sent within contiguous groups; if a Reducer receives one record from a group, it will receive all of them in a stretch, and will never again see a record from a prior group.
- Within a partition, records are sorted first by the group key, then by the sort key; this means groups themselves are ordered by group key within the Reducer input. (TECHREVIEW: Check that this is consistent with the Java API and the Pig UDF API.)
- Each Reducer's output is placed in *exactly one* uniquely-named, immutable output file in the order the records were emitted.

You can tell how important we feel it is for you to internalize this list of guarantees, or we would not have gotten all, like, formal and stuff.

How Hadoop Manages Midstream Data

The first part of this chapter (REF) described the basics of what Hadoop supplies to a Reducer: each record is sent to exactly one reducer; all records with a given label are sent to the same Reducer; and all records for a label are delivered in a continuous ordered group. Let's understand the remarkably economical motion of data Hadoop uses to accomplish this.

Mappers Spill Data In Sorted Chunks

As your Map task produces each labeled record, Hadoop inserts it into a memory buffer according to its order. Like the dextrous chimpanzee, the current performance of CPU and memory means this initial ordering imposes negligible overhead compared to the rate that data can be read and processed. When the Map task concludes or that memory buffer fills, its contents are flushed as a stream to disk. The typical Map task operates on a single HDFS block and produces an output size not much larger. A well-configured Hadoop cluster sets the sort buffer size accordingly [6].

If there are multiple spills, Hadoop performs the additional action of merge-sorting the chunks into a single spill. [7]

As you know, each record is sent to exactly one Reducer. The label for each record actually consists of two important parts: the partition key that determines which Reducer the record belongs to, and the sort key, which groups and orders those records within the Reducer's input stream. You will notice that, in the programs we have written, we only had to supply the record's natural label and never had to designate a specific Reducer; Hadoop handles this for you by applying a partitioner to the key.

Partitioners Assign Each Record To A Reducer By Label

The default partitioner, which we find meets almost all our needs, is called the "RandomPartitioner." [8] It aims to distribute records uniformly across the Reducers by giving each key the same chance to land on any given Reducer. It is not really random in the sense of nondeterministic; running the same job with the same configuration will distribute records the same way. Rather, it achieves a uniform distribution of keys by generating a cryptographic digest — a number produced from the key with the property that any change to that key would instead produce an arbitrarily distinct number. Since

6. The chapter on Hadoop Tuning For The Brave And Foolish (REF) shows you how); that most common case produces only a single spill.
7. This can be somewhat expensive, so in Chapter (REF), we will show you how to avoid unnecessary spills.) Whereas the pygmy elephants each belonged to a distinct workbench, a Hadoop Mapper produces only that one unified spill. That's ok — it is easy enough for Hadoop to direct the records as each is sent to its Reducer.
8. In the next chapter (REF), you will meet another partitioner, when you learn how to do a total sort.

the numbers thus produced have high and uniform distribution, the digest MODULO the number of Reducers reliably balances the Reducer's keys, no matter their raw shape and size. [9]

The default partitioner aims to provide a balanced distribution of *keys* — which does not at all guarantee a uniform distribution of *records* ! If 40-percent of your friends have the last name Chimpanzee and 40-percent have the last name Elephant, running a Map/Reduce job on your address book, partitioned by last name, will send all the Chimpanzees to some Reducer and all the Elephants to some Reducer (and if you are unlucky, possibly even the same one). Those unlucky Reducers will struggle to process 80-percent of the data while the remaining Reducers race through their unfairly-small share of what is left. This situation is far more common and far more difficult to avoid than you might think, so large parts of this book's intermediate chapters are, in effect, tricks to avoid that situation.

Reducers Receive Sorted Chunks From Mappers

Partway through your job's execution, you will notice its Reducers spring to life. Before each Map task concludes, it streams its final merged spill over the network to the appropriate Reducers [10]. Just as above, the Reducers file each record into a sort buffer, spills that buffer to disk as it fills and begins merge/sorting them once a threshold of spills is reached.

Whereas the numerous Map tasks typically skate by with a single spill to disk, you are best off running a number of Reducers, the same as or smaller than the available slots. This generally leads to a much larger amount of data per Reducer and, thus, multiple spills.

Reducers Read Records With A Final Merge/Sort Pass

The Reducers do not need to merge all records to a single unified spill. The elves at each workbench pull directly from the limited number of parts carts as they work' similarly, once the number of mergeable spills is small enough, the Reducer begins processing records from those spills directly, each time choosing the next in sorted order.

Your program's Reducer receives the records from each group in sorted order, outputting records as it goes. Your reducer can output as few or as many records as you like at any time: on the start or end of its run, on any record, or on the start or end of a

9. If you will recall, x MODULO y gives the remainder after dividing x and y. You can picture it as a clock with y hours on it: 15 MODULO 12 is 3; 4 MODULO 12 is 4; 12 MODULO 12 is 0.

10. NOTE: Note that this communication is direct; it does not use the HDFS.

group. It is not uncommon for a job to produce output the same size as or larger than its input — "Reducer" is a fairly poor choice of names. Those output records can also be of any size, shape or format; they do not have to resemble the input records, and they do not even have to be amenable to further Map/Reduce processing.

Reducers Write Output Data and Commit

As your Reducers emit records, they are streamed directly to the job output, typically the HDFS or S3. Since this occurs in parallel with reading and processing the data, the primary spill to the Datanode typically carries minimal added overhead.

You may wish to send your job's output not to the HDFS or S3 but to a scalable database or other external data store. (We'll show an example of this in the chapter on HBase (REF)) While your job is in development, though, it is typically best to write its output directly to the HDFS (perhaps at replication factor 1), then transfer it to the external target in a separate stage. The HDFS is generally the most efficient output target and the least likely to struggle under load. This checkpointing also encourages the best practice of sanity-checking your output and asking questions.

A Quick Note on Storage (HDFS)

If you're a Hadoop *administrator* responsible for cluster setup and maintenance, you'll want to know a lot about Hadoop's underlying storage mechanism, called HDFS. As an *analyst* who writes jobs to run on a Hadoop cluster, though, you need to know just one key fact:

HDFS likes big files.

Put another way, *HDFS doesn't like small files,* and "small" is "anything that weighs less than 64 megabytes." If you're interested in the technical specifics, you can check out the blog post on "The Small Files Problem" [11]. Really, you just want to know that small files will really gum up the works.

This often leads people to ask: "How do I use Hadoop on, say, image analysis? I want to a large number of images that are only a few kilobytes in size." For that, check out a Hadoop storage format called a *SequenceFile*. [12]

11. *http://blog.cloudera.com/blog/2009/02/the-small-files-problem/*

12. Also, Q wrote a handy tool to wrap up your small files into big SequenceFiles. Check out *forqlift* at *http://qethanm.cc/projects/forqlift/*

Outro

You've just seen how records move through a map/reduce workflow, along with aggregation of records and matching records betweent datasets — patterns that will recur in many explorations. Next, JT and Nanette will make a new friend, and we'll see another model for Hadoop analytics based on those patterns.

CHAPTER 4

Introduction to Pig

Pig Helps Hadoop work with Tables, not Records

Pig is an open-source, high-level language that enables you to create efficient Map/Reduce jobs using clear, maintainable scripts. Its interface is similar to SQL, which makes it a great choice for folks with significant experience there. (It's not identical, though, and things that are efficient in SQL may not be so in Pig; we will try to highlight those traps.)

Let's dive in with an example using the UFO dataset to estimate whether aliens tend to visit in some months over others:

```
sightings = LOAD '/path/to/geo/ufo_sightings/ufo_sightings.tsv'  AS (
    sighted_at: chararray,   reported_at: chararray,    location_str: chararray, shape: chararray,
    duration_str: chararray, description: chararray,    lng: float,              lat: float,
    city: chararray,         county: chararray,         state: chararray,        country: chararra

year_month_ct      = FOREACH sightings GENERATE SUBSTRING(sighted_at, 0, 7) AS yrmo;
sightings_hist     = FOREACH (GROUP year_month_ct BY yrmo) GENERATE
  group, COUNT_STAR(year_month_ct);
STORE sightings_hist INTO '/data/out/ufo/sightings_hist';
```

In a Wukong script or traditional Hadoop job, the focus is on the record and you're best off thinking in terms of message passing or grouping. In Pig, the focus is much more on the structure and you should think in terms of relational and set operations. In the example above, each line described an operation on the full dataset; we declared what change to make and Pig, as you'll see, executes those changes by dynamically assembling and running a set of Map/Reduce jobs.

To run the Pig job, go into the example code repository and run

```
pig 04-intro_to_pig/a-ufo_visits_by_month.pig
```

If you consult the Job Tracker Console, you should see a single Map/Reduce for each with effectively similar statistics; the dataflow Pig instructed Hadoop to run is essentially similar to the Wukong script you ran. What Pig ran was, in all respects, a Hadoop job. It calls on some of Hadoop's advanced features to help it operate but nothing you could not access through the standard Java API.

Wikipedia Visitor Counts

Let's put Pig to a sterner test. Here's the script above, modified to run on the much-larger Wikipedia dataset and to assemble counts by hour, not month:

```
SET DEFAULT_PARALLEL 3
  ;

pageviews = LOAD '/data/rawd/wikipedia/pagecounts/pagecounts-20081002-230001.log'  AS (
   filename:chararray, ns:chararray, wikipedia_id:chararray, views:long, bytes:long
    ) USING PigStorage('\t', 'tagFile');

year_month_ct      = FOREACH pageviews  GENERATE SUBSTRING(sighted_at, 0, 7) AS yrmo;
sightings_hist     = FOREACH (GROUP year_month_ct BY yrmo) GENERATE
  group, COUNT_STAR(year_month_ct);
STORE sightings_hist INTO '/data/out/ufo/sightings_hist';


LOAD SOURCE FILE
TURN RECORD INTO HOUR PART OF TIMESTAMP AND COUNT
GROUP BY HOUR
SUM THE COUNTS BY HOUR
ORDER THE RESULTS BY HOUR
STORE INTO FILE
```

Until now, we have described Pig as authoring the same Map/Reduce job you would. In fact, Pig has automatically introduced the same optimizations an advanced practitioner would have introduced, but with no effort on your part. If you compare the Job Tracker Console output for this Pig job with the earlier ones, you'll see that, although TODO:x bytes were read by the Mapper, only TODO:y bytes were output. Pig instructed Hadoop to use a Combiner. In the naive Wukong job, every Mapper output record was sent across the network to the Reducer but in Hadoop, as you will recall from (REF), the Mapper output files have already been partitioned and sorted. Hadoop offers you the opportunity to do pre-Aggregation on those groups. Rather than send every record for, say, August 8, 2008 8 pm, the Combiner outputs the hour and sum of visits emitted by the Mapper.

The second script instructed Pig to explicitly sort the output by minute, an additional operation. We did not do that in the first example because its data was so small that we had instructed Hadoop to use a single Reducer. As you will recall from the previous chapter (REF), Hadoop uses a Sort to prepare the Reducer groups, so its output was naturally ordered. If there are multiple Reducers, however, that would not be enough

to give you a Result file you can treat as ordered. By default, Hadoop assigns partitions to Reducers using the 'RandomPartitioner', designed to give each Reducer a uniform chance of claiming any given partition. This defends against the problem of one Reducer becoming overwhelmed with an unfair share of records but means the keys are distributed willy-nilly across machines. Although each Reducer's output is sorted, you will see records from 2008 at the top of each result file and records from 2012 at the bottom of each result file.

What we want instead is a total sort, the earliest records in the first numbered file in order, the following records in the next file in order, and so on until the last numbered file. Pig's 'ORDER' Operator does just that. In fact, it does better than that. If you look at the Job Tracker Console, you will see Pig actually ran three Map/Reduce jobs. As you would expect, the first job is the one that did the grouping and summing and the last job is the one that sorted the output records. In the last job, all the earliest records were sent to Reducer 0, the middle range of records were sent to Reducer 1 and the latest records were sent to Reducer 2.

Hadoop, however, has no intrinsic way to make that mapping happen. Even if it figured out, say, that the earliest buckets were in 2008 and the latest buckets were in 2012, if we fed it a dataset with skyrocketing traffic in 2013, we would end up sending an overwhelming portion of results to that Reducer. In the second job, Pig sampled the set of output keys, brought them to the same Reducer, and figured out the set of partition breakpoints to distribute records fairly.

In general, Pig offers many more optimizations beyond these and we will talk more about them in the chapter on Advanced Pig (REF). In our experience, as long as you're willing to give Pig a bit of coaching, the only times it will author a dataflow that is significantly less performant comes when Pig is *overly* aggressive about introducing an optimization. And in those cases the impact is more like a bunch of silly piglets making things take 50% longer than they should, rather than a stampede of boars blowing up your cluster. The `ORDER BY` example is a case in point: for small-to-medium tables the intermediate sampling stage to calculate partitions can have a larger time cost than the penalty for partitioning badly would carry. Sometimes you're stuck paying an extra 20 seconds on top of each one-minute job so that Pig and Hadoop can save you an order of magnitude off your ten-minute-and-up jobs.

Fundamental Data Operations

Pig's operators — and fundamental Hadoop processing patterns — can be grouped into several families.

A control operation either influences or describes the data flow itself. A pipelinable operation is one that does not require a reduce step of its own: the records can each be handled in isolation, and so they do not have to be expensively assembled into context.

All structural operations must put records into context: placing all records for a given key into common context; sorting involves placing each record into context with the record that precedes it and the record that follows it; eliminating duplicates means putting all potential duplicates into common context, and so forth.

Control Operations

- Serialization operations (LOAD, STORE) load and store data into file systems or datastores.
- Directives (DESCRIBE, ILLUSTRATE, REGISTER, and others) to Pig itself. These do not modify the data, they modify Pig's execution: outputting debug information, registering external UDFs, and so forth.

Pipelinable Operations

With no structural operations, these operations create a mapper-only job with the composed pipeline. When they come before or after a structural operation, they are composed into the mapper or reducer.

- Transformation operations (FOREACH, FOREACH..FLATTEN(tuple)) modify the contents of records individually. The count of output records is exactly the same as the count of input records, but the contents and schema of the records can change arbitrarily.
- Filtering operations (FILTER, SAMPLE, LIMIT, ASSERT) accept or reject each record individually. These can yield the same or fewer number of records, but each record has the same contents and schema as its input.
- Repartitioning operations (SPLIT, UNION) don't change records, they just distribute them into new tables or data flows. UNION outputs exactly as many records as the sum of its inputs. Since SPLIT is effectively several FILTERs run simultaneously, its total output record count is the sum of what each of its filters would produce.
- Ungrouping operations (FOREACH..FLATTEN(bag)) turn records that have bags of tuples into records with each such tuple from the bags in combination. It is most commonly seen after a grouping operation (and thus occurs within the Reduce) but can be used on its own (in which case like the other pipelinable operations it produces a Mapper-Only job). The FLATTEN itself leaves the bag contents unaltered and substitutes the bag field's schema with the schema of its contents. When flattening on a single field, the count of output records is exactly the count of elements in all bags. (Records with empty bags will disappear in the output). Multiple FLATTEN clauses yield a record for each possible combination of elements, which can be explosively higher than the input count.

Structural Operations

These jobs require a Map and Reduce phase.

- Grouping operations (GROUP, COGROUP, CUBE, ROLLUP) place records into context with each other. They make no modifications to the input records' contents, but do rearrange their schema. You will often find them followed by a FOREACH that is able to take advantage of the group context. The GROUP and COGROUP yield one output record per distinct GROUP value.
- Joining operations (JOIN, CROSS) match records between tables. JOIN is simply an optimized COGROUP/FLATTEN/FOREACH sequence, but it is importantly enough different in use that we'll so its output size follows the same logic as FLATTEN. (CROSS too, except for the "important" part: we'll have very little to say about it and discourage its use).
- Sorting operations (ORDER BY, RANK) perform a total sort on their input; every record in file 00000 is in sorted order and comes before all records in 00001 and so forth for the number of output files. These require two jobs: first, a light Mapper-Only pass to understand the distribution of sort keys, next a Map/Reduce job to perform the sort.
- Uniquing and (DISTINCT, specific COGROUP forms) select/reject/collapse duplicates, or find records associated with unique or duplicated records. these are typically accomplished with specific combinations of the above, but involve

That's everything you can do with Pig — and everything you need to do with data. Each of those operations leads to a predictable set of map and reduce steps, so it's very straightforward to reason about your job's performance. Pig is very clever about chaining and optimizing these steps. For example, a GROUP followed by a FOREACH and a FILTER will only require one map phase and one reduce phase. In that case, the FOREACH and FILTER will be done in the reduce step — and in the right circumstances, pig will "push" part of the `FOREACH` and `FILTER` *before* the `JOIN`, potentially eliminating a great deal of processing.

Pig is an extremely sparse language. By having very few Operators and very uniform syntax [1], the language makes it easy for the robots to optimize the dataflow and for humans to predict and reason about its performance.

We will not explore every nook and cranny of its syntax, only illustrate its patterns of use. The online Pig manual at *http://pig.apache.org/* is quite good and for a deeper exploration, consult *Programming Pig* by Alan Gates (*http://shop.oreilly.com/product/0636920018087.do*). If the need for a construction never arose naturally in a pattern

1. Something SQL users but non-enthusiasts like your authors appreciate.

demonstration or exploration [2], we omitted it, along with options or alternate forms of construction that are either dangerous or rarely-used [3].

In the remainder of this chapter, we'll illustrate the mechanics of using Pig and the essential of its control flow operations by demonstrating them in actual use. In the following several chapters (REF), we'll cover patterns of pipelinable and of structural operations. In each case the goal is not only to understand its use, but to understand how to implement the corresponding patterns in a plain map-reduce approach — and therefore how to reason about their performance. Finally, the chapter on Advanced Pig (TODO ref) will cover some deeper-level topics, such as a few important optimized variants of the JOIN statement and how to extend Pig with new functions and loaders.

LOAD Locates and Describes Your Data

Pig scripts need data to process, and so your pig scripts will begin with a LOAD statement and have one or many STORE statements throughout. Here's a script to find all wikipedia articles that contain the word *Hadoop*:

```
articles = LOAD './data/wp/articles.tsv' AS (
  page_id: long, namespace: int, wikipedia_id: chararray,
  revision_id: long, timestamp: long,
  title: chararray, redirect: chararray,
  text: chararray);
hadoop_articles = FILTER articles BY text MATCHES '.*Hadoop.*';
STORE hadoop_articles INTO './data/tmp/hadoop_articles.tsv';
```

Simple Types

As you can see, the `LOAD` statement not only tells pig where to find the data, it also describes the table's schema. Pig understands ten kinds of simple type. Six of them are numbers: signed machine integers, as `int` (32-bit) or `long` (64-bit); signed floating-point numbers, as `float` (32-bit) or `double` (64-bit); arbitrary-length integers as `biginteger`; and arbitrary-precision real numbers, as `bigdecimal`. If you're supplying a literal value for a long, you should append a capital *L* to the quantity: `12345L`; if you're supplying a literal float, use an *f*: `123.45f`.

The `chararray` type loads text as UTF-8 encoded strings (the only kind of string you should ever traffic in). String literals are contained in single quotes — `'hello, world'`. Regular expressions are supplied as string literals, as in the example above: `'.*[Hh]adoop.*'`. The `bytearray` type does no interpretation of its contents whatso-

2. An example of the first is `UNION ONSCHEMA` — useful but not used.

3. it's legal in Pig to load data without a schema — but you shouldn't, and so we're not going to tell you how.

ever, but be careful — the most common interchange formats (`tsv`, `xml` and `json`) cannot faithfully round-trip data that is truly freeform.

Lastly, there are two special-purpose simple types. Time values are described with `datetime`, and should be serialised in the the ISO-8601 format: `1970-01-01T00:00:00.000+00:00`. Boolean values are described with `boolean`, and should bear the values `true` or `false`.

Boolean, date and the biginteger/bigdecimal types are recent additions to Pig, and you will notice rough edges around their use.

Complex Type 1, Tuples: Fixed-length Sequence of Typed Fields

Pig also has three complex types, representing collections of fields. A `tuple` is a fixed-length sequence of fields, each of which has its own schema. They're ubiquitous in the results of the various structural operations you're about to learn. We usually don't serialize tuples, but so far `LOAD` is the only operation we've taught you, so for pretend's sake here's how you'd load a listing of major-league ballpark locations:

```
-- The address and geocoordinates are stored as tuples. Don't do that, though.
ballpark_locations = LOAD 'ballpark_locations' AS (
    park_id:chararray, park_name:chararray,
    address:tuple(full_street:chararray, city:chararray, state:chararray, zip:chararray),
    geocoordinates:tuple(lng:float, lat:float)
);
ballparks_in_texas = FILTER ballpark_locations BY (address.state == 'TX');
STORE ballparks_in_texas INTO '/tmp/ballparks_in_texas.tsv'
```

Pig displays tuples using parentheses: it would dump a line from the input file as `BOS07,Fenway Park,(4 Yawkey Way,Boston,MA,02215),(-71.097378,42.3465909)'`. As shown above, you address single values with `in a tuple using `tuple_name.subfield_name` — for example, `address.state` will have the schema `state:chararray`. You can also create a new tuple that projects or rearranges fields from a tuple by writing `tuple_name.(subfield_a, subfield_b, ...)` — for example, `address.(zip, city, state)` will have schema `address_zip_city_state:tuple(zip:chararray, city:chararray, state:chararray)`. (Pig helpfully generated a readable name for the tuple).

Tuples can contain values of any type, even bags and other tuples, but that's nothing to be proud of. We follow almost every structural operation with a `FOREACH` to simplify its schema as soon as possible, and so should you — it doesn't cost anything and it makes your code readable.

Complex Type 2, Bags: Unbounded Collection of Tuples

A `bag` is an arbitrary-length collection of tuples, all of which are expected to have the same schema. Just like with tuples, they're ubiquitous yet rarely serialized. Again for pretend's sake we can load a dataset listing for each team the year and park id of the ballparks it played in:

```
team_park_seasons = LOAD 'team_parks' AS (
    team_id:chararray,
    park_years: bag{tuple(year:int, park_id:chararray)}
    );
```

You can also address values within a bag using `bag_name.(subfield_a, subfield_b)`, but this time the result is a bag with the given projected tuples. You'll see examples of this shortly when we discuss `FLATTEN` and the various group operations. Note that the *only* type a bag holds is tuple, even if there's only one field — a bag of just park ids would have schema `bag{tuple(park_id:chararray)}`.

Complex Type 3, Maps: Collection of Key-Value Pairs for Lookup

Pig offers a `map` datatype to represent a collection of key-value pairs. The only context we've seen them used is for loading JSON data. A tweet from the twitter firehose has a sub-hash holding info about the user; the following snippet loads raw JSON data, immediately fixes the schema, and then describes the new schema to you:

```
REGISTER piggybank.jar
raw_tweets = LOAD '/tmp/tweets.json' USING org.apache.pig.piggybank.storage.JsonLoader(
             'created_at:chararray, text:chararray, user:map[]');
```

A 'map` schema is described using square brackets: `map[value_schema]`. You can leave the value schema blank if you supply one later (as in the example that follows). The keys of a map are *always* of type chararray; the values can be any simple type. Pig renders a map as `[key#value,key#value,...]`: Flip's twitter user record as a hash would look like `[name#Philip (flip) Kromer,id#1554031,screen_name#mrflip]'.

Apart from loading complex data, the `map` type is surprisingly useless. You might think it would be useful to carry around a lookup-table in a map field — a mapping from ids to names, say — and then index into it using the value of some other field, but a) you cannot do so and b) it isn't useful. The only thing you can do with a `map` field is dereference by a constant string, as we did above (`user#'id'`). Carrying around such a lookup table would be kind of silly, anyway, as you'd be duplicating it on every row. What you most likely want is either an off-the-cuff UDF or to use Pig's "replicated" `JOIN` operation; both are described in the chapter on Advanced Pig (TODO ref).

Defining the Schema of a Transformed Record

Since the map type is mostly useless, we'll seize the teachable moment and use this space to illustrate the other way schema are constructed: using a `FOREACH`. As always when given a complex schema, we took the first available opportunity to simplify it. The `FOREACH` in the snippet above dereferences the elements of the user `map` and supplies a schema for each new field with the `AS <schema>` clauses. The `DESCRIBE` directive that follows causes Pig to dump the schema to console: in this case, you should see `tweets: {created_at: chararray,text: chararray,user_id: long,user_name: charar ray,user_screen_name: chararray}`.

```
REGISTER piggybank.jar
raw_tweets = LOAD '/tmp/tweets.json' USING org.apache.pig.piggybank.storage.JsonLoader(
             'created_at:chararray, text:chararray, user:map[]');
tweets = FOREACH raw_tweets GENERATE
        created_at,
        text,
        user#'id' AS user_id:long,
        user#'name' AS user_name:chararray,
        user#'screen_name' AS user_screen_name:chararray;
DESCRIBE tweets;
```

In the chapter on Advanced Pig (REF), we'll cover some further topics: loading from alternate file formats or from databases; how Pig and Hadoop assign input file splits to mappers; and custom load/store functions.

STORE Writes Data to Disk

The STORE operation writes your data to the destination you specify (typically the HDFS).

```
articles = LOAD './data/wp/articles.tsv' AS (page_id: long, namespace: int, wikipedia_id: chararra
hadoop_articles = FILTER articles BY matches('.*[Hh]adoop.*');
STORE hadoop_articles INTO './data/tmp/hadoop_articles.tsv';
```

As with any Hadoop job, Pig creates a *directory* (not a file) at the path you specify; each task generates a file named with its task ID into that directory. In a slight difference from vanilla Hadoop, If the last stage is a reduce, the files are named like `part-r-00000` (`r` for reduce, followed by the task ID); if a map, they are named like `part-m-00000`.

Try removing the STORE line from the script above, and re-run the script. You'll see nothing happen! Pig is declarative: your statements inform Pig how it could produce certain tables, rather than command Pig to produce those tables in order.

The behavior of only evaluating on demand is an incredibly useful feature for development work. One of the best pieces of advice we can give you is to checkpoint all the time. Smart data scientists iteratively develop the first few transformations of a project, then

save that result to disk; working with that saved checkpoint, develop the next few transformations, then save it to disk; and so forth. Here's a demonstration:

```
great_start = LOAD '...' AS (...);
-- ...
-- lots of stuff happens, leading up to
-- ...
important_milestone = JOIN [...];

-- reached an important milestone, so checkpoint to disk.
STORE important_milestone INTO './data/tmp/important_milestone';
    important_milestone = LOAD './data/tmp/important_milestone' AS (...schema...);
```

In development, once you've run the job past the `STORE important_milestone` line, you can comment it out to make pig skip all the preceding steps — since there's nothing tying the graph to an output operation, nothing will be computed on behalf of `important_milestone`, and so execution will start with the following `LOAD`. The gratuitous save and load does impose a minor cost, so in production, comment out both the `STORE` and its following `LOAD` to eliminate the checkpoint step.

These checkpoints bring another benefit: an inspectable copy of your data at that checkpoint. Many newcomers to Big Data processing resist the idea of checkpointing often. It takes a while to accept that a terabyte of data on disk is cheap — but the cluster time to generate that data is far less cheap, and the programmer time to create the job to create the data is most expensive of all. We won't include the checkpoint steps in the printed code snippets of the book, but we've left them in the example code.

Development Aids: `DESCRIBE`, `ASSERT`, `EXPLAIN`, `LIMIT..DUMP`, `ILLUSTRATE`

`DESCRIBE` shows the schema of a table

You've already seen the `DESCRIBE` directive, which writes a description of a table's schema to the console. It's invaluable, and even as your project goes to production you shouldn't be afraid to leave these statements in where reasonable.

`ASSERT` checks that your data is as you think it is

The `ASSERT` operation applies a test to each record as it goes by, and fails the job if the test is ever false. It doesn't create a new table, or any new map/reduce passes — it's slipstreamed into whatever operations precede it — but it does cause per-record work. The cost is worth it, and you should look for opportunities to add assertions wherever reasonable.

DUMP shows data on the console with great peril

The DUMP directive is actually equivalent to STORE, but (gulp) writes its output to your console. Very handy when you're messing with data at your console, but a trainwreck when you unwittingly feed it a gigabyte of data. So you should never use a DUMP statement except as in the following stanza: `dumpable = LIMIT table_to_dump 10; DUMP dump able;`. (ATTN tech reviewers: should we even discuss DUMP? Is there a good alternative, given `ILLUSTRATE`s flakiness?)

ILLUSTRATE magically simulates your script's actions, except when it fails to work

The ILLUSTRATE directive is one of our best-loved, and most-hated, Pig operations. Even if you only want to see an example line or two of your output, using a DUMP or a STORE requires passing the full dataset through the processing pipeline. You might think, "OK, so just choose a few rows at random and run on that" — but if your job has steps that try to match two datasets using a JOIN, it's exceptionally unlikely that any matches will survive the limiting. (For example, the players in the first few rows of the baseball players table belonged to teams that are not in the first few rows from the baseball teams table.) ILLUSTRATE walks your execution graph to intelligently mock up records at each processing stage. If the sample rows would fail to join, Pig uses them to generate fake records that will find matches. It solves the problem of running on ad-hoc subsets, and that's why we love it.

However, not all parts of Pig's functionality work with ILLUSTRATE, meaning that it often fails to run. When is the ILLUSTRATE command is most valuable? When applied to less-widely-used operations and complex sequences of statements, of course. What parts of Pig are most likely to lack ILLUSTRATE support or trip it up? Well, less-widely-used operations and complex sequences of statements, of course. And when it fails, it does so with perversely opaque error messages, leaving you to wonder if there's a problem in your script or if ILLUSTRATE has left you short. If you, eager reader, are looking for a good place to return some open-source karma: consider making ILLUSTRATE into the tool it could be. Until somebody does, you should checkpoint often (described along with the STORE command above) and use the strategies for subuniverse sampling from the Statistics chapter (TODO ref).

Lastly, while we're on the subject of development tools that don't work perfectly in Pig: the Pig shell gets confused too easily to be useful. You're best off just running your script directly. For local mode development, tools like watchr (REF) can intelligently relaunch a script every time you hit save, streamlining development.

`EXPLAIN` shows Pig's execution graph

The `EXPLAIN` directive writes the "execution graph" of your job to the console. It's extremely verbose, showing *everything* pig will do to your data, down to the typecasting it applies to inputs as they are read. We mostly find it useful when trying to understand whether Pig has applied some of the optimizations you'll learn about in Tuning for the Wise and Lazy (TODO ref). (QUESTION for tech reviewers: move this section to advanced Pig and explain EXPLAIN?)

Pig Functions act on fields

Pig wouldn't be complete without a way to *act* on the various fields. It offers a sparse but essential set of built-in functions — the Pig cheatsheet (TODO ref) at the end of the book gives a full list. The whole middle of the book is devoted to examples of Pig and map/reduce programs in practice (and in particular a chapter on Statistics), so we'll just list the highlights here:

- **Math functions** for all the things you'd expect to see on a good calculator: `LOG`/`LOG10`/`EXP`, `RANDOM`, `ROUND`/'DOUND_TO`/`FLOOR`/`CEIL`, `ABS`, trigonometric functions, and so forth.
- **String comparison**:
  - `matches` tests a value against a regular expression:
  - Compare strings directly using `==`. `EqualsIgnoreCase` does a case-insensitive match, while `STARTSWITH`/`ENDSWITH` test whether one string is a prefix or suffix of the other.
  - `SIZE` returns the number of characters in a `chararray`, and the number of bytes in a `bytearray`. Be reminded that characters often occupy more than one byte: the string *Motörhead* has nine characters, but because of its umlaut-ed *ö* the string occupies ten bytes. You can use `SIZE` on other types, too; but to find the number of elements in a bag, use `COUNT_STAR` and not `SIZE`.
  - `INDEXOF` finds the character position of a substring within a `chararray`
- **Transform strings**:
  - `CONCAT` concatenates all its inputs into a new string; `SPRINTF` uses a supplied template to format its inputs into a new string; BagToString joins the contents of a bag into a single string, separated by a supplied delimiter
  - `LOWER` converts a string to lowercase characters; `UPPER` to all uppercase
  - `TRIM` strips leading and trailing whitespace
  - `REPLACE(string, 'regexp', 'replacement')` substitutes the replacement string wherever the given regular expression matches, as implemented by

`java.string.replaceAll`. If there are no matches, the input string is passed through unchanged.

— `REGEX_EXTRACT(string, regexp, index)` applies the given regular expression and returns the contents of the indicated matched group. If the regular expression does not match, it returns NULL. The `REGEX_EXTRACT_ALL` function is similar, but returns a tuple of the matched groups.

— `STRSPLIT` splits a string at each match of the given regular expression

— `SUBSTRING` selects a portion of a string based on position

- **Datetime Functions**, such as `CurrentTime`, `ToUnixTime`, `SecondsBetween` (duration between two given datetimes)
- **Aggregate functions** that act on bags:

  — `AVG`, `MAX`, `MIN`, `SUM`

  — `COUNT_STAR` reports the number of elements in a bag, including nulls; `COUNT` reports the number of non-null elements. `IsEmpty` tests that a bag has elements. Don't use the quite-similar-sounding `SIZE` function on bags: it's much less efficient.

- **Bag Functions** TODO COMPLETE LIST

  — Extremal

  — FirstTupleInBag

  — BagConcat

  — Stitch / Over

  — `SUBTRACT(bag_a, bag_b)` returns a new bag having all the tuples that are in the first but not in the second, and `DIFF(bag_a, bag_b)` returns a new bag having all tuples that are in either but not in both. These are rarely used, as the bags must be of modest size — in general us an inner JOIN as described below.

  — `TOP(num, column_index, bag)` selects the top `num` of elements from each tuple in the given bag, as ordered by `column_index`. This uses a clever algorithm that doesn't require an expensive total sort of the data — you'll learn about it in the Statistics chapter (TODO ref)

- **Conversion Functions** to perform higher-level type casting: `TOTUPLE`, `TOBAG`, `TOMAP`
- Add all the DataFu operations: *http://datafu.incubator.apache.org/docs/datafu/guide/bag-operations.html* and coalesce *http://datafu.incubator.apache.org/docs/datafu/guide/more-tips-and-tricks.html* and maybe others

  — Hasher

Moving right along …

This chapter was a gentle introduction to Pig and its basic operations. In the next two chapters, we'll see Pig in action. [4]

4. Your authors struggled to not make a "see Pig fly" joke. Oh, wait, looks like we did …

PART II
Tactics: Analytic Patterns

Now that you've met the fundamental analytic machinery — in both their map/reduce and table-operation form — it's time to put them to work.

This part of the book will equip you to think tactically, to think in terms of the changes you would like to make to the data. Each section introduces a repeatedly-useful data transformation pattern, demonstrated in Pig (and, where we'd like to reinforce the record-by-record action, in Wukong as well). The next part of the book will focus on *strategic* techniques, to assemble the patterns you're about to see into an explanation that tells a coherent story.

One of this book's principles is to center demonstrations around an interesting and realistic problem from some domain. And whenever possible, we endeavor to indicate how the approach would extend to other domains, especially ones with an obvious business focus. The tactical patterns, however, are exactly those tools that crop up in nearly every domain: think of them as the screwdriver, torque wrench, lathe and so forth of your toolkit. Now, if this book were called "Big Mechanics for Chimps", we might introduce those tools by repairing and rebuilding a Volkswagen Beetle engine, or by building another lathe from scratch. Those lessons would carry over to anywhere machine tools apply: air conditioner repair, fixing your kid's bike, building a rocket ship to Mars.

So we will center this part of the book on what Nate Silver calls "the perfect data set": the sea of numbers surrounding the sport of baseball. The members of the Retrosheet and Baseball Databank projects have provided an extraordinary resource: comprehensive statistics from the birth of the game in the late 1800s until the present day, freely available and redistributable. There is an overview of the stats we'll use in (REF sidebar),

and further information in the "Overview of Datasets" appendix (REF). Even if you're not a baseball fan, we've minimized the number of concepts you'll need to learn.

In particular, we will be hopping in and out of two main storylines as each pattern is introduced. One is a graphical biography of each player and team — the data tables for a website that can display timelines, maps and charts of the major events and people in the history of a team or player. This is explanatory analytics, where the goal is to summarize the answers to well-determined questions for presentation. We will demonstrate finding the geographical coordinates for each stadium or assembling the events in a player's career in a way that you can apply any time you want to show things on a map or display a timeline. When we demonstrate the self-join by listing each player's teammates, we're showing you how to list all other products purchased in the same shopping cart as a product, or all pages co-visited by a user during a website session, and any other occasion where you want to extend a relationship by one degree.

The other storyline is to find indicators of exceptional performance, supplying a quantitative basis for the age-old question "Who are the greatest players in the game?". This is exploratory analytics, where the work is as much to determine the questions as to assemble the answers. Quantifying "how many great seasons did this player have?" or "" is. As we pursue this exploration, you should recognize not just a way for fantasy baseball players to get an edge, but strategies for quantifying the behavior of any sort of outlier. Here, it's baseball players, but similar questions will apply when examining agents posing security threats, load factor on public transit routes, factors causing manufacturing defects, cell strains with a significantly positive response, and many other topics of importance.

In many cases, though, a pattern has no natural demonstration in service of those primary stories, and so we'll find questions that could support an investigation of their own: "How can we track changes in each team's roster over time?", "Is the stereotypical picture of the big brawny home-run hitter true?" For these we will usually just show the setup and stop at the trailhead. But when the data comes forth with a story so compelling it demands investigation ("Does God really hate Cleveland?", "Why are baseball players more likely to die in January and be born in August?") we will take a brief side trip to follow the tale.

Each pattern is followed by a "pattern in use" synopsis that suggests alternative business contexts for this pattern, lists important caveats and associated patterns, and how to reason about its performance. These will become most useful once you've read the book a first time and (we hope) begin using it as your go-to reference. If you find the level of detail here to be a bit intense, skim past them on the first reading.

What's most important is that you learn the mechanics of each pattern, ignoring the story if you must. The best thing you can do is to grab a data set of your own — from your work or research, or one of the datasets listed in our Overview of Datasets (REF) — and translate the patterns to that domain. Don't worry about finding an overarching

theme like our performance-outliers storyline, just get a feel for the craft of using Hadoop at scale.

CHAPTER 5

Analytic Patterns part 1: Pipeline Operations

This chapter focuses exclusively on what we'll call *pipelineable operations*. A pipelineable operations is one that can handle each record in isolation, like the translator chimps from Chimpanzee & Elephant's first job. That property makes those operations trivially parallelizable: they require no reduce phase of their own.

When a script has only pipelineable operations, they give rise to one mapper-only job which executes the composed pipeline stages. When pipelinable operations are combined with the structural operations you'll meet in the next chapter, they are composed with the stages of the mapper or reducer (depending on whether they come before or after the structural operation).

All of these are listed first and together for two reasons. One, they are largely fundamental; it's hard to get much done without `FILTER` or `FOREACH`. Two, the way you reason about the performance impact of these operations is largely the same. Since these operations are trivially paralellizable, they scale efficiently and the computation cost rarely impedes throughput. And when pipelined, their performance cost can be summarized as "kids eat free with purchase of adult meal". For datasets of any material size, it's very rare that the cost of preliminary or follow-on processing rivals the cost of the reduce phase. Finally, since these operations handle records in isolation, their memory impact is modest. So learn to think of these together.

Eliminating Data

The first round of patterns will focus on methods to shrink your dataset. This may sound counterintuitive to the novice ear: isn't the whole point of "Big Data" that we get to work with the entire dataset at once? We finally develop models based on the entire population, not a sample thereof, so why should we scale down our data?

The primary reason is to focus on a subset of records: only website requests with an external referrer, only security events with high threat levels, only accounts of than $1 million. And even when you work with every *record* in a dataset, you may be interested in a subset of *fields* relevant to your research. For reasons of memory and computational efficiency, and also your sanity, you'd do yourself a favor to immediately trim a working dataset down to just those records and fields relevant to the task at hand. [1] Furthermore, you may wish to test some code on a small sample before unleashing it on a long-running job. [2] Last, but not least, you may want to draw a random sample just to spot-check a dataset when it's too computationally expensive to inspect every element.

The goal of course isn't to *eliminate* data, it's to be *selective* about your data, and so we will introduce you to a variety of techniques for doing so.

Selecting Records that Satisfy a Condition: `FILTER` and Friends

The first step to eliminating (or being selective about) data is to reject records that don't match certain criteria. Pig's `FILTER` statement does this for you. It doesn't remove the data — all data in Hadoop and thus Pig is immutable — rather like all Pig operations it creates a new table that omits certain records from the input.

The baseball stats go back to 1871 (!), but it took a few decades for the game to reach its modern form. Let's say we're only interested in seasons since 1900. In Pig, we apply the `FILTER` operation [3]:

```
modern_stats = FILTER bats BY (year_id >= 1900);
```

The range of conditional expressions you'd expect are present: `==` (double-equals) to express an equality condition, `!=` for not-equals, and `>`, `>=`, `<`, `<=` for inequalities; `IN` for presence in a list; and `MATCHES` for string pattern matching. (More on those last two in a bit.)

1. This will certainly simplify debugging. It also plays to Q's favorite refrain of, *know your data*. If you're working on a dataset and there are additional fields or records you don't plan to use, can you be certain they won't somehow creep into your model? The worst-case scenario here is what's called a feature leak, wherein your target variable winds up in your training data. (In essence: imagine saying you can predict today's high temperature, so long as you are first provided today's high temperature.) A feature leak can lead to painful surprises when you deploy this model to the real world.

2. This is generally a good habit to develop, especially if you're one to kick off jobs before leaving the office, going to bed, or boarding a long-haul flight.

3. In this and in further scripts, we're going omit the `LOAD`, `STORE` and other boilerplate except to prove a point. See the example code (REF) for fully-working snippets

Selecting Records that Satisfy Multiple Conditions

In a data exploration, it's often important to exclude subjects with sparse data, either to eliminate small-sample-size artifacts, or because they are not in the focus of interest. In our case, we will often want to restrict analysis to regular players — those who have seen significant playing time in a season — while allowing for injury or situational replacement. Since major-league players come to bat a bit over 4 times a game on average in a season of 154 to 162 games (it increased in 1960), we can take 450 plate appearances (roughly 2/3 of the maximum) as our threshold [4].

In Pig, you can also combine conditional statements with `AND`, `OR`, `NOT`. The following selects we'll call "qualified modern seasons": regular players, competing in the modern era, in either of the two modern leagues.

```
modsig_stats = FILTER bats BY
  (PA >= 450) AND (year_id >= 1900) AND ((lg_id == 'AL') OR (lg_id == 'NL'));
```

Selecting or Rejecting Records with a `null` Value

Another table we'll be working with is the 'people` table. It describes players' vital statistics: their name; where and when they were born and died; when their career started and ended; their height and weight; and so forth. The data is quite comprehensive, but in some cases the fields have `null` values. Nulls are used in practice for many things:

- *Missing/unknown Value* — the case for a fraction of early players' birthplaces or birth dates
- *No Value Applies* — players who are still alive have `null` in the fields for date and location of death
- *Ill-formed Value* — if a corrupt line creates an unparseable cell (eg a value of `'Bob'` for an int), Pig will write a warning to the log but otherwise load it without complaint as `null`.
- *Illegal value* — Division by zero and similar misbehavior results in a null value (and not an error, warning, or log statement)
- *"Other"* — People will use a `null` value in general to represent "it's complicated, but maybe some other field has details".

We can exclude players whose birth year or birth place is unknown with a `FILTER` statement:

```
borned = FILTER people BY (birth_year IS NOT NULL) AND (birth_place IS NOT NULL);
```

4. Not coincidentally, that figure of 450 PA is close to the "qualified" season threshold of 3.1 plate appearances per team game that are required for seasonal performance awards

For those coming from a SQL background, Pig's handling of `null` values will be fairly familiar. For the rest of us, good luck. Null values generally disappear without notice from operations, and generally compare as `null` (which signifies neither `false` nor `true`). And so `null` is not less than 5.0, it is not greater than 5.0, and it is not equal to 5.0. A null value is not equal to `null`, and is not *unequal* to `null`. You can see why for programmers it can be hard to track all this. All the fiddly collection of rules are well detailed in the Pig manual, so we won't go deep into them here — we've found the best way to learn what you need is to just see lots of examples, which we endeavor to supply in abundance.

Pattern in Use

Blocks like the following will show up after each of the patterns or groups of patterns we cover. Not every field will be present every time, since there's not always anything interesting to say.

- *Where You'll Use It* — (*The business or programming context.*) Everywhere. Like the f-stop on your camera, composing a photo begins and ends with throttling its illumination.
- *Standard Snippet* — (*Just enough of the code to remind you how it's spelled.*) `somerecords = FILTER myrecords BY (criteria AND criteria ...);`
- *Hello, SQL Users* — (*A sketch of the corresponding SQL command, and important caveats for peopl coming from a SQL background.*) `SELECT bat_season.* FROM bat_season WHERE year_id >= 1900;`
- *Important to Know* — (*Caveats about its use. Things that you won't understand / won't buy into the first time through the book but will probably like to know later.*)
  - — Filter early, filter often. The best thing you can do with a large data set is make it smaller.
  - — SQL users take note: `==`, `!=` — not `=` or anything else.
  - — Programmers take note: `AND`, `OR` — not `&&`, `||`.
- *Output Count* — (*How many records in the output: fewer, same, more, explosively more?*) Zero to 100% of the input record count. Data size will decrease accordingly
- *Records* — (*A sketch of what the records coming out of this operation look like*) Identical to input
- *Data Flow* — (*The Hadoop jobs this operation gives rise to. In this chapter, all the lines will look like this one; in the next chapters that will change*) Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.

- *Exercises for You* — (*A mission to carry forward, if you choose. Don't go looking for an answer section — we haven't done any of them. In many cases you'll be the first to find the answer.*) Play around with `null`s and the conditional operators until you have a good sense of its quirks.
- *See Also* — (*Besides the patterns in its section of the book, what other topics might apply if you're considering this one? Sometimes this is another section in the book, sometimes it's a pointer elsewhere*) The Distinct operations, some Set operations, and some Joins are also used to eliminate records according to some criteria. See especially the Semi-Join and Anti-Join (REF), which select or reject matches against a large list of keys.

Selecting Records that Match a Regular Expression (MATCHES)

A `MATCHES` expression employs regular expression pattern matching against string values. Regular expressions are given as plain `chararray` strings; there's no special syntax, as Python/Ruby/Perl/etc-ists might have hoped. See the sidebar (REF) for important details and references that will help you master this important tool.

This operation uses a regular expression to select players with names similar to either of your authors' names:

```
-- Name contains a Q; is `Flip` or anything in the Philip/Phillip/... family. (?i) means be case-i
namesakes = FILTER people BY (nameFirst MATCHES '(?i).*(q|flip|phil+ip).*');
```

It's easy to forget that people's names can contain spaces, dots, dashes, apostrophes; start with lowercase letters or apostrophes, and have accented or other non-latin characters [5]. So as a less silly demonstration of `MATCHES`, this snippet extracts all names which do not start with a capital letter or which contain a non-word non-space character:

```
funnychars = FILTER people BY (nameFirst MATCHES '^([^A-Z]|.*[^\\w\\s]).*');
```

There are many players with non-word,non-space characters, but none whose names are represented as starting with a lowercase character. However, in early drafts of the book this query caught a record with the value "nameFirst" — the header rows from a source datafile had contaminated the table. Sanity checks like these are a good idea always, even moreso in Big Data. When you have billions of records, a one-in-a-million exception will appear thousands of times.

5. A demonstration of the general principle that if you believe an analysis involving people will be simple, you're probably wrong.

Important Notes about String Matching

Regular expressions are incredibly powerful and we urge all readers to acquire basic familiarity. There is no better path to mastery than the regexp.info website, and we've provided a brief cheatsheet at the end of the book (REF). Here are some essential clarifications about Pig in particular:

- Regular expressions in Pig are supplied to the MATCHES operator as plain strings. A single backslash serves the purposes of the string literal and does not appear in the string sent to the regexp engine. To pass along the shorthand `[^\\w\\s]` (non-word non-space characters), we have to use two backslashes.
- Yes, that means matching a literal backslash in the target string is done with four backslashes: `\\\\`!
- Options for matching are supplied within the string. For example, `(?i)` matches without regard to case (as we did above), `(?m)` to do multi-line matches, and so forth — see the documentation.
- Pig Regular Expressions are implicitly anchored at the beginning and end of the string, the equivalent of adding `^` at the start and `$` at the end. (This mirrors Java but is unlike most other languages.) Use `.*` at both ends, as we did above, to regain the conventional "greedy" behavior. Supplying explicit `^` or `$` when intended is a good habit for readability.
- `MATCHES` is an expression, like `AND` or `==` — you write `str MATCHES regexp`. The other regular expression mechanisms you'll meet are functions — you write `REGEX_EXTRACT(str, regexp, 1)`. You will forget we told you so the moment you finish this book.
- Appearing in the crop of results: Peek-A-Boo Veach, Quincy Trouppe, and Flip Lafferty.
- You're allowed to have the regular expression be a value from the record, though Pig is able to pre-compile a constant (literal) regexp string for a nice speedup.
- Pig doesn't offer an exact equivalent to the SQL `%` expression for simple string matching. The rough equivalents are dot-star (`.*`) for the SQL `%` (zero or more arbitrary characters), dot (`.`) for the SQL `_` (a single character); and square brackets (e.g. `[a-z]`) for a character range, similar to SQL.
- The string equality expression is case sensitive: `'Peek-A-Boo'` does not equal `'peek-a-boo'` For case-insensitive string matching, use the `EqualsIgnoreCase` function: `EqualsIgnoreCase('Peek-A-Boo', 'peek-a-boo')` is true. This simply invokes Java's `String.equalsIgnoreCase()` method and does not support regular expressions.

Sadly, the Nobel Prize-winning physicists Gerard 't Hooft, Louis-Victor Pierre Raymond de Broglie, or Tomonaga Shin'ichirō never made the major leagues. Or tried out, as far as we know. But their names are great counter-examples to keep in mind when dealing with names. Prof de Broglie's full name is 38 characters long, has a last name that starts with a lowercase letter, and is non-trivial to segment. "Tomonaga" is a family name, though it comes first. You'll see Prof. Tomonaga's name given variously as "Tomonaga Shin'ichirō", "Sin-Itiro Tomonaga", or "□□ □□□", each one of them correct, and the others not, depending on context. Prof. 't Hooft's last name starts with an apostrophe, a lower-case-letter, and contains a space. You're well advised to start a little curio shelf in your workshop for counterexample collections such as these, and we'll share some of ours throughout the book.

Pattern in Use

- *Where You'll Use It* — Wherever you need to select records by a string field. For selecting against small lists. For finding ill-formed records. Matching against a subsection of a composite key — Can you figure out what `game_id MATCHES '...(19|20).*'` in the `games` table does?
- *Standard Snippet* — `FILTER recs BY (str MATCHES '.*pattern.*')`, sure, but also `FOREACH recs GENERATE (str MATCHES '.*(kitty|cat|meow).*' ? 'cat' : 'notcat') AS catness`.
- *Hello, SQL Users* — Similar to but more powerful than the `LIKE` operator. See the sidebar (ref) for a conversion guide.
- *Important to Know* --
  - — Mostly, that these are incredibly powerful, and even if they seem arcane now they're much easier to learn than it first seems.
  - — You're far better off learning one extra thing to do with a regular expression than most of the other string conditional functions Pig offers.
  - — … and enough other Importants to Know that we made a sidebar of them (REF).
- *Records* — You can use this in a filter clause but also anywhere else an expression is permitted, like the preceding snippet
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.
- *Exercises for You* — Follow the regexp.info tutorial, but *only up to the part on Grouping & Capturing*. The rest you are far better off picking up once you find you need it.

- *See Also* — The Pig `REGEX_EXTRACT` and `REPLACE` functions. Java's Regular Expression documentation for details on its pecadilloes (but not for an education about regular expressions).

Matching Records against a Fixed List of Lookup Values

If you plan to filter by matching against a small static list of values, Pig offers the handy `IN` expression: true if the value is equal (case-sensitive) to any of the listed values. This selects the stadiums used each year by the current teams in baseball's AL-east division:

```
al_east_parks = FILTER park_team_years BY
  team_id IN ('BAL', 'BOS', 'CLE', 'DET', 'ML4', 'NYA', 'TBA', 'TOR', 'WS2');
```

Sometimes a regular expression alternation can be the right choice instead. `bubba MATCHES 'shrimp (kabobs|creole|gumbo|soup|stew|salad|and potatoes|burger|sandwich)' OR bubba MATCHES '(pineapple|lemon|coconut|pepper|pan.fried|deep.fried|stir.fried) shrimp'` is more readable than `bubba IN ('shrimp kabobs', 'shrimp creole', 'shrimp gumbo', ...)`.

When the list grows somewhat larger, an alternative is to read it into a set-membership data structure [6], but ultimately large data sets belong in data files.

The general case is handled bu using a join, as described in the next chapter (REF) under "Selecting Records Having a Match in Another Table (semi-join)". See in particular the specialized merge join and HashMap (replicated) join, which can offer a great speedup if you meet their qualifications. Finally, you may find yourself with an extremely large table but with few elements expected to match. In that case, a Bloom Filter may be appropriate. They're discussed more in the statistics chapter, where use a Bloom Filter to match every phrase in a large document set against a large list of place names, effectively geolocating the documents.

Pattern in Use

- *Where You'll Use It* — File types or IP addresses to select/reject from web logs. Keys for exemplar records you're tracking through a dataflow. Stock symbols you're researching. Together with "Summarizing Multiple Subsets of a Group Simultaneously" (REF), enumerate members of a cohort (`(state IN ('CA', 'WA', 'OR') ? 1 : 0) AS is_western, ...`).
- *Standard Snippet* — `foo IN ('this', 'that', 'the_other')`, or any of the other variants given above

6. For a dynamic language such as Ruby, it can often be both faster and cleaner to reformat the table into the language itself than to parse a data file. Loading the table is now a one-liner (`require "lookup_table"`), and there's nothing the Ruby interpreter does faster than interpret Ruby.

- *Hello, SQL Users* — This isn't anywhere near as powerful as SQL's `IN` expression. Most importantly, you can't supply another table as the list.
- *Important to Know* — A regular expression alternation is often the right choice instead.
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values. Data size should decrease greatly.
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.

Project Only Chosen Columns by Name

While a `FILTER` selects *rows* based on an expression, Pig's `FOREACH` selects specific *fields* chosen by name. The fancy word for this simple action is "projection". We'll try to be precise in using *project* for choosing columns, *select* for choosing rows by any means, and *filter* where we specifically mean selecting rows that satisfy a conditional expression.

The tables we're using come with an overwhelming wealth of stats, but we only need a few of them to do fairly sophisticated explorations. The gamelogs table has more than 90 columns; to extract just the teams and the final score, use a FOREACH:

```
game_scores = FOREACH games GENERATE
  away_team_id, home_team_id, home_runs_ct, away_runs_ct;
```

Using a FOREACH to Select, Rename and Reorder fields

You're not limited to simply restricting the number of columns; you can also rename and reorder them in a projection. Each record in the table above has *two* game outcomes, one for the home team and one for the away team. We can represent the same data in a table listing outcomes purely from each team's perspective:

```
games_a = FOREACH games GENERATE
  year_id, home_team_id AS team,
  home_runs_ct AS runs_for, away_runs_ct AS runs_against, 1 AS is_home:int;

games_b = FOREACH games GENERATE
  away_team_id AS team,     year_id,
  away_runs_ct AS runs_for, home_runs_ct AS runs_against, 0 AS is_home:int;

team_scores = UNION games_a, games_b;

DESCRIBE team_scores;
--   team_scores: {team: chararray,year_id: int,runs_for: int,runs_against: int,is_home: int}
```

The first projection puts the `home_team_id` into the team slot, renaming it `team`; retains the `year_id` field unchanged; and files the home and away scores under `runs_for` and

`runs_against`. Lastly, we slot in an indicator field for home games, supplying both the name and type as a matter of form. Next we generate the corresponding table for away games, then stack them together with the `UNION` operation (to which you'll be properly introduced in a few pages). All the tables have the identical schema shown, even though their values come from different columns in the original tables.

Pattern in Use

- *Where You'll Use It* — Nearly everywhere. If `FILTER` is the f-stop of our camera, this is the zoom lens.
- *Standard Snippet* — `FOREACH recs GENERATE only, some, columns;`
- *Important to Know* — As you can see, we take a lot of care visually aligning subexpressions within the code snippets. That's not because we've tidied up the house for students coming over — this is what the code we write and the code our teammates expect us to write looks like.
- *Output Count* — Exactly the same as the input.
- *Records* — However you define them to be
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.
- *See Also* — "Assembling Literals with Complex Type" (REF)

Extracting a Random Sample of Records

Another common operation is to extract a *uniform* sample — one where every record has an equivalent chance of being selected. For example, you could use this to test new code before running it against the entire dataset (and possibly having a long-running job fail due to a large number of mis-handled records). By calling the `SAMPLE` operator, you ask Pig to pluck out some records at random.

The following Pig code will return a randomly-selected 10% (that is, 1/10 = 0.10) of the records from our baseball dataset:

```
some_seasons_samp = SAMPLE bat_seasons 0.10;
```

The `SAMPLE` operation does so by generating a random number to select records, which means each run of a script that uses `SAMPLE` will yield a different set of records. Sometimes this is what you want, or in the very least, you don't mind. In other cases, you may want to draw a uniform sample once, then repeatedly work through those *same* records. (Consider our example of spot-checking new code against a dataset: you'd need to run your code against the same sample in order to confirm your changes work as expected.)

Experienced software developers will reach for a "seeding" function — such as R's `set.seed()` or Python's `random.seed()` — to make the randomness a little less so. At the moment, Pig does not have an equivalent function. Even worse, it is not consistent *within the task* — if a map task fails on one machine, the retry attempt will generate different data sent to different reducers. This rarely causes problems, but for anyone looking to contribute back to the Pig project, this is a straighforward high-value issue to tackle.

Pattern in Use

- *Where You'll Use It* — At the start of the exploration, to cut down on data size. In many machine learning algorithms. Don't use it for simulations — you need to be taking aggressive charge of the sampling algorithm.
- *Important to Know*
  - — A consistent sample is a much better practice, though we admit that can be more of a hassle. But records that dance around mean you can't Know Thy Data as you should.
  - — The DataFu package has UDFs for sampling with replacement and other advanced features.
- *Output Count* — Determined by the sampling fraction. As a rule of thumb, variances of things are square-root-ish; expect the size of a 10% sample to be in the 7%-13% range.
- *Records* — Identical to the input
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.
- *Exercises for You* — Modify Pig's SAMPLE function to accept a seed parameter, and submit that patch back to the open-source project. This is a bit harder to do than it seems: sampling is key to efficient sorting and so the code to sample data is intertwingled with a lot of core functionality.

Extracting a Consistent Sample of Records by Key

A good way to stabilize the sample from run to run is to use a *consistent hash digest*. A hash digest function creates a fixed-length fingerprint of a string whose output is otherwise unpredictable from the input and uniformly distributed — that is, you can't tell which string the function will produce except by computing the digest, and every string is equally likely. For example, the hash function might give the hexadecimal-string digest `3ce3e909` for *Chimpanzee* but `07a05f9c` for *Chimp*. Since all hexadecimal strings have effectively equal likelihood, one-sixteenth of them will start with a zero, and so this filter would reject `Chimpanzee` but select `Chimp`.

Unfortunately, Pig doesn't have a good built-in hash digest function! Do we have to give up all hope? You'll find the answer later in the chapter (REF) [7], but for now instead of using a good built-in hash digest function let's use a terrible hash digest function. A bit under 10% of player_ids start with the letter *s*, and any coupling between a player's name and performance would be far more subtle than we need to worry about. So the following simple snippet gives a 10% sample of batting seasons whose behavior should reasonably match that of the whole:

```
some_seasons  = FILTER bat_seasons BY (SUBSTRING(player_id, 0, 1) == 's');
```

We called this a terrible hash function, but it does fit the bill. When applied to an arbitrary serial identifier it's not terrible at all — the Twitter firehose provides a 1% service tier which returns only tweets from users whose numeric ID ends in *00*, and a 10% tier with user IDs ending in `0`. We'll return to the subject with a proper hash digest function later on in the chapter, once you're brimming with even more smartitude than you are right now. We'll also have a lot more to say about sampling in the Statistics chapter (REF).

- *Where You'll Use It* — At the start of the exploration,
- *Important to Know*
  - — If you'll be spending a bunch of time with a data set, using any kind of random sample to prepare your development sample might be a stupid idea. You'll notice that Red Sox players show up a lot of times in our examples — that's because our development samples are "seasons by Red Sox players" and "seasons from 2000-2010", which lets us make good friends with the data.
- *Output Count* — Determined by the sampling fraction. As a rule of thumb, variances of things are square-root-ish; expect the size of a 10% sample to be in the 7%-13% range.
- *Records* — Identical to the input
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.

Sampling Carelessly by Only Loading Some `part-` Files

Sometimes you just want to knock down the data size while developing your script, and don't much care about the exact population. If you find a prior stage has left you with 20 files `part-r-00000` through `part-r-00019`, specifying `part-r-0000[01]` (the first two out of twenty files) as the input to the next stage is a hamfisted but effective way to get a 10% sample. You can cheat even harder by adjusting the parallelism of the pre-

7. Spoiler alert: No, you don't have to give up all hope when Pig lacks a built-in function you require.

ceding stage to get you the file granularity you need. As long as you're mindful that some operations leave the reducer with a biased selection of records, toggling back and forth between say `my_data/part-r-0000[01]` (two files) and `my_data/` (all files in that directory) can really speed up development.

Selecting a Fixed Number of Records with `LIMIT`

A much blunter way to create a smaller dataset is to take some fixed number *K* of records. Pig offers the `LIMIT` operator for this purpose. To select 25 records from our `bat_seasons` data, you would run:

```
some_players = LIMIT player_year_stats 25;
```

This is somewhat similar to running the `head` command in Unix-like operating systems, or using the `LIMIT` clause in a SQL `SELECT` statement. However, unless you have explicitly imparted some order to the table (probably by sorting it with `ORDER`, which we'll cover later (REF)), Pig gives you *no guarantee over which records it selects*. In the big data regime, where your data is striped across many machines, there's no intrinsic notion of a record order. Changes in the number of mappers or reducers, in the data, or in the cluster may change which records are selected. In practice, you'll find that it takes the first *K* records of the first-listed file (and so, as opposed to `SAMPLE`, generally gives the same outcome run-to-run), but it's irresponsible to rely on that.

When you have a very large dataset, as long as you really just need any small piece of it, you can apply the previous trick as well and just specify a single input file. Invoking `LIMIT` on one file will prevent a lot of trivial map tasks from running.

Other Data Elimination Patterns

There are two tools we'll meet in the next chapter that can be viewed as data elimination patterns as well. The `DISTINCT` and related operations are used to identify duplicated or unique records. Doing so requires putting each record in context with its possible duplicates — meaning they are not pure pipeline operations like the others here. Above, we gave you a few special cases of selecting records against a list of values. We'll see the general case — selecting records having or lacking a match in another table, also known as semi-join and anti-join — when we meet all the flavors of the `JOIN` operation in the next chapter.

Transforming Records

Besides getting rid of old records, the second-most exciting thing to do with a big data set is to rip through them manufacturing new records [8]. We've been quietly sneaking `FOREACH` into snippets, but it's time to make its proper acquaintance

Transform Records Individually using FOREACH

The `FOREACH` lets you develop simple transformations based on each record. It's the most versatile Pig operation and the one you'll spend the most time using.

To start with a basic example, this `FOREACH` statement combines the fields giving the city, state and country of birth for each player into the familiar comma-space separated combined form (`Austin, TX, USA`) [9].

```
birthplaces = FOREACH people GENERATE
    player_id,
    CONCAT(birth_city, ', ', birth_state, ', ', birth_country) AS birth_loc
    ;
```

The syntax should be largely self-explanatory: this runs through the people table, and outputs a table with two columns, the player ID and our synthesized string. In the output you'll see that when `CONCAT` encounters records with `null` values, it returned `null` as well without an error.

For the benefit of SQL aficionados, here's an equivalent SQL query:

```
SELECT
    player_id,
    CONCAT(birth_city, ', ', birth_state, ', ', birth_country) AS birth_loc
  FROM people;
```

You'll recall we took some care when loading the data to describe the table's schema, and Pig makes it easy to ensure that the data continues to be typed. Run `DESCRIBE birthplaces;` to return the schema:

```
birthplaces: {player_id: chararray,birth_loc: chararray}
```

Since `player_id` carries through unchanged, its name and type convey to the new schema. Pig figures out that the result of `CONCAT` is a `chararray`, but it's up to us to award it with a new name (`birth_loc`).

8. Although you might re-rank things when we show you how to misuse Hadoop to stress-test a webserver with millions of concurrent requests per minute (REF)

9. The country field uses some ad-hoc mixture of full name and arbitrary abbreviations. In practice, we would have converted the country fields to use ISO two-letter abbreviations — and that's just what we'll do in a later section (REF)

A FOREACH won't cause a new Hadoop job stage: it's chained onto the end of the preceding operation (and when it's on its own, like this one, there's just a single a mapper-only job). It always produces exactly the same count of output records as input records, although as you've seen it can change the number of columns.

A nested FOREACH Allows Intermediate Expressions

Earlier we promised you a storyline in the form of an extended exploration of player performance. We've now gathered enough tactical prowess to set out [10].

The stats in the 'bat_seasons` table are all "counting stats" — total numbers of hits, of games, and so forth — and certainly from the team's perspective the more hits the more better. But for comparing players, the counting stats don't distinguish between the player who eared 70 hits in a mere 200 trips to the plate before a season-ending injury, and the player who squandered 400 of his team's plate appearances getting to a similar total [11]. We should also form "rate stats", normalizing those figures against plate appearances. The following simple metrics do quite a reasonable job of characterizing players' performance:

- *On-base percentage* (OBP) indicates how well the player meets offensive goal #1: get on base, thus becoming a potential run and *not* consuming a precious out. It is given as the fraction of plate appearances that are successful: (`(H + BB + HBP) / PA`) [12]. An OBP over 0.400 is very good (better than 95% of significant seasons).
- *Slugging Percentage* (SLG) indicates how well the player meets offensive goal #2: advance the runners on base, thus converting potential runs into points towards victory. It is given by the total bases gained in hitting (one for a single, two for a double, etc) divided by the number of at bats: (`TB / AB`, where `TB := (H + h2B + 2*h3B + 3*HR)`). An SLG over 0.500 is very good.
- *On-base-plus-slugging* (OPS) combines on-base and slugging percentages to give a simple and useful estimate of overall offensive contribution. It's found by simply adding the figures: (`OBP + SLG`). Anything above 0.900 is very good.

Doing this with the simple form of FOREACH we've been using would be annoying and hard to read — for one thing, the expressions for OBP and SLG would have to be repeated in the expression for OPS, since the full statement is evaluated together. Pig

10. We also warned you we'd wander away from it frequently — the bulk of it sits in the next chapter.
11. Here's to you, 1970 Rod Carew and 1979 Mario Mendoza
12. Although known as percentages, OBP and SLG are always given as fractions to 3 decimal places. For OBP, we're also using a slightly modified formula to reduce the number of stats to learn. It gives nearly identical results but you will notice small discrepancies with official figures

provides a fancier form of FOREACH (a *nested* FOREACH) that allows intermediate expressions:

```
bat_seasons = FILTER bat_seasons BY PA > 0 AND AB > 0;
core_stats  = FOREACH bat_seasons {
  TB   = h1B + 2*h2B + 3*h3B + 4*HR;
  OBP  = 1.0f*(H + BB + HBP) / PA;
  SLG  = 1.0f*TB / AB;
  OPS  = SLG + OBP;
  GENERATE
    player_id, name_first, name_last,   --  $0- $2
    year_id,   team_id,   lg_id,        --  $3- $5
    age,  G,   PA,  AB,   HBP, SH,  BB, --  $6-$12
    H,    h1B, h2B, h3B,  HR,  R,  RBI, -- $13-$19
    SLG, OBP, OPS;                      -- $20-$22
};
```

This alternative { curly braces form of FOREACH lets you describe its transformations in smaller pieces, rather than smushing everything into the single GENERATE clause. New identifiers within the curly braces (such as player) only have meaning within those braces, but they do inform the schema.

You'll notice that we multiplied by 1.0 while calculating OBP and SLG. If all the operands were integers, Pig would use integer arithmetic; instead of fractions between 0 and 1, the result would always be integer 0. Multiplying by the floating-point value 1.0 forces Pig to use floating-point math, preserving the fraction. Using a typecast — SLG = (float)TB / AB — as described below is arguably more efficient but inarguably uglier. The above is what we'd write in practice.

By the way, the filter above is sneakily doing two things. It obviously eliminates records where PA is equal to zero, but it also eliminates records where PA is null. (See the section "Selecting or Rejecting Records with null Values" (REF) above for details.)

In addition to applying arithmetic expressions and functions, there are a set of *operations* (ORDER, DISTINCT, FOREACH, FILTER, LIMIT) you can apply to bags within a nested FOREACH. We'll wait until the section on grouping operations to introduce their nested-foreach ("inner bag") forms.

Formatting a String According to a Template

The SPRINTF function is a great tool for assembling a string for humans to look at. It uses the printf-style templating convention common to C and many other languages to assemble strings with consistent padding and spacing. It's best learned by seeing it in action:

```
formatted = FOREACH bat_seasons GENERATE
  SPRINTF('%4d\t%-9s %-19s\tOBP %5.3f / %-3s %-3s\t%4$012.3e',
    year_id,  player_id,
```

```
    CONCAT(name_first, ' ', name_last),
    1.0f*(H + BB + HBP) / PA,
    (year_id >= 1900 ? '.'   : 'pre'),
    (PA >= 450       ? 'sig' : '.')
  ) AS OBP_summary:chararray;
```

So you can follow along, here are some scattered lines from the results:

```
1954    aaronha01 Hank Aaron            OBP 0.318 / .   sig     0003.183e-01
1897    ansonca01 Cap Anson             OBP 0.372 / pre sig     0003.722e-01
1970    carewro01 Rod Carew             OBP 0.407 / .   .       0004.069e-01
1987    gwynnto01 Tony Gwynn            OBP 0.446 / .   sig     0004.456e-01
2007    pedrodu01 Dustin Pedroia        OBP 0.377 / .   sig     0003.769e-01
1995    vanlawi01 William Van Landingham        OBP 0.149 / .   .       0001.489e-01
1941    willite01 Ted Williams          OBP 0.553 / .   sig     0005.528e-01
```

The parts of the template are as follows:

- `%4d`: render an integer, right-aligned, in a four character slot. All the `year_id` values have exactly four characters, but if Pliny the Elder's rookie season from 43 AD showed up in our dataset, it would be padded with two spaces: `` `  43` ``. Writing `%04d` (i.e. with a zero after the percent) causes zero-padding: `0043`.
- `\\t` (backslash-t): renders a literal tab character. This is done by Pig, not in the `SPRINTF` function.
- `%-9s`: a nine-character string. Like the next field, it …
- `%-20s`: has a minus sign, making it left-aligned. You usually want this for strings.
  - — We prepared the name with a separate `CONCAT` statement and gave it a single string slot in the template, rather than using say `%-8s %-11s`. In our formulation, the first and last name are separated by only one space and share the same 20-character slot. Try modifying the script to see what happens with the alternative.
  - — Any value shorter than its slot width is padded to fit, either with spaces (as seen here) or with zeros (as seen in the last field. A value longer than the slot width is not truncated — it is printed at full length, shifting everything after it on the line out of place. When we chose the 19-character width, we didn't count on William Van Landingham's corpulent cognomen contravening character caps, correspondingly corrupting columnar comparisons. Still, that only messes up Mr. Van Landingham's line — subsequent lines are unaffected.
- `OBP`: Any literal text you care to enter just carries through. In case you're wondering, you can render a literal percent sign by writing `%%`.
- `%5.3f`: for floating point numbers, you supply two widths. The first is the width of the full slot, including the sign, the integer part, the decimal point, and the fractional part. The second number gives the width of the fractional part. A lot of scripts that

use arithmetic to format a number to three decimal places (as in the prior section) should be using `SPRINTF` instead.

- `%-3s %-3s`: strings indicating whether the season is pre-modern (\<\= 1900) and whether it is significant (>= 450 PA). We could have used true/false, but doing it as we did here — one value tiny, the other with visual weight — makes it much easier to scan the data.
  - By inserting the `/` delimiter and using different phrases for each indicator, it's easy to grep for matching lines later — `grep -e '/.*sig'` — without picking up lines having `'sig'` in the player id.
- `%4$09.3e`: Two things to see here:
  - Each of the preceding has pulled its value from the next argument in sequence. Here, the `4$` part of the specifier uses the value of the fourth non-template argument (the OBP) instead.
  - The remaining `012.3e` part of the specifier says to use scienfific notation, with three decimal places and twelve total characters. Since the strings don't reach full width, their decimal parts are padded with zeroes. When you're calculating the width of a scientific notation field, don't forget to include the *two* sign characters: one for the number and one for the exponent

We won't go any further into the details, as the `SPRINTF` function is well documented (REF) and examples of printf-style templating abound on the web. But this is a useful and versatile tool, and if you're able to mimic the elements used above you understand its essentials.

Assembling Literals with Complex Types

Another reason you may need the nested form of `FOREACH` is to assemble a complex literal. If we wanted to draw key events in a player's history — birth, death, start and end of career — on a timeline, or wanted to place the location of their birth and death on a map, it would make sense to prepare generic baskets of events and location records. We will solve this problem in a few different ways to demonstrate assembling complex types from simple fields.

Parsing a Date

Assembling Complex Types.

```
date_converted = FOREACH people {
  beg_dt   = ToDate(CONCAT(beg_date, 'T00:00:00.000Z'));
  end_dt   = ToDate(end_date, 'yyyy-MM-dd', '+0000');
  birth_dt = ToDate(SPRINTF('%s-%s-%sT00:00:00Z', birth_year, Coalesce(birth_month,1), Coalesce(bi
  death_dt = ToDate(SPRINTF('%s-%s-%sT00:00:00Z', death_year, Coalesce(death_month,1), Coalesce(de
```

```
  GENERATE player_id, birth_dt, death_dt, beg_dt, end_dt, name_first, name_last;
};
```

One oddity of the people table's structure as it arrived to us is that the birth/death dates are given with separate fields, while the beginning/end of career dates are given as ISO date strings. We left that alone because this kind of inconsistency is the reality of data sets in practice — in fact, this is about as mild a case as you'll find. So one thing we'll have to do is pick a uniform date representation and go forward with it.

You may have heard the saying "The two hardest things in Computer Science are cache coherency and naming things". Our nominations for the two most horrible things in Computer Science are time zones and character encoding [13] Elsewhere you'll hear ". Our rule for Time Zones is "put it in UTC *immediately* and never speak of it again [14]. A final step in rendering data for an end-user interface may convert to local time, but at no point in data analysis should you tolerate anything but UTC. We're only working with dates right here, but we'll repeat that rule every chance we have in the book.

There are two and a half defensible ways to represent a date or time:

- As an **ISO 8601 Date/Time string in the UTC time zone**. It sounds scary when we say "ISO 8601", but it's self-explanatory and you see all over the place: `'2007-08-09T10:11:12Z'` is an example of a time, and `'2007-08-09'` is an example of a date. It's compact enough to not worry about, there's little chance of it arriving in that format by accident, everything everywhere can parse it, and you can do ad-hoc manipulation of it using string functions (eg `(int)SUBSTRING(end_date, 0,4)` to extract a year). Use this format only if you are representing instants that come after the 1700s, only need seconds-level precision, and where human readability is more important than compactness (which we encourage).
- As an **integer number of epoch milliseconds in the UTC time zone**, which is to say as the number of elapsed milliseconds since midnight January 1st, 1970 UTC. (You may see this referred to as *UNIX time*.) It allows you to easily calculate durations, and is nearly universal as well. Its value fits nicely in an unsigned 64-bit `long`. We believe using fractional epoch time — e.g. 1186654272892.657 to mean 657 microseconds into the given second — is carrying the joke too far. If you care about micro- or nano-seconds, then you need to care about floating point error, and the leading part of the number consumes too much of your precision. Use this format only if you are representing instants that come after the start of the epoch; only need millisecond precision; and don't care about leap seconds.

13. Many people add "…and off-by-one errors" to the hardest-things list. If we are allowed to re-use the same joke, the two most horrible things in Computer Science are #1 Time Zones, #2 Character Enco, #2 Threads.ding.

14. You can guess our rule for character encoding: "put it in UTF-8 *immediately* and never speak of it again

- A **domain representation chosen judiciously by an expert**. If neither of the above two representations will work for you then sorry: you need to get serious. Astronomers and anyone else working at century scale will likely use some form of Julian Date; those working at nanosecond scale should look at TAI; there are dozens of others. You'll probably have to learn things about leap seconds or sidereal times or the fluid space-time discontinuum that is the map of Time Zones, and you will wish you didn't have to. We're not going to deal with this category as it's far, far beyond the scope of the book.

In general we will leave times in their primitive data type (`long` for epoch milliseconds, `chararray` for ISO strings) until we need them to be proper `datetime` data structures. The lines above show a couple ways to create `datetime` values; here's the fuller catalog.

Epoch milliseconds are easily converted by calling `ToDate(my_epoch_millis)`. For an ISO format string with date, time and time zone, pass it as a single `chararray` string argument: `ToDate(beg_date)`. If its lacks the time-of-day or time zone part, you must fill it out first: `ToDate(CONCAT(beg_date, 'T00:00:00.000Z'))`. If the string has a non-standard format, supply two additional arguments: a template according to Java's SimpleDateFormat, and unless the input has a timezone, the UTC time zone string *+0000*. For example, `ToDate(end_date, 'yyyy-MM-dd', '+0000')` demonstrates anoter way to parse an ISO date string: viable, but more expensive than the one-arg version.

For composite year-month-day-etc fields, create an ISO-formatted string and pass it to `ToDate`. Here's the snippet we used, in slow motion this time:

```
ToDate(
  SPRINTF('%s-%s-%sT00:00:00Z',              -- ISO format template
    birth_year,                              -- if year is NULL, value will be null
    (birth_month IS NULL ? 1 : birth_month), -- but coerce null month or day to 1
    (birth_day IS NULL ? 1 : birth_day)
  ));
```

Apart from subtracting one epoch milliseconds from another to get a duration in milliseconds, you must *never do any date/time manipulation except through a best-in-class date library*. You can't calculate the difference of one year by adding one to the year field (which brought down Microsoft's cloud storage product on the leap day of February 29th, 2012), and you can't assume that the time difference from one minute to the next is 60 seconds (which brought down HBase servers worldwide when the leap second of `2012-06-30T23:59:60Z` — note the `:60` — occurred). This is no joke — companies go out of business because of mistakes like these.

Assembling a Bag

Assembling Complex Types.

```
graphable = FOREACH people {
  birth_month = Coalesce(birth_month, 1); birth_day = Coalesce(birth_day, 1);
  death_month = Coalesce(death_month, 1); death_day = Coalesce(death_day, 1);
  beg_dt   = ToDate(beg_date);
  end_dt   = ToDate('yyyy-MM-dd', end_date);
  birth_dt = ToDate(SPRINTF('%s-%s-%s', birth_year, birth_month, birth_day));
  death_dt = ToDate(SPRINTF('%s-%s-%s', death_year, death_month, death_day));
  --
  occasions = {
      ('birth', birth_year, birth_month, birth_day),
      ('death', death_year, death_month, death_day),
      ('debut', (int)SUBSTRING(beg_date,0,4), (int)SUBSTRING(beg_date,5,7), (int)SUBSTRING(beg_dat
      ('lastg', (int)SUBSTRING(end_date,0,4), (int)SUBSTRING(end_date,5,7), (int)SUBSTRING(end_dat
    };
  --
  places = (
    (birth_dt, birth_city, birth_state, birth_country),
    (birth_dt, death_city, death_state, death_country),
    (beg_dt,   null,       null,        null),
    (end_dt));

  GENERATE
    player_id,
    occasions AS occasions:bag{t:(occasion:chararray, year:int, month:int, day:int)},
    places    AS places:tuple( birth:tuple(city, state, country),
                               death:tuple(city, state, country) )
    ;
};
```

The `occasions` intermediate alias is a bag of event tuples holding a chararray and three ints. Bags are disordered (unless you have transiently applied an explicit sorted), and so we've prefixed each event with a slug naming the occasion.

You can do this inline (non-nested `FOREACH`) but we wouldn't. If you find yourself with the error `Error during parsing. Encountered " "as" "AS "" at line X`, just pay for the ext

Assembing a Tuple

- how tupple is made

Specifying Schema for Complex Types

TODO: clean up

- how bag is made
- We may not have needed to write out the types — it's likely that `occasions:bag{t:(occasion, year, month, day)}` would suffice. But this is another scenario where

if you ask the question "Hey, do I need to specify the types or will Pig figure it out?" you've answered the question: yes, state them explicitly. The important point isn't whether Pig will figure it out, it's whether stupider-you at 3 am will figure it out.

- how tupple is made

Manipulating the Type of a Field

We used 'CONCAT` to combine players' city, state and country of birth into a combined field without drama. But if we tried to do the same for their date of birth by writing `CONCAT(birth_year, '-', birth_month, '-', birth_day)`, Pig would throw an error: `Could not infer the matching function for org.apache.pig.builtin.CONCAT...`. You see, `CONCAT` understandably wants to consume and deliver strings, and so isn't in the business of guessing at and fixing up types. What we need to do is coerce the `int` values — eg, `1961`, a 32-bit integer — into `chararray` values — eg `'1961'`, a string of four characters. You do so using C-style typecast expression: `(chararray)birth_year`. Here it is in action:

```
birthplaces = FOREACH people GENERATE
    player_id,
    CONCAT((chararray)birth_year, '-', (chararray)birth_month, '-', (chararray)birth_day) AS birth
  ;
```

In other cases you don't need to manipulate the type going in to a function, you need to manipulate the type going out of your `FOREACH`. Here are several takes on a `FOREACH` statement to find the slugging average:

```
obp_1 = FOREACH bat_seasons {
  OBP = 1.0f * (H + BB + HBP) / PA; -- constant is a float
  GENERATE OBP;                     -- making OBP a float
};
-- obp_1: {OBP: float}

obp_2 = FOREACH bat_seasons {
  OBP = 1.0 * (H + BB + HBP) / PA;  -- constant is a double
  GENERATE OBP;                     -- making OBP a double
};
-- obp_2: {OBP: double}

obp_3 = FOREACH bat_seasons {
  OBP = (float)(H + BB + HBP) / PA; -- typecast forces floating-point arithmetic
  GENERATE OBP AS OBP;              -- making OBP a float
};
-- obp_3: {OBP: float}

obp_4 = FOREACH bat_seasons {
  OBP = 1.0 * (H + BB + HBP) / PA;  -- constant is a double
  GENERATE OBP AS OBP:float;        -- but OBP is explicitly a float
};
```

```
-- obp_4: {OBP: float}

broken = FOREACH bat_seasons {
  OBP = (H + BB + HBP) / PA;        -- all int operands means integer math and zero as result
  GENERATE OBP AS OBP:float;        -- even though OBP is explicitly a float
};
-- broken: {OBP: float}
```

The first stanza matches what was above. We wrote the literal value as `1.0f` — which signifies the `float` value 1.0 — thus giving OBP the implicit type `float` as well. In the second stanza, we instead wrote the literal value as `1.0` — type `double` — giving OBP the implicit type double as well. The third stanza takes a different tack: it forces floating-point math by typecasting the result as a `float`, thus also implying type `float` for the generated value [15].

In the fourth stanza, the constant was given as a double. However, this time the `AS` clause specifies not just a name but an explicit type, and that takes precedence [16]. The fifth stanza exists just to re-prove the point that if you care about the types Pig will use, say something. Although the output type is a float, the intermediate expression is calculated with integer math and so all the answers are zero. Even if that worked, you'd be a chump to rely on it: use any of the preceding four stanzas instead.

Ints and Floats and Rounding, Oh My!

Another occasion for type conversion comes when you are trying to round or truncate a fractional number. The first four fields of the following statement turn the full-precision result of calculating OBP (`0.31827113`) into a result with three fractional digits (`0.318`), as OBP is usually represented.

```
rounded = FOREACH bat_seasons GENERATE
  (ROUND(1000.0f*(H + BB + HBP) / PA)) / 1000.0f AS round_and_typecast,
  ((int)(1000.0f*(H + BB + HBP) / PA)) / 1000.0f AS typecast_only,
  (FLOOR(1000.0f*(H + BB + HBP) / PA)) / 1000    AS floor_and_typecast,
  ROUND_TO( 1.0f*(H + BB + HBP) / PA, 3)         AS what_we_would_use,
  SPRINTF('%5.3f', 1.0f*(H + BB + HBP) / PA)     AS but_if_you_want_a_string_just_say_so,
  1.0f*(H + BB + HBP) / PA                       AS full_value
  ;
```

15. As you can see, for most of the stanzas Pig picked up the name of the intermediate expression (OBP) as the name of that field in the schema. Weirdly, the typecast in the third stanza makes the current version of Pig lose track of the name, so we chose to provide it explicitly

16. Is the intermediate result calculated using double-precision math, because it starts with a `double`, and then converted to `float`? Or is it calculated with single-precision math, because the result is a `float`? We don't know, and even if we did we wouldn't tell you. Don't resolve language edge cases by consulting the manual, resolve them by using lots of parentheses and typecasts and explicitness. If you learn fiddly rules like that — operator precedence is another case in point — there's a danger you might actually rely on them. Remember, you write code for humans to read and only incidentally for robots to run.

The `round_and_typecast` field shows a fairly common (and mildly flawed) method for chunking or partially rounding values: scale-truncate-rescale. Multiplying `0.31827113` by `1000.0f` gives a float result `318.27113`; rounding it gets an integer value `318`; rescaling by `1000.0f` gives a final result of `0.318f`, a `float`. The second version works mostly the same way, but has no redeeming merits. Use a typecast expression when you want to typecast, not for its side effects. This muddy formulation leads off with a story about casting things to type `int`, but only a careful ticking off of parentheses shows that we swoop in at the end and implicitly cast to float. If you want to truncate the fractional part, say so by using the function for truncating the fractional part, as the third formulation does. The `FLOOR` method uses machine numeric functions to generate the value. This is likely more efficient, and it is certainly more correct.

Floating-point arithmetic, like unicode normalization and anything cryptography, has far more complexity than anyone who wants to get things done can grasp. At some point, take time to become aware of the built-in math functions that are available [17]. You don't have to learn them, just stick the fact of their existence in the back of your head. If the folks at the IEEE have decided every computer on the planet should set aside silicon for a function to find the log of 1 plus x (`log1p`), or a function to find the remainder when dividing two numbers (`IEEEremainder`), you can bet there's a really good reason why your stupid way of doing it is some mixture of incorrect, inaccurate, or fragile.

That is why the formulation we would actually use to find a rounded number is the fourth one. It says what we mean ("round this number to three decimal places") and it draws on Java library functions built for just this purpose. The error between the `ROUND` formulation and the `ROUND_TO` formulation is almost certainly miniscule. But multiply "miniscule" by a billion records and you won't like what comes out.

Calling a User-Defined Function (UDF) from an External Package

TODO: clean up

In the section on "Extracting a Consistent Sample of Records by Key",

You can extend Pig's functionality with *User-Defined Functions* (UDFs) written in Java, Python, Ruby, Javascript and others. These have first-class functionality — almost all of Pig's native functions are actually Java UDFs that just happen to live in a builtin namespace. We'll describe how to author a UDF in a later chapter (REF), but this is a good time to learn how to call one.

The DataFu package is an collection of Pig extensions open-sourced by LinkedIn, and in our opinion everyone who uses Pig should install it. It provides the most important flavors of hash digest and checksum you need in practice, and explains how to choose

17. either as Pig built-ins, or through the Piggybank UDF library

the right one. For consistent hashing purposes, the right choice is the "Mumur 3" function [18], and since we don't need many bytes we'll use the 32-bit flavor.

You must do two things to enable use of a UDF. First, so that pig can load the UDF's code, call the `REGISTER` command with the path to the UDF's `.jar` file. You only need to `REGISTER` a jar once, even if you'll use more than one of its UDFs.

Second, use the `DEFINE` command to construct it. `DEFINE` takes two arguments, separated by spaces: the short name you will use to invoke the command, and the fully-qualified package name of its class (eg `datafu.pig.hash.Hasher`). Some UDFs, including the one we're using, accept or require constructor arguments (always strings). These are passed function-call style, as shown below. There's nothing wrong with `DEFINE`-ing a UDF multiple times with different constructor arguments — for example, adding a line `DEFINE DigestMD5 datafu.pig.hash.Hasher('md5');` would create a hash function that used the MD5 (REF) algorithm.

```
-- Please substitute the right path (and for citizens of the future, the right version number)
REGISTER       '/path/to/data_science_fun_pack/pig/datafu/datafu-pig/build/libs/datafu-pig-1.2.1.j
-- Murmur3, 32 bit version: a fast statistically smooth hash digest function
DEFINE Digest  datafu.pig.hash.Hasher('murmur3-32');

-- Prepend a hash of the player_id
keyed_seasons = FOREACH bat_seasons GENERATE Digest(player_id) AS keep_hash, *;

some_seasons  = FOREACH (
    FILTER keyed_seasons BY (SUBSTRING(keep_hash, 0, 1) == '0')
  ) GENERATE $0..;
```

There are three ways to accomplish this.

One is to use the `REGISTER` keyword, demonstrated below. This is by far the simplest option, but our least favorite. Every source file becomes contaminated by a line that is machine-dependent and may break when packages are updated.

Enabling UDFs by Importing a Macro File

Instead, we recommend you create and `IMPORT` a macro file containing the `REGISTER` and `DEFINE` statements. This is what we use in the sample code repo:

```
-- Paths
%DEFAULT dsfp_dir          '/path/to/data_science_fun_pack';

-- Versions; must include the leading dash when version is given
%DEFAULT datafu_version    '-1.2.1';
```

18. Those familiar with the MD5 or SHA hashes might have expected we'd use one of them. Those would work as well, but Murmur3 is faster and has superior statistical properties; for more, see the DataFu documentation. Oh and if you're not familiar with any of the stuff we just said: don't worry about it, just know that `'murmur3-32'` is what you should type in.

```
%DEFAULT piggybank_version '';
%DEFAULT pigsy_version     '-2.1.0-SNAPSHOT';

REGISTER           '$dsfp_dir/pig/pig/contrib/piggybank/java/piggybank$piggybank_version.jar';
REGISTER           '$dsfp_dir/pig/datafu/datafu-pig/build/libs/datafu-pig$datafu_version.jar';
REGISTER           '$dsfp_dir/pig/pigsy/target/pigsy$pigsy_version.jar';

DEFINE Transpose   datafu.pig.util.TransposeTupleToBag();
DEFINE Digest      datafu.pig.hash.Hasher('murmur3-32');
```

First, we define a few string defaults. Making the common root path a `%DEFAULT` means you can override it at runtime, and simplifies the lines that follow. Parameterizing the versions makes them visible and also lets you easily toggle between versions from the commandline for smoke testing.

Next we register the jars, interpolating the paths and versions; then define the standard collection of UDFs we use. These definitions are executed for all scripts that import the file, but we were unable to detect any impact on execution time.

Enabling UDFs using Java Properties

Lastly, you can set the `pig.additional.jars` and `udf.import.list` java properties. For packages that you want to regard as being effectively built-in, this is our favorite method — but the hardest to figure out. We can't go into the details (see the Pig documentation, there are many) but we can show you how to match what we used above:

Using Pig Properties to Enable UDFs.

```
# Remove backslashes and spaces: these must sit on the same line
pig.additional.jars=\
  /path/to/data_science_fun_pack/pig/datafu/datafu-pig/build/libs/datafu-pig-1.2.1.jar:\
  /path/to/data_science_fun_pack/pig/pig/contrib/piggybank/java/piggybank.jar:\
  /path/to/data_science_fun_pack/pig/pigsy/target/pigsy-2.1.0.jar

# Remove backslashes and spaces: these also must sit on the same line
udf.import.list=\
  datafu.pig.bags:datafu.pig.hash:datafu.pig.stats:datafu.pig.sets:datafu.pig.util:\
  org.apache.pig.piggybank.evaluation:pigsy.text
```

A Quick Look into Baseball

Nate Silver calls Baseball the "perfect data set". There are not many human-centered systems for which this comprehensive degree of detail is available, and no richer set of tables for truly demonstrating the full range of analytic patterns.

For readers who are not avid baseball fans, we provide a simple — some might say "oversimplified" — description of the sport and its key statistics. Please refer to Joseph Adler's *Baseball Hacks* (O'Reilly) or Marchi and Albert's *Analyzing Baseball Data with R* (Chapman & Hall) for more details.

The stats come in tables at multiple levels of detail. Putting people first as we like to do, the `people` table lists each player's name and personal stats such as height and weight, birth year, and so forth. It has a primary key, the `player_id`, formed from the first five letters of their last name, first two letters of their first name, and a two digit disambiguation slug. There are also primary tables for ballparks (`parks`) listing information on every stadium that has ever hosted a game and for teams (`teams`) giving every major-league team back to the birth of the game.

The core statistics table is `bat_seasons`, which gives each player's batting stats by season. (To simplify things, we only look at offensive performance.) The `player_id, year_id` fields form a primary key, and the `team_id` foreign key represents the team they played the most games for in a season. The `park_teams` table lists, for each team, all "home" parks they played in by season, along with the number of games and range of dates. We put "home" in quotes because technically it only signifies the team that bats last (a significant advantage), though teams nearly always play those home games at a single stadium in front of their fans. However, there are exceptions as you'll see in the next chapter (REF). The `park_id,team_id,year_id` fields form its primary key, so if a team did in fact have multiple home ballparks there will be multiple rows in the table.

There are some demonstrations where we need data with some real heft — not so much that you can't run it on a single-node cluster, but enough that parallelizing the computation becomes important. In those cases we'll go to the `games` table (100+ MB), which holds the final box score summary of every baseball game played, or to the full madness of the `events` table (1+ GB), which records every play for nearly every game back to the 1940s and before. These tables have nearly a hundred columns each in their original form. Not to carry the joke quite so far, we've pared them back to only a few dozen columns each, with only a handful seeing actual use.

We denormalized the names of players, parks and teams into some of the non-prime tables to make their records more recognizeable. In many cases you'll see us carry along the name of a player, ballpark or team to make the final results more readable, even where they add extra heft to the job. We always try to show you sample code that represents the code we'd write professionally, and while we'd strip these fields from the script before it hit production, you're seeing just what we'd do in development. "Know your Data".

Acronyms and terminology

We use the following acronyms (and, coincidentally, field names) in our baseball dataset:

- `G`, *Games*
- `PA`: *Plate Appearances*, the number of completed chances to contribute offensively. For historical reasons, some stats use a restricted subset of plate appearances called AB (At Bats). You should generally prefer PA to AB, and can pretend they represent the same concept.
- `H`: *Hits*, either singles (`h1B`), doubles (`h2B`), triples (`h3B`) or home runs (`HR`)

- `BB`: *Walks*, pitcher presented too many unsuitable pitches
- `HBP`: *Hit by Pitch*, like a walk but more painful
- `OBP`: *On-base Percentage*, indicates effectiveness at becoming a potential run
- `SLG`: *Slugging Percentage*, indicates effectiveness at converting potential runs into runs
- `OPS`: *On-base-plus-Slugging*, a reasonable estimate of overall offensive contribution

For those who consider sporting events to be the dull province of jocks, holding no interest at all: when we say the "On-Base Percentage" is a simple matter of finding `(H + BB + HBP) / AB`, just trust us that (a) it's a useful statistic; (b) that's how you find its value; and then (c) pretend it's the kind of numbers-in-a-table example abstracted from the real world that many books use.

The Rules and Goals

Major League Baseball teams play a game nearly every single day from the start of April to the end of September (currently, 162 per season). The team on offense sends its players to bat in order, with the goal of having its players reach base and advance the full way around the diamond. Each time a player makes it all the way to home, their team scores a run, and at the end of the game, the team with the most runs wins. We count these events as `G` (games), `PA` (plate appearances on offense) and `R` (runs).

The best way to reach base is by hitting the ball back to the fielders and reaching base safely before they can retrieve the ball and chase you down — a hit (`H`) . You can also reach base on a *walk* (`BB`) if the pitcher presents too many unsuitable pitches, or from a *hit by pitch* (`HBP`) which is like a walk but more painful. You advance on the basepaths when your teammates hit the ball or reach base; the reason a hit is valuable is that you can advance as many bases as you can run in time. Most hits are singles (h1B), stopping safely at first base. Even better are doubles (`h2B`: two bases), triples (`h3B`: three bases, which are rare and require very fast running), or home runs (`HR`: reaching all the way home, usually by clobbering the ball out of the park).

Your goal as a batter is both becomes a potential run and helps to convert players on base into runs. If the batter does not reach base it counts as an out, and after three outs, all the players on base lose their chance to score and the other team comes to bat. (This threshold dynamic is what makes a baseball game exciting: the outcome of a single pitch could swing the score by several points and continue the offensive campaign, or it could squander the scoring potential of a brilliant offensive position.)

Performance Metrics

The above are all "counting stats", and generally the more games the more hits and runs and so forth. For estimating performance and comparing players, it's better to use "rate stats" normalized against plate appearances.

On-base percentage (`OBP`) indicates how well the player meets offensive goal #1: get on base, thus becoming a potential run and *not* consuming a precious out. It is given as the fraction of plate appearances that are successful: (`(H + BB + HBP) / PA`) [19]. An `OBP` over 0.400 is very good (better than 95% of significant seasons).

Slugging Percentage (`SLG`) indicates how well the player meets offensive goal #2: advance the runners on base, thus converting potential runs into points towards victory. It is given by the total bases gained in hitting (one for a single, two for a double, etc) divided by the number of at bats: (`(H + h2B + 2*h3B + 3*HR) / AB`). An `SLG` over 0.500 is very good.

On-base-plus-slugging (`OPS`) combines on-base and slugging percentages to give a simple and useful estimate of overall offensive contribution. It's found by simply adding the figures: (`OBP + SLG`). Anything above 0.900 is very good.

Just as a professional mechanic has an assortment of specialized and powerful tools, modern baseball analysis uses statistics significantly more nuanced than these. But when it comes time to hang a picture, they use the same hammer as the rest of us. You might think that using the on-base, slugging, and OPS figures to estimate overall performance is a simplification we made for you. In fact, these are quite actionable metrics that analysts will reach for when they want to hang a sketch that anyone can interpret.

19. Although known as percentages, OBP and SLG are always given as fractions to 3 decimal places. For OBP, we're also using a slightly modified formula to reduce the number of stats to learn. It gives nearly identical results but you will notice small discrepancies with official figures

CHAPTER 6

Analytic Patterns: Grouping Operations

Introduction

Grouping Records into a Bag by Key

The GROUP BY operation is at the heart of every structural operation. It's a one-liner in Pig to collect all the stadiums a team has played for in its history:

```
park_teams_g = GROUP park_teams BY team_id;
```

The result of a `GROUP BY` operation is always a field called *group*, followed by one field per grouped table, each named for the table it came from. The shape of the `group` field depends on whether you specified one or many group keys. If you specified a single key, the new `group` field is a scalar with the same schema. If you specified multiple keys, the new `group` field is a tuple whose schema corresponds to those keys. In this example, we grouped on the `team_id` chararray, and so the `group` field is a scalar chararray as well. In a moment we'll group on `year_id` and `team_id`, and so the `group` field would have schema `group:tuple(year_id:int, team_id:chararray)`.

Each of the following fields is a bag, holding tuples whose schema matches the corresponding table. Notice that the name we used to refer to the *table* is now also the name for a *field*. This will confuse you at first, but soon become natural, especially if you use `DESCRIBE` liberally:

```
DESCRIBE park_teams_g;
-- park_teams_g: {
--    group: chararray,
--    park_teams: {
--        ( park_id: chararray, team_id: chararray, year_id: long,
--          beg_date: chararray, end_date: chararray, n_games: long ) } }
```

Notice that the *full record* is kept, even including the keys:

```
(ALT,{(ALT01,ALT,1884,1884-04-30,1884-05-31,18)})
(ANA,{(ANA01,ANA,2001,2001-04-10,2001-10-07,81),(ANA01,ANA,2010,2010-04-05,2010-09-29,81),...})
```

To eliminate the redundant data, you'll almost always immediately project using a FOREACH. Pig allows you to put the `GROUP` statement inline:

```
team_pkyr_pairs = FOREACH (GROUP park_teams BY team_id) GENERATE
  group AS team_id, park_teams.(park_id, year_id);
-- (ALT,{(ALT01,1884)})
-- (ANA,{(ANA01,2001),(ANA01,2010),(ANA01,2002),...})
```

Notice the `park_teams.(park_id,year_id)` form, which gives us a bag of (park_id,year_id) pairs. Using `park_teams.park_id, park_teams.year_id` instead gives two bags, one with park_id tuples and one with year_id tuples:

```
team_pkyr_bags = FOREACH (GROUP park_teams BY team_id) GENERATE
  group AS team_id, park_teams.park_id, park_teams.year_id;
-- (ALT, {(ALT01)}, {(1884)})
-- (ANA, {(ANA01),(ANA01),(ANA01),...}, {(2001),(2010),(2002),...})

DESCRIBE team_pkyr_pairs;
-- team_parks: { team_id: chararray, { (park_id: chararray, year_id: long) } }

DESCRIBE team_pkyr_bags;
-- team_parks: { team_id: chararray, { (park_id: chararray) }, { (year_id: long) } }
```

You can group on multiple fields. For each team and year, we can find the park(s) that team called home:

```
team_yr_parks_g = GROUP park_teams BY (year_id, team_id);
```

The first field is still called *group*, but it's now a tuple.

```
DESCRIBE team_yr_parks_g;
--   team_yr_parks_g: {
--     group: (year_id: long,team_id: chararray),
--     park_teams: {(park_id: chararray, team_id: chararray, year_id: long, ...)}}
```

Our `FOREACH` statement now looks a bit different:

```
team_yr_parks = FOREACH(GROUP park_teams BY (year_id, team_id)) GENERATE
  group.team_id, park_teams.park_id;
--
=> LIMIT team_yr_parks 4; DUMP @;
--   (BS1,{(BOS01),(NYC01)})
--   (CH1,{(NYC01),(CHI01)})
--   (CL1,{(CIN01),(CLE01)})
--   (FW1,{(FOR01)})
```

Pattern in Use

- *Where You'll Use It* — Rarely on its own, but otherwise everywhere

- *Standard Snippet* — `FOREACH (GROUP recs BY (key1, key2)) GENERATE group.key1, group.key2, recs AS bag_of_recs_records;`
- *Hello, SQL Users* — Similar to the windowed functionality supplied by high-end SQL databases. MySQL, PostgreSQL, etc don't have similar functionality.
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values
- *Records* — Output is `group, bag of records`, with record contents within the bag unchanged.
- *Data Flow* — Map & Reduce

Counting Occurrences of a Key

The typical reason to group records is to operate on the bag of values it forms, and that's how we'll spend much of this chapter — the data bag is a very powerful concept. Let's take a quickie tour of what we can do to a group; afterwards we'll see the internals of how a group works before moving on to its broader applications.

You'll notice from the result of the last query that sometimes a team has more than one "home" stadium in a season. That's a bit unexpected, but on consideration teams occasionally face stadium repairs or late-season makeups for cancelled games. But cases where there were even three home parks should be quite rare. Let's confirm our feel for the data using `COUNT_STAR`, which counts all elements of a bag:

```
team_n_parks = FOREACH (GROUP park_teams BY (team_id,year_id)) GENERATE
  group.team_id, COUNT_STAR(park_teams) AS n_parks;
vagabonds = FILTER team_n_parks BY n_parks >= 3;

DUMP vagabonds;
(CL4,7)
(CLE,5)
(WS3,4)
(CLE,3)
(DET,3)
...
```

Always, always look through the data and seek *second stories*.

Our script is reporting that CL4 (the Cleveland Spiders) called seven (!) different stadiums home during a season. Is this some weirdness in the data? Could we possibly have messed up this three-line script? Or is it really the case that some teams have had four, five, even seven home stadiums? This demands a closer look.

Pattern in Use

- *Where You'll Use It* — Anywhere you're summarizing counts

- *Standard Snippet* — `FOREACH (GROUP recs BY mykey) GENERATE group AS mykey, COUNT_STAR(recs) AS ct;`
- *Hello, SQL Users* — `SELECT key, COUNT(*) as CT from recs GROUP BY key;`. Remember: `COUNT_STAR(recs)`, not `COUNT(*)`.
- *Important to Know* — See "Pattern in Use" for Aggregate Functions, below (REF)
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values
- *Records* — Output is `mykey, ct:long`
- *Data Flow* — Map, Combiner & Reduce; combiners very effective unless cardinality extremely high

Representing a Collection of Values with a Delimited String

Let's keep the count of parks, but also list the parks themselves for inspection. We could keep dumping the values in Pig's oddball output format, but this is a good opportunity to introduce a very useful pattern: denormalizing a collection of values into a single delimited field.

The format Pig uses to dump bags and tuples to disk wastes characters and is not safe to use in general: any string containing a comma or bracket will cause its record to be mis-interpreted. For simple data structures such as a list, we are better off concatenating the values together using a delimiter: a character with no other meaning that does not appear in any of the values. This preserves the rows-and-columns representation of the table that Pig handles best. It also lets us keep using the oh-so-simple TSV format for interchange with Excel, `cut` and other commandline tools, and later runs of Pig itself. Storing data this way means we do have to pack and unpack the value ourselves, which is an added burden when we need access to the array members. But if accessing the list contents is less frequent this can act as a positive feature: we can move the field around as a simple string and only pay the cost of constructing the full data structure when necessary.

The BagToString function will serialize a bag of values into a single delimited field as follows:

```
team_year_w_parks = FOREACH (GROUP park_teams BY (team_id, year_id)) GENERATE
  group.team_id,
  COUNT_STAR(park_teams) AS n_parks,
  BagToString(park_teams.park_id, '^') AS park_ids;
-- (ALT,1,ALT01)
-- (ANA,1,ANA01)
-- ...
-- (CL4,7,CHI08^CLE05^CLL01^PHI09^ROC02^ROC03^STL05)
```

This script ouputs four fields — park_id, year, count of stadiums, and the names of the stadiums used separated by a `^` caret delimiter. Like colon :, comma `,`, and slash /, it doesn't need to be escaped at the commandline; like those and semicolon `;`, pipe `|`, and bang `!`, it is visually lightweight and can be avoided within a value. Don't use the wrong delimiter for addresses ("Fargo, ND"), dates ("2014-08-08T12:34:56+00:00"), paths (`/tmp/foo`) or unsanitized free text (`It's a girl! ^_^ \m/ |:-`)). If you are considering the use of quoting or escaping to make your strings delimiter safe, you're getting carried away. Stop, step away from the delimiter, and see "Representing a Complex Data Structure as a JSON-encoded String" (REF) below.

Since the park ids are formed from the first characters of the city name, we can recognize that the Spiders' home fields include two stadiums in Cleveland plus "home" stadiums in Philadelphia, Rochester, St. Louis, and Chicago. These aren't close enough to be alternatives in case of repairs, and 1898 baseball did not call for publicity tours. Were they rotating among these fields, or just spending a day or so at each? Let's see how many were played at each stadium.

Pattern in Use

- *Where You'll Use It* — Creating a URL for a batch request. Hiding a list you don't always want to deserialize. Writing a table in a format that will work everywhere.
- *Standard Snippet* — `FOREACH (GROUP recs BY key) GENERATE group AS mykey, BagToString(recs, '|') AS recs_list;`
- *Hello, SQL Users* — Similar to `GROUP_CONCAT`, but you prepare the input bag first; no fiddly in-line `DISTINCT` calls.
- *Important to Know* — Be careful with your choice of delimiter. Keep it simple. Don't stringify huge groups.
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values
- *Records* — Output is `mykey, recs_list:chararray`
- *Data Flow* — Map & Reduce; no real data reduction or explosion as assumedly you're turning all the data into strings.

Representing a Complex Data Structure with a Delimited String

Instead of serializing the simple list of park ids we had before, we'd now like to prepare and serialize the collection of (park id, number of games) pairs. We can handle this by using two delimiters: one for separating list elements and one for delimiting its contents. (This is also how you would handle an object with simple attribute-value pairs such as a hash map.)

```
team_year_w_pkgms = FOREACH (GROUP park_teams BY (team_id,year_id)) {
  pty_ordered     = ORDER park_teams BY n_games DESC;
  pk_ng_pairs     = FOREACH pty_ordered GENERATE
    CONCAT(park_id, ':', (chararray)n_games) AS pk_ng_pair;
  GENERATE group.team_id, group.year_id,
    COUNT_STAR(park_teams) AS n_parks,
    BagToString(pk_ng_pairs,'|') AS pk_ngs;
  };
```

Whoa, a few new things going on here. We've snuck the `ORDER BY` statement into a few previous examples even though it won't be covered until later in the chapter (REF), but always as a full-table operator. Here we're using it within the body of a `FOREACH` to sort each bag locally, rather than as a total sort of the whole table. One nice thing about this `ORDER BY`: it's essentially free, as Pig just instructs Hadoop to do a secondary-sort on the data as it lands on the reducer. So there's no reason not to make the data easier to read.

After the `ORDER BY` statement, we use a *nested* `FOREACH` to staple each park onto the number of games at that park, delimited with a colon. (Along the way you'll see we also typecast the `n_games` value, since the `CONCAT` method expects a `chararray`.) The final `GENERATE` line creates records naming the team, the count of parks, and the list of park-usages pairs:

```
ALT  1   ALT01:18
ANA  1   ANA01:82
...
CL4  7   CLE05:40|PHI09:9|STL05:2|ROC02:2|CLL01:2|CHI08:1|ROC03:1
```

Out of 156 games that season, the Spiders played only 42 in Cleveland. Between the 15 "home" games in other cities, and their *ninety-nine* away games, they spent nearly three-quarters of their season on the road.

The Baseball Library Chronology sheds some light. It turns out that labor problems prevented play at their home or any other stadium in Cleveland for a stretch of time, and so they relocated to Philadelphia while that went on. What's more, on June 19th police *arrested the entire team* during a home game [1] for violating the Sunday "blue laws" [2]. Little wonder the Spiders decided to take their talents away from Cleveland! The following year they played 50 straight on the road, won fewer than 13% of their games overall (20-134, the worst single-season record ever) and immediately disbanded at season's end.

1. The Baseball Library Chronology does note that "not so coincidentally, the Spiders had just scored to go ahead 4-3, so the arrests assured Cleveland of a victory." Sounds like the officers, not devoid of hometown pride, might have enjoyed a few innings of the game first.
2. As late as 1967, selling cookery on Sunday in Ohio was still enough to get you convicted

Pattern in Use

See Previous.

Representing a Complex Data Structure with a JSON-encoded String

So the result for the Spiders isn't a mistake. Is the team a sole anomalous outlier, or are there other cases, less extreme but similar? The Spiders' season stands out for at least these three reasons: an unusual number of alternate parks; "home" games played in other cities; and a pre-modern (1898) setting. So let's include a field for the city (we'll take the first three characters of the park id to represent the city name) and not throw away the field for year.

```
-- Prepare the city field
pktm_city     = FOREACH park_teams GENERATE
  team_id, year_id, park_id, n_games,
  SUBSTRING(park_id, 0,3) AS city;

-- First grouping: stats about each city of residence
pktm_stats = FOREACH (GROUP pktm_city BY (team_id, year_id, city)) {
  pty_ordered   = ORDER   pktm_city BY n_games DESC;
  pk_ct_pairs   = FOREACH pty_ordered GENERATE CONCAT(park_id, ':', (chararray)n_games);
  GENERATE
    group.team_id,
    group.year_id,
    group.city                  AS city,
    COUNT_STAR(pktm_city)       AS n_parks,
    SUM(pktm_city.n_games)      AS n_city_games,
    MAX(pktm_city.n_games)      AS max_in_city,
    BagToString(pk_ct_pairs,'|') AS parks
    ;
};
```

The records we're forming are significantly more complex this time. With fields of numbers or constrained categorical values, stapling together delimited values is a fine approach. But when fields become this complex, or when there's any danger of stray delimiters sneaking into the record, if you're going to stick with TSV you are better off using JSON encoding to serialize the field. It's a bit more heavyweight but nearly as portable, and it happily bundles complex structures and special characters to hide within TSV files. [3]

```
-- Next, assemble full picture:
farhome_gms = FOREACH (GROUP pktm_stats BY (team_id, year_id)) {
  pty_ordered   = ORDER   pktm_stats BY n_city_games DESC;
```

3. And if nether JSON nor simple-delimiter is appropriate, use Parquet or Trevni, big-data optimized formats that support complex data structures. As we'll explain in chapter (REF), those are your three choices: TSV with delimited fields; TSV with JSON fields or JSON lines on their own; or Parquet/Trevni. We don't recommend anything further.

```
  city_pairs    = FOREACH pty_ordered GENERATE CONCAT(city, ':', (chararray)n_city_games);
  n_home_gms    = SUM(pktm_stats.n_city_games);
  n_main_city   = MAX(pktm_stats.n_city_games);
  n_main_park   = MAX(pktm_stats.max_in_city);
  -- a nice trick: a string vs a blank makes it easy to scan the data for patterns:
  is_modern     = (group.year_id >= 1905 ? 'mod' : NULL);
  --
  GENERATE group.team_id, group.year_id,
    is_modern                     AS is_modern,
    n_home_gms                    AS n_home_gms,
    n_home_gms - n_main_city      AS n_farhome_gms,
    n_home_gms - n_main_park      AS n_althome_games,
    COUNT_STAR(pktm_stats)        AS n_cities,
    BagToString(city_pairs,'|')   AS cities,
    BagToString(pktm_stats.parks,'|')    AS parks
    ;
};
farhome_gms = ORDER farhome_gms BY n_cities DESC, n_farhome_gms DESC;
```

Here's a sample of the output:

JSON-formatted Values.

```
CL4  1898       57  17  17  6   CLE:40|PHI:9|ROC:3|STL:2|CLL:2|CHI:1    CLE05:40|PHI09:9|ROC02:2..
CLE  1902       65  5   5   5   CLE:60|FOR:2|COL:1|CAN:1|DAY:1          CLE05:60|FOR03:2|COL03:1..
...
MON  2003  mod  81  22  22  2   MON:59|SJU:22                           MON02:59|SJU01:22
MON  2004  mod  80  21  21  2   MON:59|SJU:21                           MON02:59|SJU01:21
...
CHA  1969  mod  81  11  11  2   CHI:70|MIL:11                           CHI10:70|MIL05:11
CHA  1968  mod  81  9   9   2   CHI:72|MIL:9                            CHI10:72|MIL05:9
BRO  1957  mod  77  8   8   2   NYC:69|JER:8                            NYC15:69|JER02:8
```

Pattern in Use

- *Where You'll Use It* — Creating the POST body for a json batch request. Hiding a complex value you don't always want to deserialize. Writing a table in a format that will work everywhere. Creating a string free of non-keyboard characters.
- *Standard Snippet* — `FOREACH (GROUP recs BY key) GENERATE group AS mykey, Jsonify(recs) AS recs_json;`
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values
- *Records* — Output is `mykey, recs_json:chararray`
- *Data Flow* — Map & Reduce; mild data expansion as JSON repeats the sub-field names on each row.

Does God Hate Cleveland?

Probably. But are the Spiders a particularly anomalous exhibition? No. Considered against the teams of their era, they look much more normal. In the early days baseball was still literally getting its act together and teams hopped around frequently. Since 1905, no team has seen home bases in three cities, and the three cases where a team spent any significant time in an alternate city each tell a notable story.

In 2003 and 2004, les pauvres Montreal Expos were sentenced to play 22 "home" games in San Juan (Puerto Rico) and only 59 back in Montreal. The rudderless franchise had been sold back to the league itself and was being shopped around in preparation for a move to Washington, DC. With no real stars, no home-town enthusiasm, and no future in Montreal, MLB took the opportunity to build its burgeoning fanbase in Latin America and so deployed the team to Puerto Rico part-time. The 1968-1969 Chicago White Sox (CHA) were similarly nation-building in Milwaukee; the owner of the 1956-1957 Brooklyn Dodgers slipped them away for a stint in New Jersey in order to pressure Brooklyn for a new stadium.

You won't always want to read a second story to the end as we have here, but it's important to at least identify unusual features of your data set — they may turn out to explain more than you'd think.

In traditional analysis with sampled data, edge cases undermine the data, presenting the spectre of a non-representative sample or biased result. In big data analysis on comprehensive data, the edge cases *prove* the data. Here's what we mean. Since 1904, only a very few teams have multiple home stadiums, and no team has had more than two home stadiums in a season. Home-field advantage gives a significant edge: the home team plays the deciding half of the final inning, their roster is constructed to take advantage of the ballpark's layout, and players get to eat home-cooked meals, enjoy the cheers of encouraging fans, and spend a stretch of time in one location. The Spiders and Les Expos and a few others enjoyed only part of those advantages. XX % of our dataset is pre-modern and Y% had six or more home games in multiple cities.

With a data set this small there's no good way to control for these unusual circumstances, and so they represent outliers that taint our results. With a large and comprehensive data set those small fractions would represent analyzable populations of their own. With millions of seasons, we could conceivably baseline the jet-powered computer-optimized schedules of the present against the night-train wanderjahr of Cleveland Spiders and other early teams.

Group and Aggregate

Some of the happiest moments you can have analyzing a massive data set come when you are able to make it a slightly less-massive data set. Aggregate functions — ones that turn the whole of a group into a scalar value — are the best path to this joy.

Aggregate Statistics of a Group

In the previous chapter, we used each player's seasonal counting stats — hits, home runs, and so forth — to estimate seasonal rate stats — how well they get on base (OPS), how well they clear the bases (SLG) and an overall estimate of offensive performance (OBP). But since we were focused on pipeline operations, we only did so on a season-by-season basis. The group-and-aggregate pattern lets us combine those seasonal stats in order to characterize each player's career.

Aggregate Statistics of a Group.

```
bat_careers = FOREACH (GROUP bat_seasons BY player_id) {
  totG   = SUM(bat_seasons.G);
  totPA  = SUM(bat_seasons.PA);  totAB  = SUM(bat_seasons.AB);
  totHBP = SUM(bat_seasons.HBP); totSH  = SUM(bat_seasons.SH);
  totBB  = SUM(bat_seasons.BB);  totH   = SUM(bat_seasons.H);
  toth1B = SUM(bat_seasons.h1B); toth2B = SUM(bat_seasons.h2B);
  toth3B = SUM(bat_seasons.h3B); totHR  = SUM(bat_seasons.HR);
  totR   = SUM(bat_seasons.R);   totRBI = SUM(bat_seasons.RBI);
  OBP    = 1.0*(totH + totBB + totHBP) / totPA;
  SLG    = 1.0*(toth1B + 2*toth2B + 3*toth3B + 4*totHR) / totAB;
  team_ids = DISTINCT bat_seasons.team_id;
  GENERATE
    group                          AS player_id,
    COUNT_STAR(bat_seasons)        AS n_seasons,
    COUNT_STAR(team_ids)           AS card_teams,
    MIN(bat_seasons.year_id)       AS beg_year,
    MAX(bat_seasons.year_id)       AS end_year,
    totG   AS G,
    totPA  AS PA,  totAB  AS AB,  totHBP AS HBP,    --  $6 -  $8
    totSH  AS SH,  totBB  AS BB,  totH   AS H,      --  $9 - $11
    toth1B AS h1B, toth2B AS h2B, toth3B AS h3B,    -- $12 - $14
    totHR AS HR,   totR   AS R,   totRBI AS RBI,    -- $15 - $17
    OBP AS OBP, SLG AS SLG, (OBP + SLG) AS OPS      -- $18 - $20
    ;
};
```

We first gather together all seasons by a player by grouping on `player_id`, then throw a barrage of `SUM`, `COUNT_STAR`, `MIN` and `MAX` functions at the accumulated fields to find the career totals. Using the nested `FOREACH` form means we can use intermediate values such as `totPA` in both the calculation of `OBP` and as a field in the new table directly.

The nested `FOREACH` also lets us apply the `DISTINCT` bag operation, creating a new bag holding only the distinct `team_id` values across all seasons. That statement has, in principle, two steps: projection of a bag-with-just-team_id followed by `DISTINCT` to eliminate duplicates. But behind the scenes, Pig uses a special kind of bag (`DistinctDataBag`) that in all respects meets the data bag interface, but which uses an efficient internal data structure to eliminate duplicates as they're added. So rather than (list of seasons) → (list of team_ids) → (list of distinct team_ids) you only have to pay for (list of seasons) → (list of distinct team_ids)

We will use the `bat_careers` table in several later demonstrations, so keep its output file around.

Pattern in Use

See the Pattern in Use for the next section too (REF).

- *Where You'll Use It* — Everywhere. Turning manufactured items into statistics about batches. Summarizing a cohort. Rolling up census block statistics to state-level statistics.
- *Standard Snippet* — `FOREACH (GROUP recs BY key) GENERATE group AS mykey, AggregateFunction(recs), AggregateFunction(recs), ...;`
- *Hello, SQL Users* — Directly comparable for the most part.
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values. Big decrease in output size from turning bags into scalars
- *Records* — Something like `mykey, aggregated_value, aggregated_value, ...`
- *Data Flow* — Map, Combiner & Reduce; combiners quite effective unless cardinality is very high.

Completely Summarizing a Field

In the preceding case, the aggregate functions were used to create an output table with similar structure to the input table, but at a coarser-grained relational level: career rather than season. The result was a new table to analyze, not a conceptual report.

Statistical aggregations also let you summarize groups and tables with well-understood descriptive statistics. By sketching their essential characteristics at dramatically smaller size, we make the data easier to work with but more importantly we make it possible to comprehend.

The following functions are built in to Pig:

- Count of all values: `COUNT_STAR(bag)`

- Count of non-null values: `COUNT(bag)`
- Minimum / Maximum non-null value: `MIN(bag)` / `MAX(bag)`
- Sum of non-null values: `SUM(bag)`
- Average of non-null values: `AVG(bag)`

There are a few additional summary functions that aren't native features of Pig, but are offered by Linkedin's might-as-well-be-native DataFu package. [4].

- Cardinality (i.e. the count of distinct values): combine the `DISTINCT` operation and the `COUNT_STAR` function as demonstrated below, or use the DataFu `HyperLogLogPlusPlus` UDF
- Variance of non-null values: `VAR(bag)`, using the `datafu.pig.stats.VAR` UDF
- Standard Deviation of non-null values: `SQRT(VAR(bag))`
- Quantiles: `Quantile(bag)` or `StreamingQuantile(bag)`
- Median (50th Percentile Value) of a Bag: `Median(bag)` or `StreamingMedian(bag)`

The previous chapter (REF) has details on how to use UDFs, and so we're going to leave the details of that to the sample code. You'll also notice we list two functions for quantile and for median. Finding the exact median or other quantiles (as the Median/Quantile UDFs do) is costly at large scale, and so a good approximate algorithm (StreamingMedian/StreamingQuantile) is well appreciated. Since the point of this stanza is to characterize the values for our own sense-making, the approximate algorithms are appropriate. We'll have much more to say about why finding quantiles is costly, why finding averages isn't, and what to do about it in the Statistics chapter (REF).

```
weight_yr_stats = FOREACH (GROUP bat_seasons BY year_id) {
  dist         = DISTINCT bat_seasons.weight;
  sorted_a     = FILTER   bat_seasons.weight BY weight IS NOT NULL;
  sorted       = ORDER    sorted_a BY weight;
  some         = LIMIT    dist.weight 5;
  n_recs       = COUNT_STAR(bat_seasons);
  n_notnulls   = COUNT(bat_seasons.weight);
  GENERATE
    group,
    AVG(bat_seasons.weight)        AS avg_val,
```

4. If you've forgotten/never quite learned what those functions mean, hang on for just a bit and we'll demonstrate them in context. If that still doesn't do it, set a copy of Naked Statistics or Head First Statistics next to this book. Both do a good job of efficiently imparting what these functions mean and how to use them without assuming prior expertise or interest in mathematics. This is important material though. Every painter of landscapes must know how to convey the essence of a happy little tree using a few deft strokes and not the prickly minutae of its 500 branches; the above functions are your brushes footnote:[Artist/Educator Bob Ross: "Anyone can paint, all you need is a dream in your heart and a little bit of practice" — hopefully you're feeling the same way about Big Data analysis.

```
    SQRT(VAR(bat_seasons.weight))  AS stddev_val,
    MIN(bat_seasons.weight)        AS min_val,
    FLATTEN(ApproxEdgeile(sorted)) AS (p01, p05, p50, p95, p99),
    MAX(bat_seasons.weight)        AS max_val,
    --
    n_recs                         AS n_recs,
    n_recs - n_notnulls            AS n_nulls,
    COUNT_STAR(dist)               AS cardinality,
    SUM(bat_seasons.weight)        AS sum_val,
    BagToString(some, '^')         AS some_vals
    ;
};
```

Pattern in Use

- *Where You'll Use It* — Everywhere. Quality statistics on manufacturing batches. Response times of webserver requests. A/B testing in eCommerce.
- *Standard Snippet* — `FOREACH (GROUP recs BY key) { ... ; GENERATE ...; };`
- *Hello, SQL Users* — Directly comparable for the most part.
- *Important to Know*
  - — Say `COUNT_STAR(recs)`, not `COUNT_STAR(recs.myfield)` — the latter creates a new bag and interferes with combiner'ing.
  - — Use `COUNT_STAR` and never `SIZE` on a bag.
  - — Say `SUM(recs.myfield)`, not `SUM(myfield)` (which isn't in scope).
  - — Get in the habit of writing `COUNT_STAR` and never `COUNT`, unless you explicitly mean to only count non-`null`s.
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values. Big decrease in output size from turning bags into scalars
- *Records* — Something like `mykey, aggregated_value, aggregated_value, ...`
- *Data Flow* — Map, Combiner & Reduce; combiners quite effective unless cardinality is very high.

Summarizing Aggregate Statistics of a Full Table

To summarize the statistics of a full table, we use a `GROUP ALL` statement. That is, instead of `GROUP [table] BY [key]`, write `GROUP [table] ALL`. Everything else is as usual:

Summary of Weight Field.

```
weight_summary = FOREACH (GROUP bat_seasons ALL) {
  dist         = DISTINCT bat_seasons.weight;
  sorted_a     = FILTER   bat_seasons.weight BY weight IS NOT NULL;
  sorted       = ORDER    sorted_a BY weight;
```

```
  some         = LIMIT    dist.weight 5;
  n_recs       = COUNT_STAR(bat_seasons);
  n_notnulls   = COUNT(bat_seasons.weight);
  GENERATE
    group,
    AVG(bat_seasons.weight)             AS avg_val,
    SQRT(VAR(bat_seasons.weight))       AS stddev_val,
    MIN(bat_seasons.weight)             AS min_val,
    FLATTEN(ApproxEdgeile(sorted))  AS (p01, p05, p50, p95, p99),
    MAX(bat_seasons.weight)             AS max_val,
    n_recs                          AS n_recs,
    n_recs - n_notnulls             AS n_nulls,
    COUNT_STAR(dist)                AS cardinality,
    SUM(bat_seasons.weight)         AS sum_val,
    BagToString(some, '^')          AS some_vals
    ;
};
```

As we hope you readily recognize, using the `GROUP ALL` operation can be dangerous, as it requires bringing all the data onto a single reducer.

We're safe here, even on larger datasets, because all but one of the functions we supplied above are efficiently *algebraic*: they can be significantly performed in the map phase and combiner'ed. This eliminates most of the data before the reducer. The cardinality calculation, done here with a nested `DISTINCT` operation, is the only real contributor to reducer-side data size. For this dataset its size is manageable, and if it weren't there is a good approximate cardinality function. We'll explain the why and the how of algebraic functions and these approximate methods in the Statistics chapter. But you'll get a good feel for what is and isn't efficient through the examples in this chapter.)

Pattern in Use

Everything we said for "Completely Summarizing a Group" (REF), plus

- *Where You'll Use It* — Getting to know your data. Computing relative statistics or normalizing values. Topline totals and summaries.
- *Standard Snippet* — See the `summarizer_bot_9000.pig` macro
- *Hello, SQL Users* — Aggregate functions *without* a `GROUP BY`
- *Important to Know*
  - — You're sending all the data to one reducer, so make sure the aggregate functions are highly reductive
  - — Note the syntax of the full-table group statement. There's no I in TEAM, and no `BY` in `GROUP ALL`.
- *Output Count* — Single row

- *Data Flow* — Map, Combiner, and **single** reducer

(TODO-qem: should "Note the syntax of the full-table group statement. There's no I in TEAM, and no `BY` in `GROUP ALL`. " be an "Important to Know" or a "NOTE\:"?

Summarizing a String Field

We showed how to examine the constituents of a string field in the preceding chapter, under "Tokenizing a String" (REF). But for forensic purposes similar to the prior example, it's useful to summarize their length distribution.

Summary of a String Field.

```
name_first_summary_0 = FOREACH (GROUP bat_seasons ALL) {
  dist       = DISTINCT bat_seasons.name_first;
  lens       = FOREACH  bat_seasons GENERATE SIZE(name_first) AS len;
  --
  n_recs     = COUNT_STAR(bat_seasons);
  n_notnulls = COUNT(bat_seasons.name_first);
  --
  examples   = LIMIT    dist.name_first 5;
  snippets   = FOREACH  examples GENERATE (SIZE(name_first) > 15 ? CONCAT(SUBSTRING(name_first, 0,
  GENERATE
    group,
    'name_first'                  AS var:chararray,
    MIN(lens.len)                 AS minlen,
    MAX(lens.len)                 AS maxlen,
    --
    AVG(lens.len)                 AS avglen,
    SQRT(VAR(lens.len))           AS stdvlen,
    SUM(lens.len)                 AS sumlen,
    --
    n_recs                        AS n_recs,
    n_recs - n_notnulls           AS n_nulls,
    COUNT_STAR(dist)              AS cardinality,
    MIN(bat_seasons.name_first)   AS minval,
    MAX(bat_seasons.name_first)   AS maxval,
    BagToString(snippets, '^')    AS examples,
    lens  AS lens
    ;
};

name_first_summary = FOREACH name_first_summary_0 {
  sortlens   = ORDER lens  BY len;
  pctiles    = ApproxEdgeile(sortlens);
  GENERATE
    var,
    minlen, FLATTEN(pctiles) AS (p01, p05, p10, p50, p90, p95, p99), maxlen,
    avglen, stdvlen, sumlen,
    n_recs, n_nulls, cardinality,
    minval, maxval, examples
```

```
    ;
};
```

Pattern in Use

Everything we said for "Completely Summarizing a Group" (REF), plus

- *Where You'll Use It* — Getting to know your data. Sizing string lengths for creating a database schema. Making sure there's nothing ill-formed or outrageously huge. Making sure all values for a categorical field or string key is correct.
- *Standard Snippet* — See the `summarizer_bot_9000.pig` macro
- *Hello, SQL Users* — Corresponding functions *without* a `GROUP BY`
- *Important to Know*
  - — You're sending all the data to one reducer, so make sure the aggregate functions are highly reductive
  - — Note the syntax of the full-table group statement. There's no I in TEAM, and no `BY` in `GROUP ALL`.
- *Output Count* — Single row
- *Data Flow* — Map, Combiner, and **single** reducer

Calculating the Distribution of Numeric Values with a Histogram

One of the most common uses of a group-and-aggregate is to create a histogram showing how often each value (or range of values) of a field occur. This calculates the distribution of seasons played — that is, it counts the number of players whose career lasted only a single season; who played for two seasons; and so forth.

Histogram of Number of Seasons.

```
vals = FOREACH bat_careers GENERATE n_seasons AS bin;
seasons_hist = FOREACH (GROUP vals BY bin) GENERATE
  group AS bin, COUNT_STAR(vals) AS ct;

vals = FOREACH (GROUP bat_seasons BY (player_id, name_first, name_last)) GENERATE
  COUNT_STAR(bat_seasons) AS bin, flatten(group);
seasons_hist = FOREACH (GROUP vals BY bin) {
  some_vals = LIMIT vals 3;
  GENERATE group AS bin, COUNT_STAR(vals) AS ct, BagToString(some_vals, '|');
};
```

So the pattern here is to:

- Project only the values,

- Group by the values,
- Produce the group as key and the count as value.

Pattern in Use

- *Where You'll Use It* — Anywhere you need a more detailed sketch of your data than average/standard deviation or simple quantiles can provide
- *Standard Snippet* — `vals = FOREACH recs GENERATE myfield AS bin; hist = FOREACH (GROUP vals BY bin) GENERATE group AS bin, COUNT_STAR(vals) AS ct;`. Or see `summarizer_bot_9000.pig` for a macro (REF).
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values
- *Records* — Output is `bin, ct:long`. You've turned records-with-values into values-with-counts
- *Data Flow* — Map, Combiner & Reduce; combiners very effective unless cardinality extremely high

Binning Data for a Histogram

Generating a histogram for games just as above produces mostly-useless output. There's no material difference between a career of 2000 games and one of 2001 games, but each value receives its own count — making it hard to distinguish the density of 1-, 2-, and 3-count bins near 1000 games from the 1-, 2-, and 3-count bins near 1500 games.

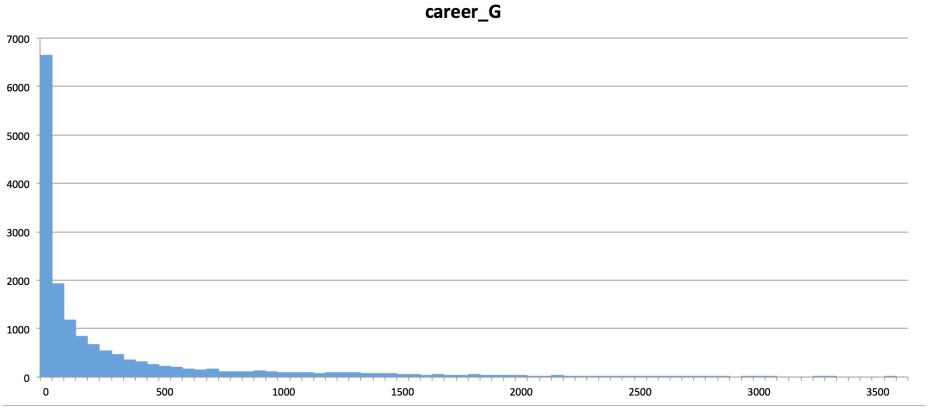
```
-- Meaningless
G_vals = FOREACH bat_seasons GENERATE G AS val;
G_hist = FOREACH (GROUP G_vals BY val) GENERATE
  group AS val, COUNT_STAR(G_vals) AS ct;
```

Instead, we will bin the data: divide by the bin size (50 in this case), and then multiply back by the bin size. The result of the division is an integer (since both the value and the bin size are of type `int`), and so the resulting value of `bin` is always an even multiple of the bin size. Values of 0, 12 and 49 all go to the `0` bin; 150 games goes to the `150` bin; and Pete Rose's total of 3,562 games played becomes the only occupant of bin `3550`.

```
-- Binning makes it sensible
G_vals = FOREACH bat_seasons GENERATE 50*FLOOR(G/50) AS val;
G_hist = FOREACH (GROUP G_vals BY val) GENERATE
  group AS val, COUNT_STAR(G_vals) AS ct;
```

Histogram of Career Games Played

The histogram on the binned data is now quite clear:

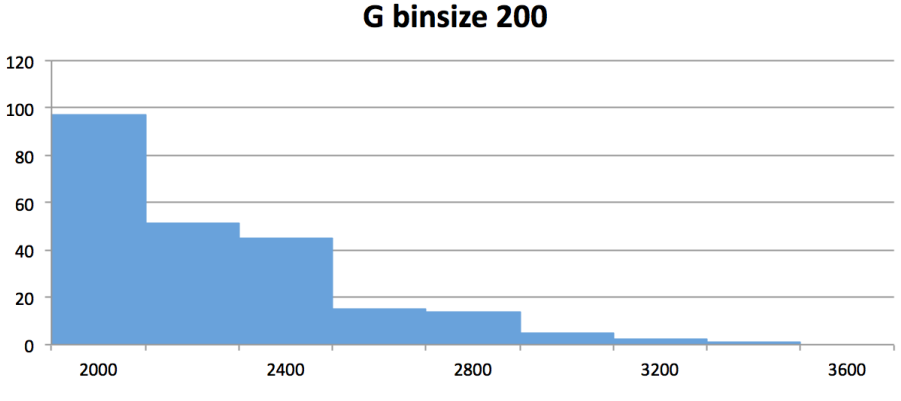


Choosing a Bin Size

How do you choose a binsize? The following three graphs zoom in on the tail (2000 or more games) to show bin sizes that are too large, too small, and just right.

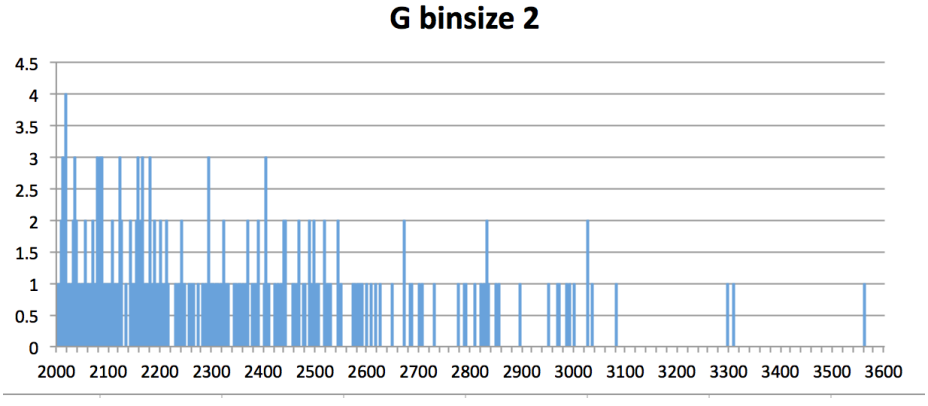
Binsize too large

A bin size of 200 is too coarse, washing out legitimate gaps that tell a story.



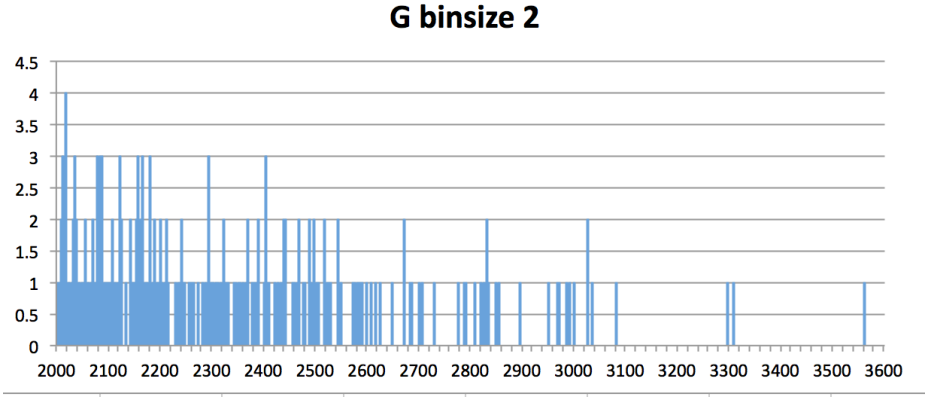
Binsize too small

The bin size of 2 is too fine — the counts are small, there are many trivial gaps, and there is a lot of non-meaningful bin-to-bin variation.



Binsize too small

The bin size we chose, 50 games, works well. It's a meaningful number (50 games represents about 1/3 of a season), it gives meaty counts per bin even when the population starts to become sparse, and yet preserves the gaps that demonstrate the epic scope of Pete Rose and our other outliers' careers.



Interpreting Histograms and Quantiles

Different underlying mechanics will give different distributions.

Games Played — linear

The histogram of career games shows that most players see only one game their whole career, and the counts drop off continuously at higher and higher career totals. You can't play 30 games unless you were good enough to make it in to 29 games; you can't play

100 games unless you continued to be good, didn't get injured, didn't get old, didn't go to war between the thirtieth and ninety-ninth game, and so on.

images::images/06-histograms-career_G-linear.png[Histogram of Career Games, Linear Axis]

Games Played — Log-Log plot

Distributions, such as this one, that span many orders of magnitude in value and count, are easier to understand using a *log-log graph*. The "log" is short for "logarithm," in which successive values represent orders of magnitude difference. On a log-log graph, then, the axes arrange the displayed values so that the same distance separates 1 from 10 as separates 10 from 100 and so on, for any *ratio* of values.

Though the career games data shows a very sharp dropoff, it is *not* a long-tail distribution, as you can see by comparing a power-law fit (which is always a straight line on a log-log graph) to the actual histogram.

images::images/06-histograms-career_G-loglog.png[Histogram of Career Games, Log-Log plot]

Binning Data into Exponentially Sized Buckets

In contrast, webpage views known to be are one of many phenomena that obey the "long-tail" distribution, as we can see by generating a histogram of hourly pageview counts for each Wikipedia page [5]. Since the data is so sharply exponential, we are better off binning it *logarithmically*. To do so we take the log of the value, chunk it (using the multiply-floor-undo method again), and then take the exponential to restore a representative value for the bin. (You'll notice we avoid trouble taking the logarithm of zero by feeding it an insignificantly small number instead. This lets zero be included in the processing without materially altering the result)

```
pagecount_views = LOAD '/data/out/wikipedia/pagecount-views.tsv' AS (val:long);
SET eps 0.001
;

view_vals = FOREACH pagecount_views GENERATE
  (long)EXP( FLOOR(LOG((val == 0 ? $eps : val)) * 10)/10.0 ) AS bin;
hist_wp_view = FOREACH (GROUP view_vals BY bin) GENERATE
  group AS bin, COUNT_STAR(view_vals) AS ct;
```

images::06-histograms-pageviews-loglog.png[Histogram of Wikipedia Hourly Pageviews, Log-Log plot]

5. For 11pm UTC on Oct 2nd, 2008, because that was what was nearby

The result indeed is a nice sharp line on the log-log plot, and the logarithmic bins did a nice job of accumulating robust counts while preserving detail. Logarithmic bins are generally a better choice any time you're using a logarithmic x-axis because it means that the span of each bin is visually the same size, aiding interpretation.

As you can see, you don't have to only bin linearly. Apply any function that takes piecewise segments of the domain and maps them sequentially to the integers, then undo that function to map those integers back to a central value of each segment. The Wikipedia webserver logs data also includes the total *bytes* transferred per page; this data spans such a large range that we end up binning both logarithmically (to tame the upper range of values) and linearly (to tame the lower range of values) — see the sample code for details.

Pattern in Use

See Pattern in Use for Histograms, above (REF)

- *Where You'll Use It* — Anywhere the values make sense exponentially; eg values make sense as 1, 100, 1000, …, 10 million rather than 1 million, 2 million, …, 10 million. Anywhere you will use a logarithmic *X* axis for displaying the bin values.
- *Important to Know* — The result is a representative value from the bin (eg `100`), and not the log of that value (eg `log(100)`). Decide whether representative should be a central value from the bin or the minimum value in the bin.
- *Standard Snippet* — `(long)EXP( FLOOR(LOG((val == 0 ? $eps : val)) * bin_sf)/bin_sf )` for scale factor `bin_sf`. Instead of substituting `$eps` for zero you might prefer to filter them out.

Creating Pig Macros for Common Stanzas

Rather than continuing to write the histogram recipe over and over, let's take a moment and generalize. Pig allows you to create macros that parameterize multiple statements:

```
DEFINE histogram(table, key) RETURNS dist {
  vals = FOREACH $table GENERATE $key;
  $dist = FOREACH (GROUP vals BY $key) GENERATE
    group AS val, COUNT_STAR(vals) AS ct;
};

DEFINE binned_histogram(table, key, binsize, maxval) RETURNS dist {
  numbers = load_numbers_10k();
  vals = FOREACH $table GENERATE (long)(FLOOR($key / $binsize) * $binsize) AS bin;
  all_bins = FOREACH numbers GENERATE (num0 * $binsize) AS bin;
  all_bins = FILTER  all_bins BY (bin <= $maxval);
  $dist = FOREACH (COGROUP vals BY bin, all_bins BY bin) GENERATE
    group AS bin, (COUNT_STAR(vals) == 0L ? null : COUNT_STAR(vals)) AS ct;
};
```

Distribution of Games Played

Call the histogram macro as follows:

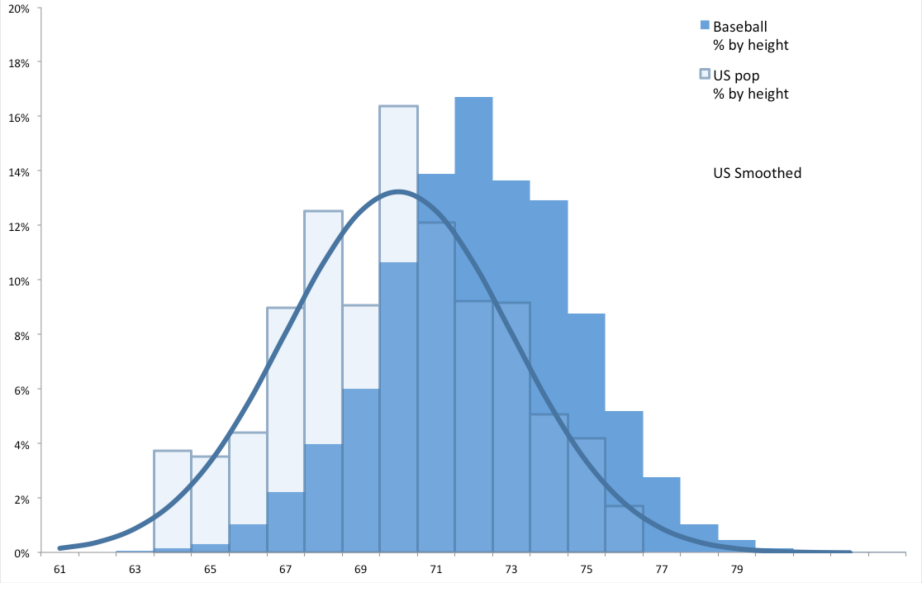
```
career_G_hist     = binned_histogram(bat_careers, 'G', 50, 3600);
career_G_hist_2   = binned_histogram(bat_careers, 'G', 2, 3600);
career_G_hist_200 = binned_histogram(bat_careers, 'G', 200, 3600);

height_hist       = binned_histogram(people, 'height_in', 40, 80);
weight_hist       = binned_histogram(people, 'weight_lb', 10, 300);

birthmo_hist      = histogram(people, 'birth_month');
deathmo_hist      = histogram(people, 'death_month');
```

Now that finding a histogram is effortless, let's examine more shapes of distributions.

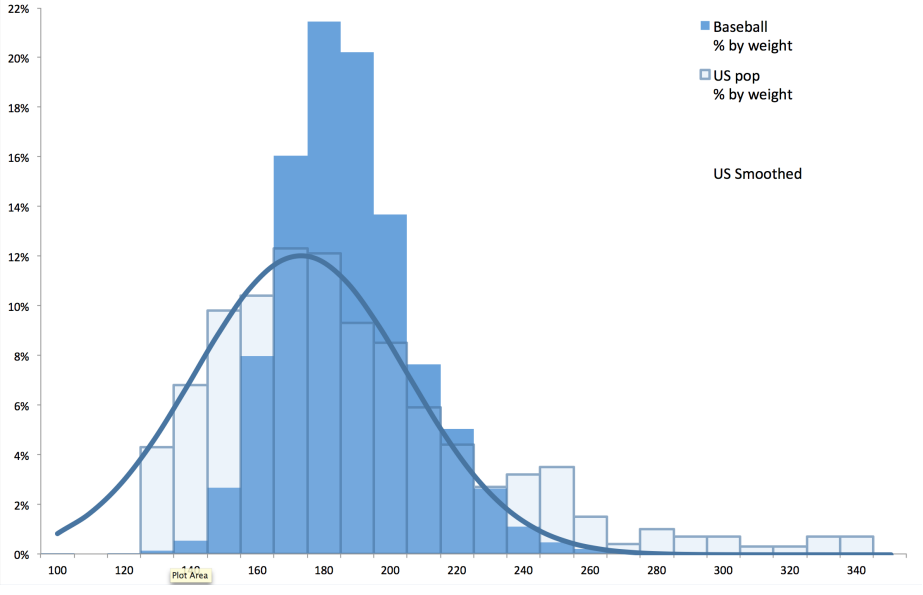
Extreme Populations and Confounding Factors

To reach the major leagues, a player must possess multiple extreme attributes: ones that are easy to measure, like being tall or being born in a country where baseball is popular; and ones that are not, like field vision, clutch performance, the drive to put in outlandishly many hours practicing skills. Any time you are working with extremes as we are, you must be very careful to assume their characteristics resemble the overall population's.

Height



Weight



Here again are the graphs for players' height and weight, but now graphed against (in light blue) the distribution of height/weight for US males aged 20-29 [6].

The overall-population distribution is shown with light blue bars, overlaid with a normal distribution curve for illustrative purposes. The population of baseball players deviates predictably from the overall population: it's an advantage to The distribution of player weights, meanwhile, is shifted somewhat but with a dramatically smaller spread.

Distribution of Birth and Death day of year

Surely at least baseball players are born and die like the rest of us, though?

With a little Pig action, we can generate some histograms to answer that question:

Vital Stats pt 1.

```
vitals = FOREACH peeps GENERATE
  height_in,
  10*CEIL(weight_lb/10.0) AS weight_lb,
  birth_month,
  death_month;

birth_month_hist = histogram(vitals, 'birth_month');
```

6. US Census Department, Statistical Abstract of the United States. Tables 206 and 209, Cumulative Percent Distribution of Population by (Weight/Height) and Sex, 2007-2008; uses data from the U.S. National Center for Health Statistics

```
death_month_hist = histogram(vitals, 'death_month');
height_hist = histogram(vitals, 'height_in');
weight_hist = histogram(vitals, 'weight_lb');
```

Vital Stats pt 2.

```
peep_stats = FOREACH (GROUP attr_vals_nn ALL) GENERATE
  BagToMap(CountVals(attr_vals_nn.attr)) AS cts:map[long];
peep_hist = FOREACH (GROUP attr_vals BY (attr, val)) {
  ct = COUNT_STAR(attr_vals);
  GENERATE
    FLATTEN(group) AS (attr, val),
    ct             AS ct
    -- , (float)ct / ((float)peep_stats.ct) AS freq
    ;
};
peep_hist = ORDER peep_hist BY attr, val;
one = LOAD '$data_dir/stats/numbers/one.tsv' AS (num:int);
ht = FOREACH one GENERATE peep_stats.cts#'height';
```

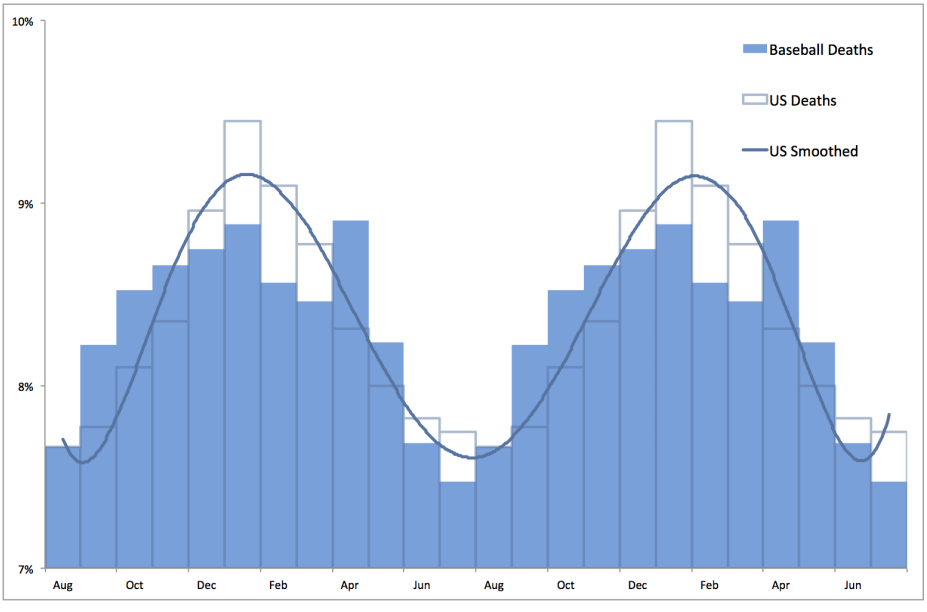
Deaths

These graphs show the relative seasonable distribution of death rates, with adjustment for the fact that there are fewer days in February than July and so forth. As above, the background US rates are shown as darker outlined bars and the results from our data set as solid blue bars.

We were surprised to see how seasonal the death rate is. We all probably have a feel there's more birthday party invitations in September than in March, but hopefully not so much for funerals. This pattern is quite consistent and as you might guess inverted in the Southern Hemisphere. Most surprisingly of all, it persists even in places with a mild climate. The most likely cause of fewer deaths in the summer is *not* fewer snow-covered driveways to shovel, it is that people take vactions — lowering stress, improving mood, and synthesizing vitamin D. (And there's no clear signal of "hanging on for Christmas" in the data).

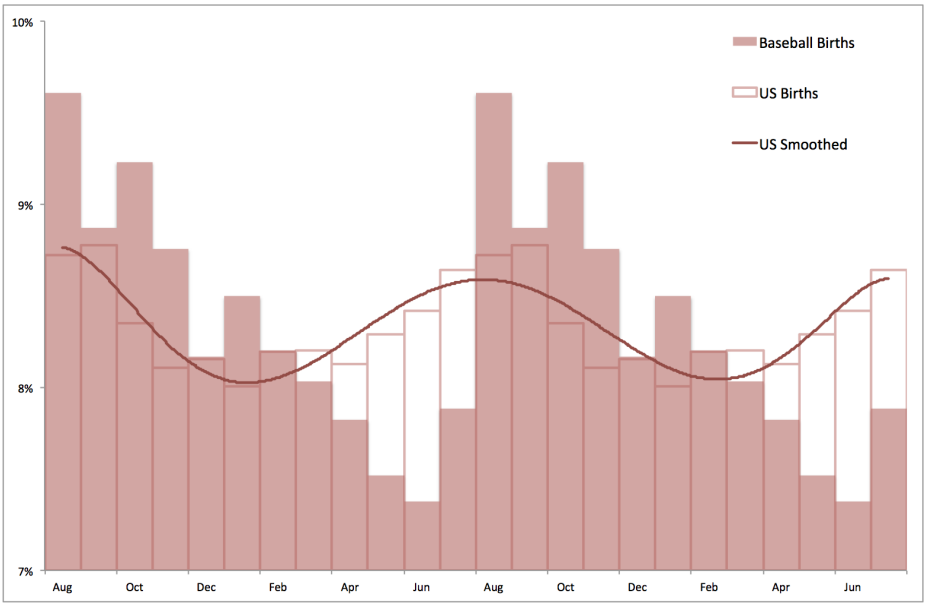
The baseball distribution is lumpier, as you'd expect from its smaller sample size [7], but matches the background distribution. Death treats baseball players, at least in this regard, as it does us all.

7. We don't think the April spike is anything significant ("Hanging on for one more Opening Day celebration?"); sometimes lumpy data is lumpy



Births

That is not true for the birth data! The format of the graph is the same as above, and again we see a seasonal distribution — with a peak nine months after the cold winter temperatures induce people to stay home and find alternative recreations. But the baseball data does *not* match the background distribution at all. The sharp spike in August following the nadir in May and June appears nowhere in the background data, and its phase (where it crosses the centerline) is shifted later by several months. In this data set, a player born in August is about 25% more likely to make the major leagues than a player born in June; restricting it to players from the United States born after 1950 makes august babies *50%* more likely to earn a baseball card than June babies.



The reason is that since the 1940s, American youth leagues have used July 31st as an age cutoff. If Augusta were born on August 1st, then four calendar years and 364 days later she would still technically be four years old. Julien, who showed up the day before her and thus has spent five years and no days orbiting the Sun, is permitted to join the league as a five-year-old. The Augustas may be initially disappointed, but when they do finally join the league as five-year-and-364-day-old kids, they have nearly an extra year of growth compared to the Juliens who sign up with them, which on the whole provides a huge advantage at young ages. This earns the Augustas extra attention from their coaches, extra validation of their skill, and extra investement of "I'm good at Baseball!" in their identity.

Don't Trust Distributions at the Tails

A lot of big data analyses explore population extremes: manufacturing defects, security threats, disease carriers, peak performers. Elements arrive into these extremes exactly because multiple causative features drive them there (such as an advantageous height or birth month); and a host of other conflated features follow from those deviations (such as those stemming from the level of fitness athletes maintain).

So whenever you are examining populations of outliers, you cannot depend on their behavior resembling the universal population. Normal distributions may not remain normal and may not even retain a central tendency; independent features in the general population may become tightly coupled in the outlier group; and a host of other easy assumptions become invalid. Stay alert.

Calculating a Relative Distribution Histogram

The histograms we've calculated have results in terms of counts. The results do a better general job of enforcing comparisons if express them as relative frequencies: as fractions of the total count. You know how to find the total:

```
HR_stats = FOREACH (GROUP bats BY ALL) GENERATE COUNT_STAR(bats) AS n_players;
```

The problem is that HR_stats is a single-row table, and so not something we can use directly in a FOREACH expression. Pig gives you a piece of syntactic sugar for this specific case of a one-row table [8]: project the value as tablename.field as if it were an inner bag, but slap the field's type (in parentheses) in front of it like a typecast expression:

```
HR_stats = FOREACH (GROUP bats BY ALL) GENERATE COUNT_STAR(bats) AS ct;
HR_hist  = FOREACH (GROUP bats BY HR) {
  ct = COUNT_STAR(bats);
  GENERATE HR as val,
    ct/( (long)HR_stats.ct ) AS freq,
    ct;
};
```

Typecasting the projected field as if you were simply converting the schema of a field from one scalar type to another acts as a promise to Pig that what looks like column of possibly many values will turn out to have only row. In return, Pig will understand that you want a sort of über-typecast of the projected column into what is effectively its literal value.

Pattern in Use

See Pattern in Use for "Histograms", above (REF), and "Re-injecting Global Values", following (REF).

- *Where You'll Use It* — Histograms on sampled populations. Whenever you want frequencies rather than counts, i.e. proportions rather than absolute values.
- *Standard Snippet* — Same as for a histogram, but with `COUNT_STAR(vals)/((long)recs_info.ct) AS freq`. See `summarizer_bot_9000.pig` for a macro (REF).

Re-injecting Global Values

Sometimes things are more complicated, and what you'd like to do is perform light synthesis of the results of some initial Hadoop jobs, then bring them back into your script as if they were some sort of "global variable". But a pig script just orchestrates the top-level motion of data: there's no good intrinsic ways to bring the result of a step into

8. called *scalar projection* in Pig terminology

the declaration of following steps. You can use a backhoe to tear open the trunk of your car, but it's not really set up to push the trunk latch button. The proper recourse is to split the script into two parts, and run it within a workflow tool like Rake, Drake or Oozie. The workflow layer can fish those values out of the HDFS and inject them as runtime parameters into the next stage of the script.

In the case of global counts, it would be so much faster if we could sum the group counts to get the global totals; but that would mean a job to get the counts, a job to get the totals, and a job to get the relative frequencies. Ugh.

If the global statistic is relatively static, there are occasions where we prefer to cheat. Write the portion of the script that finds the global count and stores it, then comment that part out and inject the values statically — the sample code shows you how to do it with with a templating runner, as runtime parameters, by copy/pasting, or using the `cat` Grunt shell statement. Then, to ensure your time-traveling shenanigans remain valid, add an `ASSERT` statement comparing the memoized values to the actual totals. Pig will not only run the little checkup stage in parallel if possible, it will realize that the data size is small enough to run as a local mode job — cutting the turnaround time of a tiny job like that in half or better.

```
-- cheat mode:
-- HR_stats = FOREACH (GROUP bats BY ALL) GENERATE COUNT_STAR(bats) AS n_total;
SET HR_stats_n_total = `cat $out_dir/HR_stats_n_total`;

HR_hist  = FOREACH (GROUP bats BY HR) {
ct = COUNT_STAR(bats);
GENERATE HR as val, ct AS ct,
-- ct/( (long)HR_stats.n_total ) AS freq,
ct/( (long)HR_stats_n_total) AS freq,
ct;
};
-- the much-much-smaller histogram is used to find the total after the fact
--
ASSERT (GROUP HR_hist ALL)
IsEqualish( SUM(freq), 1.0 ),
(HR_stats_n_total == SUM(ct);
```

As we said, this is a cheat-to-win scenario: using it to knock three minutes off an eight minute job is canny when used to make better use of a human data scientist's time, foolish when applied as a production performance optimization.

Calculating a Histogram Within a Group

As long as the groups in question do not rival the available memory, counting how often each value occurs within a group is easily done using the DataFu `CountEach` UDF. There's been a trend over baseball's history for increased specialization

http://datafu.incubator.apache.org/docs/datafu/guide/bag-operations.html

You'll see the

```
DEFINE CountVals              datafu.pig.bags.CountEach('flatten');
binned = FOREACH sig_seasons GENERATE
  ( 5 * ROUND(year_id/ 5.0f)) AS year_bin,
  (20 * ROUND(H      /20.0f)) AS H_bin;

hist_by_year_bags = FOREACH (GROUP binned BY year_bin) {
H_hist_cts = CountVals(binned.H_bin);
GENERATE group AS year_bin, H_hist_cts AS H_hist_cts;
};
```

We want to normalize this to be a relative-fraction histogram, so that we can make comparisons across eras even as the number of active players grows. Finding the total count to divide by is a straightforward COUNT_STAR on the group, but a peccadillo of Pig's syntax makes using it a bit frustrating. Annoyingly, a nested `FOREACH` can only "see" values from the bag it's operating on, so there's no natural way to reference the calculated total from the `FOREACH` statement.

```
-- Won't work:
hist_by_year_bags = FOREACH (GROUP binned BY year_bin) {
H_hist_cts = CountVals(binned.H_bin);
tot        = 1.0f*COUNT_STAR(binned);
H_hist_rel = FOREACH H_hist_cts GENERATE H_bin, (float)count/tot;
GENERATE group AS year_bin, H_hist_cts AS H_hist_cts, tot AS tot;
};
```

The best current workaround is to generate the whole-group total in the form of a bag having just that one value. Then we use the CROSS operator to graft it onto each (bin,count) tuple, giving us a bag with (bin,count,total) tuples — yes, every tuple in the bag will have the same group-wide value. Finally, iterate across the tuples to find the relative frequency.

It's more verbose than we'd like, but the performance hit is limited to the CPU and GC overhead of creating three bags (`{(result,count)}`, `{(result,count,total)}`, `{(result,count,freq)}`) in quick order.

Histogram within a Group.

```
hist_by_year_bags = FOREACH (GROUP binned BY year_bin) {
  H_hist_cts = CountVals(binned.H_bin);
  tot        = COUNT_STAR(binned);
  GENERATE
    group      AS year_bin,
    H_hist_cts AS H_hist,
    {(tot)}    AS info:bag{(tot:long)}; -- single-tuple bag we can feed to CROSS
};
hist_by_year = FOREACH hist_by_year_bags {
  -- Combines H_hist bag {(100,93),(120,198)...} and dummy tot bag {(882.0)}
  -- to make new (bin,count,total) bag: {(100,93,882.0),(120,198,882.0)...}
  H_hist_with_tot = CROSS   H_hist, info;
```

```
  -- Then turn the (bin,count,total) bag into the (bin,count,freq) bag we want
  H_hist_rel      = FOREACH H_hist_with_tot
    GENERATE H_bin, count AS ct, count/((float)tot) AS freq;
  GENERATE year_bin, H_hist_rel;
};
```

Pattern in Use

- *Where You'll Use It* — Summarizing Cohorts. Comparatively plotting histograms as a small multiples plot (REF) or animation
- *Standard Snippet* — `DEFINE CountVals datafu.pig.bags.CountEach('flatten'); FOREACH (GROUP recs BY bin) GENERATE group, CountVals(recs.bin);`. Must download and enable the DataFu package (REF)
- *Important to Know* — This is done largely in-memory at the reducer, so watch your data sizes
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values
- *Records* — Output is `group, bag of (count, bin) tuples`. You've turned bags of records-with-values into bags of values-with-counts
- *Data Flow* — Map & Reduce. As you'll learn in "Advanced Pig" (REF), `CountEach` is not an algebraic, but is an accumulator

Dumping Readable Results

We are of course terribly anxious to find out the results, so much so that having to switch over to R to graph our totals is more delay than we can bear. It's also often nice to have production jobs dump a visual summary of the results that an operator can easily scan and sanity-check. And so let's apply the "Formatting a String According to a Template" (REF) pattern to dump a readable summary of our results to the screen.

```
year_hists_HH = FOREACH year_hists {
  HH_hist_rel_o = ORDER HH_hist_rel BY bin ASC;
  HH_hist_rel_x = FILTER HH_hist_rel_o BY (bin >= 90);
  HH_hist_vis   = FOREACH HH_hist_rel_x GENERATE
    SPRINTF('%1$3d: %3$4.0f', bin, ct, ROUND_TO(100*freq, 1));
  GENERATE year_bin, BagToString(HH_hist_vis, '  ');
  };
```

TODO-reviewers: previous version without comments, or following? In practice I would write it without comments.

```
year_hists_HH = FOREACH year_hists {
  -- put all bins in regular order
  HH_hist_rel_o = ORDER HH_hist_rel BY bin ASC;
  -- The PA threshold makes the lower bins ragged, exclude them
```

```
HH_hist_rel_x = FILTER HH_hist_rel_o BY (bin >= 90);
-- Format each bin/freq into a readable string
HH_hist_vis   = FOREACH HH_hist_rel_x GENERATE
  SPRINTF('%1$3d: %3$4.0f', bin, ct, ROUND_TO(100*freq, 1));
-- Combine those strings into readable table
GENERATE year_bin, BagToString(HH_hist_vis, '  ');
};
```

In this snippet, we first put all bins in regular order and exclude the lower bins (the minimum-plate appearances threshold makes them ragged). Next, we transform each bin-count-frequency triple into a readable string using `SPRINTF`. Since we used positional specifiers (the `1$` part of `%1$3d`), it's easy to insert or remove fields in the display depending on what question you're asking. Here, we've omitted the count as it wasn't helpful for the main question we have: "What are the long-term trends in offensive production?". Finally, we use `BagToString` to format the row. We first met that combination of formatting-elements-formatting-bag in "Representing a Complex Data Structure with a Delimited String" (REF) above. (We hope you're starting to feel like Danielsan in Karate Kid when all his work polishing cars comes together as deadly martial arts moves.)

Relative Distribution of Total Hits per Season by Five-Year Period, 1900-.

```
1900    100:   21  125:   38  150:   27  175:    9  200:    2  225:    1
1905    100:   30  125:   37  150:   20  175:    4  200:    2
1910    100:   22  125:   40  150:   25  175:    9  200:    1  225:    1
1915    100:   25  125:   38  150:   20  175:    6  200:    1  225:    0
1920    100:   12  125:   26  150:   29  175:   21  200:    9  225:    1  250:    0
1925    100:   13  125:   29  150:   26  175:   19  200:    9  225:    2  250:    0
1930    100:   12  125:   30  150:   26  175:   20  200:    9  225:    1  250:    0
1935    100:   13  125:   29  150:   29  175:   19  200:    8  225:    1
1940    100:   20  125:   35  150:   29  175:   11  200:    2
1945    100:   26  125:   36  150:   22  175:   11  200:    2  225:    1
1950    100:   21  125:   29  150:   32  175:   12  200:    3
1955    100:   27  125:   31  150:   22  175:   14  200:    2
1960    100:   24  125:   29  150:   29  175:   12  200:    3  225:    0
1965    100:   26  125:   34  150:   24  175:    8  200:    2  225:    0
1970    100:   26  125:   35  150:   23  175:    9  200:    2  225:    0
1975    100:   23  125:   33  150:   26  175:   11  200:    3  225:    0
1980    100:   22  125:   34  150:   25  175:   11  200:    3  225:    0
1985    100:   27  125:   31  150:   26  175:    9  200:    3  225:    0
1990    100:   29  125:   33  150:   24  175:   10  200:    1
1995    100:   20  125:   31  150:   29  175:   14  200:    3  225:    0
2000    100:   22  125:   30  150:   29  175:   13  200:    3  225:    0  250:    0
2005    100:   19  125:   32  150:   28  175:   15  200:    3  225:    0
2010    100:   22  125:   36  150:   26  175:   11  200:    2
```

Relative Distribution of Total Home Runs per Season by Five-Year Period, 1900-.

```
1900    0:   97   10:    3
1905    0:   99   10:    1
1910    0:   93   10:    6   20:    0
```

```
1915    0:   96   10:    3   20:    1
1920    0:   77   10:   18   20:    3   30:    1   40:    1   50:    0
1925    0:   71   10:   20   20:    4   30:    3   40:    1   50:    0   60:    0
1930    0:   62   10:   25   20:    6   30:    5   40:    2   50:    0
1935    0:   57   10:   27   20:   10   30:    4   40:    1   50:    0
1940    0:   64   10:   24   20:    8   30:    3   40:    0
1945    0:   58   10:   27   20:   10   30:    4   40:    1   50:    1
1950    0:   39   10:   33   20:   18   30:    7   40:    3
1955    0:   34   10:   32   20:   23   30:    8   40:    4   50:    1
1960    0:   33   10:   34   20:   22   30:    8   40:    3   50:    0   60:    0
1965    0:   38   10:   34   20:   19   30:    8   40:    2   50:    0
1970    0:   39   10:   34   20:   20   30:    5   40:    2
1975    0:   42   10:   33   20:   19   30:    6   40:    1   50:    0
1980    0:   41   10:   34   20:   18   30:    6   40:    1
1985    0:   33   10:   34   20:   25   30:    8   40:    1
1990    0:   36   10:   35   20:   20   30:    7   40:    2   50:    0
1995    0:   24   10:   32   20:   25   30:   13   40:    6   50:    1   60:    0   70:    0
2000    0:   19   10:   35   20:   26   30:   14   40:    5   50:    1   60:    0   70:    0
2005    0:   22   10:   34   20:   28   30:   12   40:    3   50:    1
2010    0:   24   10:   37   20:   27   30:   11   40:    2   50:    0
```

We'll need to draw graphs to get any nuanced insight, but the long-term trends in production of Hits and Home Runs is strong enough that this chart tells a clear story. Baseball has seen two offensive booms: one in the 1920-1939 period, and one in the 1990-2009 period. However, the first was an on-base boom, with a larger proportion of players crossing the 200-hit mark than ever have since. The recent one was decidedly a power-hitting boom. There is an increase in the fraction of players reaching high seasonal hit totals, but the chart above shouts how large the increase in the proportion of players hitting 30-, 40-, and 50-home runs per year is.

Pattern in Use

- *Where You'll Use It* — Production jobs, to give the operator a readable summary that the job not only ran to completion but gave meaningful results. In development, to Know Thy Data.
- *Standard Snippet* — A mashup of the Format with a Template, Represent Complex Data Structures, and Group-and-Aggregate patterns
- *Important to Know* — This is more valuable, and more used by experts, than you might think. You'll see.
- *Records* — Up to you; enough for your brain, not too much for your eyes.
- *Exercises for you*: Create a macro to generate such a table. It should accept parameters for sprintf template, filter limits and sort key. Consult the `summariz er_bot_9000.pig` file in the example code repository for other examples of macros.

The Summing Trick

There's a pattern-of-patterns we like to call the "Summing trick", a frequently useful way to act on subsets of a group without having to perform multiple `GROUP BY` or `FILTER` operations. Call it to mind every time you find yourself thinking "gosh, this sure seems like a lot of reduce steps on the same key". Before we describe its generic nature, it will help to see an example

Counting Conditional Subsets of a Group — The Summing Trick

Whenever you are exploring a dataset, you should determine figures of merit for each of the key statistics — easy-to-remember values that separate qualitatively distinct behaviors. You probably have a feel for the way that 30 C / 85 deg F reasonably divides a "warm" day from a "hot" one; and if I tell you that a sub-three-hour marathon distinguishes "really impress your friends" from "really impress other runners", you are equipped to recognize how ludicrously fast a 2:15 (the pace of a world-class runner) marathon is.

For our purposes, we can adopt 180 hits (H), 30 home runs (HR), 100 runs batted in (RBI), a 0.400 on-base percentage (OBP) and a 0.500 slugging percentage (SLG) each as the dividing line between a good and a great performance.

One reasonable way to define a great career is to ask how many great seasons a player had. We can answer that by counting how often a player's season totals exceeded each figure of merit. The obvious tactic would seem to involve filtering and counting each bag of seasonal stats for a player's career; that is cumbersome to write, brings most of the data down to the reducer, and exerts GC pressure materializing multiple bags.

```
-- Create indicator fields on each figure of merit for the season
standards = FOREACH mod_seasons {
  OBP    = 1.0*(H + BB + HBP) / PA;
  SLG    = 1.0*(h1B + 2*h2B + 3*h3B + 4*HR) / AB;
  GENERATE
    player_id,
    (H   >=   180 ? 1 : 0) AS hi_H,
    (HR  >=    30 ? 1 : 0) AS hi_HR,
    (RBI >=   100 ? 1 : 0) AS hi_RBI,
    (OBP >= 0.400 ? 1 : 0) AS hi_OBP,
    (SLG >= 0.500 ? 1 : 0) AS hi_SLG
    ;
};
```

Next, count the seasons that pass the threshold by summing the indicator value

```
career_standards = FOREACH (GROUP standards BY player_id) GENERATE
    group AS player_id,
    COUNT_STAR(standards) AS n_seasons,
    SUM(standards.hi_H)   AS hi_H,
    SUM(standards.hi_HR)  AS hi_HR,
```

```
    SUM(standards.hi_RBI) AS hi_RBI,
    SUM(standards.hi_OBP) AS hi_OBP,
    SUM(standards.hi_SLG) AS hi_SLG
    ;
```

The summing trick involves projecting a new field whose value is based on whether it's in the desired set, forming the desired groups, and aggregating on those new fields. Irrelevant records are assigned a value that will be ignored by the aggregate function (typically zero or `null`), and so although we operate on the group as a whole, only the relevant records contribute.

In this case, instead of sending all the hit, home run, etc figures directly to the reducer to be bagged and filtered, we send a `1` for seasons above the threshold and `0` otherwise. After the group, we find the *count* of values meeting our condition by simply *summing* the values in the indicator field. This approach allows Pig to use combiners (and so less data to the reducer); and more importantly it doesn't cause a bag of values to be collected, only a running sum (and so way less garbage-collector pressure).

Another example will help you see what we mean — next, we'll use one `GROUP` operation to summarize multiple subsets of a table at the same time.

First, though, a side note on these figures of merit. As it stands, this isn't a terribly sophisticated analysis: the numbers were chosen to be easy-to-remember, and not based on the data. For actual conclusion-drawing, we should use the z-score (REF) or quantile (REF) figures (we'll describe both later on, and use them for our performance analysis instead). And yet, for the exploratory phase we prefer the ad-hoc figures. A 0.400 OBP is a number you can hold in your hand and your head; you can go click around ESPN and see that it selects about the top 10-15 players in most seasons; you can use paper-and-pencil to feed it to the run expectancy table (REF) we'll develop later and see what it says a 0.400-on-base hitter would produce. We've shown you how useful it is to identify exemplar records; learn to identify these touchstone values as well.

Summarizing Multiple Subsets of a Group Simultaneously

We can use the summing trick to apply even more sophisticated aggregations to conditional subsets. How did each player's career evolve — a brief brilliant flame? a rise to greatness? sustained quality? Let's classify a player's seasons by whether they are "young" (age 21 and below), "prime" (22-29 inclusive) or "older" (30 and older). We can then tell the story of their career by finding their OPS (our overall performance metric) both overall and for the subsets of seasons in each age range [9].

9. these breakpoints are based on where www.fangraphs.com/blogs/how-do-star-hitters-age research by fangraphs.com showed a performance drop-off by 10% from peak.

The complication here over the previous exercise is that we are forming compound aggregates on the group. To apply the formula `career SLG = (career TB) / (career AB)`, we need to separately determine the career values for `TB` and `AB` and then form the combined `SLG` statistic.

Project the numerator and denominator of each offensive stat into the field for that age bucket. Only one of the subset fields will be filled in; as an example, an age-25 season will have values for PA_all and PA_prime and zeros for PA_young and PA_older.

```
age_seasons = FOREACH mod_seasons {
  young = (age <= 21               ? true : false);
  prime = (age >= 22 AND age <= 29 ? true : false);
  older = (age >= 30               ? true : false);
  OB = H + BB + HBP;
  TB = h1B + 2*h2B + 3*h3B + 4*HR;
  GENERATE
    player_id, year_id,
    PA AS PA_all, AB AS AB_all, OB AS OB_all, TB AS TB_all,
    (young ? 1 : 0) AS is_young,
      (young ? PA : 0) AS PA_young, (young ? AB : 0) AS AB_young,
      (young ? OB : 0) AS OB_young, (young ? TB : 0) AS TB_young,
    (prime ? 1 : 0) AS is_prime,
      (prime ? PA : 0) AS PA_prime, (prime ? AB : 0) AS AB_prime,
      (prime ? OB : 0) AS OB_prime, (prime ? TB : 0) AS TB_prime,
    (older ? 1 : 0) AS is_older,
      (older ? PA : 0) AS PA_older, (older ? AB : 0) AS AB_older,
      (older ? OB : 0) AS OB_older, (older ? TB : 0) AS TB_older
    ;
};
```

After the group, we can sum across all the records to find the plate-appearances-in-prime-seasons even though only some of the records belong to the prime-seasons subset. The irrelevant seasons show a zero value in the projected field and so don't contribute to the total.

Career Epochs.

```
career_epochs = FOREACH (GROUP age_seasons BY player_id) {
  PA_all    = SUM(age_seasons.PA_all  );
  PA_young  = SUM(age_seasons.PA_young);
  PA_prime  = SUM(age_seasons.PA_prime);
  PA_older  = SUM(age_seasons.PA_older);
  -- OBP = (H + BB + HBP) / PA
  OBP_all   = 1.0f*SUM(age_seasons.OB_all)   / PA_all  ;
  OBP_young = 1.0f*SUM(age_seasons.OB_young) / PA_young;
  OBP_prime = 1.0f*SUM(age_seasons.OB_prime) / PA_prime;
  OBP_older = 1.0f*SUM(age_seasons.OB_older) / PA_older;
  -- SLG = TB / AB
  SLG_all   = 1.0f*SUM(age_seasons.TB_all)   / SUM(age_seasons.AB_all);
  SLG_prime = 1.0f*SUM(age_seasons.TB_prime) / SUM(age_seasons.AB_prime);
  SLG_older = 1.0f*SUM(age_seasons.TB_older) / SUM(age_seasons.AB_older);
```

```
    SLG_young = 1.0f*SUM(age_seasons.TB_young) / SUM(age_seasons.AB_young);
    --
    GENERATE
      group AS player_id,
      MIN(age_seasons.year_id)  AS beg_year,
      MAX(age_seasons.year_id)  AS end_year,
      --
      OBP_all   + SLG_all       AS OPS_all:float,
      (PA_young >= 700 ? OBP_young + SLG_young : null) AS OPS_young:float,
      (PA_prime >= 700 ? OBP_prime + SLG_prime : null) AS OPS_prime:float,
      (PA_older >= 700 ? OBP_older + SLG_older : null) AS OPS_older:float,
      --
      COUNT_STAR(age_seasons)   AS n_seasons,
      SUM(age_seasons.is_young) AS n_young,
      SUM(age_seasons.is_prime) AS n_prime,
      SUM(age_seasons.is_older) AS n_older
      ;
};
```

If you do a sort on the different OPS fields, you'll spot Ted Williams (player ID willite01) as one of the top three young players, top three prime players, and top three old players. He's pretty awesome.

Pattern in Use

- *Where You'll Use It* — Summarizing the whole and a small number of discrete subsets: all/true/false, country/region/region/region/.., all visitors/cohort A/cohort B.
- *Standard Snippet* — Project dummy fields for each subset you'll track, having an ignorable value for records not in that subset. Aggregating over the whole then aggregates only over that subset
- *Hello, SQL Users* — This is a common trick in SQL cookbooks. Thanks y'all!
- *Important to Know* — You have to manufacture one field per subset. At some point you should use finer-grained grouping instead — see "Group-Flatten-Decorate" (REF) and "Cube and Rollup" (REF).
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values. Data size should decrease greatly.
- *Data Flow* — Similar to any group-and-aggregate. Combiners become highly effective as most of the values will be ignorable

Testing for Absence of a Value Within a Group

We don't need a trick to answer "which players have ever played for the Red Sox" — just select seasons with team id `BOS` and eliminate duplicate player ids:

```
-- Players who were on the Red Sox at some time
onetime_sox_ids = FOREACH (FILTER bat_seasons BY (team_id == 'BOS')) GENERATE player_id;
onetime_sox     = DISTINCT onetime_sox_ids;
```

The summing trick is useful for the complementary question "which players have *never* played for the Red Sox?" You might think to repeat the above but filter for `team_id != 'BOS'` instead, but what that gives you is "which players have ever played for a non-Red Sox team?". The right approach is to generate a field with the value `1` for a Red Sox season and the irrelevant value `0` otherwise. The never-Sox are those with zeroes for every year.

```
player_soxness   = FOREACH bat_seasons GENERATE
  player_id, (team_id == 'BOS' ? 1 : 0) AS is_soxy;

player_soxness_g = FILTER
  (GROUP player_soxness BY player_id)
  BY MAX(is_soxy) == 0;

never_sox = FOREACH player_soxness_g GENERATE group AS player_id;
```

Pattern in Use

- *Where You'll Use It* — Security: badges that have "entered reactor core" but no "signed in at front desk" events. Users that clicked on three or more pages but never bought an item. Devices that missed QA screening.
- *Standard Snippet* — create indicator field: `mt_f = FOREACH recs GENERATE ..., (test_of_fooness ? 1 : 0) is_foo;`; find the non-foos: `non_foos = FILTER (GROUP mt_f BY mykey) BY MAX(is_foo) == 0;` then project just the keys: `non_foos = FOREACH non_foos GENERATE group AS mykey`.
- *Hello, SQL Users* — Another classic pattern from the lore
- *Important to Know* — If you're thinking "gosh, once I've got that indicator field I could not only test its non-zeroness but sum it and average it and …" then you're thinking along the right lines.
- *Output Count* — As many records as the cardinality of its key, i.e. the number of distinct values. Data size should decrease dramatically.
- *Records* — List of keys
- *Data Flow* — Map, Combiner & Reducer. Combiners should be extremely effective.

Refs

- Born at the Wrong Time: Selection Bias in the NHL Draft by Robert O. Deaner, Aaron Lowen, Stephen Cobley. February 27, 2013DOI: 10.1371/journal.pone.0057753
- The Impact Of Baseball Age-Cutoff Date Rules, waswatching.com, May 23rd, 2013
- The Boys of Late Summer, Greg Spira, April 16 2008.

CHAPTER 7

Analytic Patterns: Joining Tables

In database terminology, a *join* combines the rows of two or more tables based on some matching information, known as a *key*. For example, you could join a table of names and a table of mailing addresses, so long as both tables had a common field for the user ID. You could also join a table of prices to a table of items, given an item ID column in both tables. Joins are useful because they permit people to *normalize* data — that is to say, eliminate redundant content between multiple tables — yet still bring several tables' content to a single view on-the-fly.

Joins are pedestrian fare in relational databases. Far less so for Hadoop, since MapReduce wasn't really created with joins in mind, and you have to go through acrobatics to make it work. [1] Pig's `JOIN` operator provides the syntactical ease of a SQL query. While Pig will shield you from hand-writing joins in MapReduce, it's still all MapReduce behind the scenes, so your joins are still subject to certain performance considerations. This section will dig into the basics of Pig joins, then explain how to avoid certain mishaps.

Matching Records Between Tables (Inner Join)

An *inner join* drops records that don't have matching keys in both tables. This means that the result of an inner join may have fewer rows than either of the original tables.

Joining Records in a Table with Directly Matching Records from Another Table (Direct Inner Join)

There is a stereotypical picture in baseball of a "slugger": a big fat man who comes to plate challenging your notion of what an athlete looks like, and challenging the pitcher

1. Hence why you may see Hadoop joins on data scientist tech interviews.

to prevent him from knocking the ball for multiple bases (or at least far enough away to lumber up to first base). To examine the correspondence from body type to ability to hit for power (i.e. high SLG), we will need to join the `people` table (listing height and weight) with their hitting stats.

```
fatness = FOREACH peeps GENERATE
  player_id, name_first, name_last,
  height_in, weight_lb;
-- only players w/ statistically significant careers (about two regular-player-season's worth)
slugging_stats = FOREACH (FILTER bat_careers BY (PA > 1000))
  GENERATE player_id, SLG;
```

The syntax of the join statement itself shouldn't be much of a surprise:

```
slugging_fatness_join = JOIN
  fatness        BY player_id,
  slugging_stats BY player_id;

LIMIT slugging_fatness_join 20; DUMP @;
...
```

Disambiguating Field Names With `::`

As a consequence of flattening records from the fatness table next to records from the slugging_stats table, the two tables each contribute a field named `player_id`. Although *we* privately know that both fields have the same value, Pig is right to insist on an unambiguous reference. The schema helpfully prefixes the field names with a slug, separated by `::`, to make it unambiguous. You'll need to run a `FOREACH` across the joined data, specifying the qualified names of the fields you want to keep.

Body Type vs Slugging Average

So having done the join, we finish by preparing the output:

```
FOREACH(JOIN fatness BY player_id, slugging_stats BY player_id) {
  BMI = ROUND_TO(703.0*weight_lb/(height_in*height_in),1) AS BMI;
  GENERATE bat_careers::player_id, name_first, name_last,
    SLG, height_in, weight_lb, BMI;
};
```

We added a field for BMI (Body Mass Index), a simple measure of body type. It is found by diving a person's weight by their height squared, and, since we're stuck with english units, multiplying by 703 to convert to metric. Though BMI can't distinguish between 180 pounds of muscle and 180 pounds of flab, it reasonably controls for weight-due-to-tallness vs weight-due-to-bulkiness: beanpole Randy Johnson (6'10"/2.1m, 225lb/102kg) and pocket rocket Tim Raines (5'8"/1.7m, 160lb/73kb) both have a low BMI of 23; Babe Ruth (who in his later days was 6'2"/1.88m 260lb/118kb) and Cecil Fielder (of whom Bill James wrote "…his reported weight of 261 leaves unanswered the question

of what he might weigh if he put his other foot on the scale") both have high BMIs well above 30 [2]

```
SELECT bat.player_id, peep.nameCommon, begYear,
    peep.weight, peep.height,
    703*peep.weight/(peep.height*peep.height) AS BMI, -- measure of body type
    PA, OPS, ISO
  FROM bat_career bat
  JOIN people peep ON bat.player_id = peep.player_id
  WHERE PA > 500 AND begYear > 1910
  ORDER BY BMI DESC
  ;
```

A Join is a Map/Reduce Job with a secondary sort on the Table Name

The way to perform a join in map-reduce is similarly a particular application of the COGROUP we stepped through above. Even still, we'll walk through it mostly on its own. The mapper receives its set of input splits either from the bat_careers table or from the peep table and makes the appropriate transformations. Just as above (REF), the mapper knows which file it is receiving via either framework metadata or environment variable in Hadoop Streaming. The records it emits follow the COGROUP pattern: the join fields, anointed as the partition fields; then the index labeling the origin file, anointed as the secondary sort fields; then the remainder of the fields. So far this is just a transform (FOREACH) inlined into a cogroup.

```
mapper do
  self.processes_models
  config.partition_fields 1 # player_id
  config.sort_fields      2 # player_id, origin_key
RECORD_ORIGINS = [
  /bat_careers/ => ['A', Baseball::BatCareer],
  /players/     => ['B', Baseball::Player],
]
def set_record_origin!
  RECORD_ORIGINS.each do |origin_name_re, (origin_index, record_klass)|
    if config[:input_file]
      [@origin_key, @record_klass] = [origin_index, record_klass]
      return
    end
  end
  # no match, fail
  raise RuntimeError, "The input file name #{config[:input_file]} must match one of #{RECORD_ORIGI
end
def start(*) set_record_origin! ; end
def recordize(vals) @record_klass.receive(vals)
def process(record)
```

2. The dataset we're using unfortunately only records players' weights at the start of their career, so you will see different values listed for Mr. Fielder and Mr. Ruth.

```
    case record
    when CareerStats
      yield [rec.player_id, @origin_idx, rec.slg]
    when Player
      yield [rec.player_id, @origin_key, rec.height_in, rec.weight_lb]
    else raise "Impossible record type #{rec.class}"
    end
  end
  end
```

For each key, the reducer spools all the records matching that key from the initial table into an array in memory. The lastmost-named table, however, does not need to be accumulated. As the framework streams in each record in the current group, you simply compose it with each record in the accumulated array

Join in Wukong: Reducer Part.

```
  reducer do
    def gather_records(group, origin_key)
      records = []
      group.each do |*vals|
        if vals[1] != origin_key # We hit start of next table's keys
          group.shift(vals)      # put it back before Mom notices
          break                  # and stop gathering records
        end
        records << vals
      end
      return records
    end

    BMI_ENGLISH_TO_METRIC = 0.453592 / (0.0254 * 0.254)
    def bmi(ht, wt)
      BMI_ENGLISH_TO_METRIC * wt / (ht * ht)
    end

    def process_group(group)
      # remainder are slugging stats
      group.each do |player_id, _, slg|
        players = gather_records(group, 'A')
        players.each do |player_id, _, height_in, weight_lb|
          #   The result of the JOIN in Pig would be all the fields, keys and not, in order by origi
          # after_the_join = [
          #   player_id, slg,                  # fields from 'A'
          #   player_id, height_in, weight_lb  # fields from 'B'
          # ]

          #   But Pig then pipelines the post-join FOREACH into the reducer, and so do we:
          yield [player_id, slg, height_in, weight_lb, bmi(height_in, weight_lb)]
        end
      end
    end
  end
```

The output of the Join job will have one record for each discrete combination of A and B. As you will notice in our Wukong version of the Join, the secondary sort ensures that for each key the reducer receives all the records for table A strictly followed by all records for table B. We gather all the A records in to an array, then on each B record emit the A records stapled to the B records. All the A records have to be held in memory at the same time, while all the B records simply flutter by; this means that if you have two datasets of wildly different sizes or distribution, it is worth ensuring the Reducer receives the smaller group first. In map/reduce, the table with the largest number of records per key should be assigned the last-occurring field group label; in Pig, that table should be named last in the `JOIN` statement.

```
stats_and_fatness = FOREACH (JOIN fatness BY player_id, stats BY player_id)
  GENERATE fatness::player_id..BMI, stats::n_seasons..OPS;
```

Pattern in Use

- *Exercise* — Explore the correspondence of weight, height and BMI to SLG using a medium-data tool such as R, Pandas or Excel. Spoiler alert: the stereotypes of the big fat slugger is quire true.

Handling Nulls and Non-matches in Joins and Groups

It's important to understand how Null keys are handled in Join and Group operations. Briefly:

- In map-reduce, Nulls are respected as keys:
- In a single-table Pig `GROUP`, Nulls are also respected as keys.
- In a multi-table `COGROUP`, Nulls are respected as keys, *but not grouped together*
- In a `JOIN` operation, rows with Nulls *do not take place in the join* at all, but are *processed anyway*
- If you have a lot of Null keys, watch out: it is somewhere between costly and foolish.

When we say *null key*, we mean that if the group or join key is a scalar expression, that it has a null result; and if the key is a tuple, that all elements of the tuple are null. So

- these are null keys: `Null`, `(Null,Null,Null)`, `("hi",Null,"howareyou")` (even one non-null field)
- these are not: `""` (empty string), `0` (zero); An empty bag `{}` and a bag with a tuple holding null `{()}` are bot not-null, but a bag cannot be used as a join or group key.

In the base Hadoop infrastructure, there's not much to understand: a key is a key, and Hadoop doesn't treat nulls specially in any way. Anything different is up to your program, and Pig does in fact supply something different.

A single-table `GROUP` statement does treat Nulls as keys. It's pretty easy to come up with a table having many Null values for the key you're grouping on; and if you do, all of them will be sent to the same reducer. If you actually need those keys, well, whaddaya-gonnado: sounds like one of the reducers will have to endure a bad day at work. But if you don't need the groups having Null keys, get rid of them as early as possible.

A `COGROUP` statement with multiple tables also treats Nulls as keys (so get rid of them if unwanted). But take note! Multi-table groups treat *each table's Nulls as distinct*. That is, if table A had 4 records with null keys, and table B had 2 records with null keys, `COGROUP A by key, B by key` would produce

- a row whose three fields are the null key; a bag holding the four associated records from A, and an empty bag; and
- a row whose three fields are the null key; an empty bag; and a bag holding the two associated records from B.

What do you do if you want null keys treated like any other tuple? Add an indicator field saying whether the value is null, and coalesce the actual key to non-null value. So instead of `JOIN aa BY has_nulls, bb BY has_nulls`, write

Join on NULL Fields.

```
JOIN
  aa BY ( (has_nulls IS NULL ? 'x' : 'Y'), (has_nulls IS NULL ? -999 : has_nulls) ),
  bb BY ( (has_nulls IS NULL ? 'x' : 'Y'), (has_nulls IS NULL ? -999 : has_nulls) );
```

Even if there are records whose value is -999, they will have `'Y'` for the indicator, while the null-keyed records will have `'x'`, and so they will not meet up. (For your sanity, if it's possible to choose a replacement value that can't occur in the data set do so). The file `j-important_notes_about_joins.pig` in the sample code repo has a bunch more demonstrations of edge cases in groups and joins.

Pattern in Use: Inner Join

- *Where You'll Use It* — Any time you need to match records among tables. Reattaching metadata about a record to the record. Combining incidences of defective products with the manufacturing devices that made them.
- *Standard Snippet* — `JOIN aa BY key, bb BY key;`
- *Hello, SQL Users* — The only join that Hadoop admits is the "equi-join" — equality of values. Much more on this to follow.
- *Important to Know*

— List the tables in the statement from smallest to largest (largest table last)

— You can do a multi-way join; see the documentation

— The key does not appear in the output

— `::` is for disambiguation, `.` is for projecting tuples in a bag. `JOIN` doesn't create new bags, so `::` is probably what you want.

- *Output Count* — For each key that matches, the number of pairings among keys. This can be anywhere from much smaller to explosively bigger.
- *Records* — Schema of the result is the schema from each table stapled end-to-end. Values are unchanged from their input.
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.
- *See Also*

  — DataFu's bag left outer join;

  — Left outer join on three tables: *http://datafu.incubator.apache.org/docs/datafu/guide/more-tips-and-tricks.html*

  — Time-series chapter: Range query using cross

  — Time-series chapter: Range query using prefix and UDFs (the ip-to-geo example)

  — Time-series chapter: Self-join for successive row differences

  — Advanced Pig: Sparse joins for filtering, with a HashMap (replicated)

  — The internet, for information on Bitmap index or Bloom filter joins

Enumerating a Many-to-Many Relationship

In the previous examples there's been a direct pairing of each line in the main table with the unique line from the other table that decorates it. Therefore, there output had exactly the same number of rows as the larger input table. When there are multiple records per key, however, the the output will have one row for each *pairing* of records from each table. A key with two records from the left table and 3 records from the right table yields six output records.

```
player_team_years = FOREACH bat_seasons GENERATE year_id, team_id, player_id;
park_team_years   = FOREACH park_teams  GENERATE year_id, team_id, park_id;

player_stadia = FOREACH (JOIN
  player_team_years BY (year_id, team_id),
  park_team_years   BY (year_id, team_id)
  ) GENERATE
```

```
    player_team_years::year_id AS year_id, player_team_years::team_id AS team_id,
    player_id,  park_id;
```

By consulting the Jobtracker counters (map input records vs reduce output records) or by explicitly using Pig to count records, you'll see that the 77939 batting_seasons became 80565 home stadium-player pairings. The cross-product behavior didn't cause a big explosion in counts — as opposed to our next example, which will generate much more data.

Joining a Table with Itself (self-join)

Joining a table with itself is very common when you are analyzing relationships of elements within the table (when analyzing graphs or working with datasets represented as attribute-value lists it becomes predominant.) Our example here will be to identify all teammates pairs: players listed as having played for the same team in the same year. The only annoying part about doing a self-join in Pig is that you can't, at least not directly. Pig won't let you list the same table in multiple slots of a JOIN statement, and also won't let you just write something like `"mytable_dup = mytable;"` to assign a new alias [3]. Instead you have to use a FOREACH or somesuch to create a duplicate representative. If you don't have any other excuse, use a project-star expression: `p2 = FOREACH p1 GENERATE *;`. In this case, we already need to do a projection; we feel the most readable choice is to repeat the statement twice.

```
-- Pig disallows self-joins so this won't work:
wont_work = JOIN bat_seasons BY (team_id, year_id), bat_seasons BY (team_id, year_id);
"ERROR ... Pig does not accept same alias as input for JOIN operation : bat_seasons"
```

That's OK, we didn't want all those stupid fields anyway; we'll just make two copies and then join the table copies to find all teammate pairs. We're going to say a player isn't their their own teammate, and so we also reject the self-pairs.

```
p1 = FOREACH bat_seasons GENERATE player_id, team_id, year_id;
p2 = FOREACH bat_seasons GENERATE player_id, team_id, year_id;

teammate_pairs = FOREACH (JOIN
    p1 BY (team_id, year_id),
    p2 by (team_id, year_id)
  ) GENERATE
    p1::player_id AS pl1,
    p2::player_id AS pl2;
teammate_pairs = FILTER teammate_pairs BY NOT (pl1 == pl2);
```

As opposed to the slight many-to-many expansion of the previous section, there are on average ZZZ players per roster to be paired. The result set here is explosively larger:

3. If it didn't cause such a surprisingly hairy set of internal complications, it would have long ago been fixed

YYY pairings from the original XXX player seasons, an expansion of QQQ [4]. Now you might have reasonably expected the expansion factor to be very close to the average number of players per team, thinking "QQQ average players per team, so QQQ times as many pairings as players." But a join creates as many rows as the product of the records in each tables' bag — the square of the roster size in this case — and the sum of the squares necessarily exceeds the direct sum.

The 78,000 player seasons we joined onto the team-parks-years table In contrast, a similar `JOIN` expression turned 78,000 seasons into 2,292,658 player-player pairs, an expansion of nearly thirty times

(A simplification was made) [5]

Joining Records Without Discarding Non-Matches (Outer Join)

The Baseball Hall of Fame is meant to honor the very best in the game, and each year a very small number of players are added to its rolls. It's a significantly subjective indicator, which is its cardinal virtue and its cardinal flaw — it represents the consensus judgement of experts, but colored to some small extent by emotion, nostalgia, and imperfect quantitative measures. But as you'll see over and over again, the best basis for decisions is the judgement of human experts backed by data-driven analysis. What we're assembling as we go along this tour of analytic patterns isn't a mathematical answer to who the highest performers are, it's a basis for centering discussion around the right mixture of objective measures based on evidence and human judgement where the data is imperfect.

So we'd like to augment the career stats table we assembled earlier with columns showing, for hall-of-famers, the year they were admitted, and a `Null` value for the rest. (This allows that column to also serve as a boolean indicator of whether the players were inducted). If you tried to use the JOIN operator in the form we have been, you'll find

4. See the example code for details

5. (or, what started as a footnote but should probably become a sidebar or section in the timeseries chapter — QEM advice please) Our bat_seasons table ignores mid-season trades and only lists a single team the player played the most games for, so in infrequent cases this will identify some teammate pairs that didn't actually overlap. There's no simple option that lets you join on players' intervals of service on a team: joins must be based on testing key equality, and we would need an "overlaps" test. In the time-series chapter you'll meet tools for handling such cases, but it's a big jump in complexity for a small number of renegades. You'd be better off handling it by first listing every stint on a team for each player in a season, with separate fields for the year and for the start/end dates. Doing the self-join on the season (just as we have here) would then give you every *possible* teammate pair, with some fraction of false pairings. Lastly, use a FILTER to reject the cases where they don't overlap. Any time you're looking at a situation where 5% of records are causing 150% of complexity, look to see whether this approach of "handle the regular case, then fix up the edge cases" can apply.

that it doesn't work. A plain JOIN operation keeps only rows that have a match in all tables, and so all of the non-hall-of-famers will be excluded from the result. (This differs from COGROUP, which retains rows even when some of its inputs lack a match for a key). The answer is to use an *outer join*

```
career_stats = FOREACH (
  JOIN
    bat_careers BY player_id LEFT OUTER,
    batting_hof BY player_id) GENERATE
  bat_careers::player_id..bat_careers::OPS, allstars::year_id AS hof_year;
```

Since the batting_hof table has exactly one row per player, the output has exactly as many rows as the career stats table, and exactly as many non-null rows as the hall of fame table.

6

```
-- (sample data)
-- (Hank Aaron)... Year
```

In this example, there will be some parks that have no direct match to location names and, of course, there will be many, many places that do not match a park. The first two JOINs we did were "inner" JOINs — the output contains only rows that found a match. In this case, we want to keep all the parks, even if no places matched but we do not want to keep any places that lack a park. Since all rows from the left (first most dataset) will be retained, this is called a "left outer" JOIN. If, instead, we were trying to annotate all places with such parks as could be matched — producing exactly one output row per place — we would use a "right outer" `JOIN` instead. If we wanted to do the latter but (somewhat inefficiently) flag parks that failed to find a match, you would use a "full outer" JOIN. (Full JOINs are pretty rare.)

In a Pig `JOIN` it is important to order the tables by size — putting the smallest table first and the largest table last. (You'll learn why in the "Map/Reduce Patterns" (REF) chapter.) So while a right join is not terribly common in traditional SQL, it's quite valuable in Pig. If you look back at the previous examples, you will see we took care to always put the smaller table first. For small tables or tables of similar size, it is not a big deal — but in some cases, it can have a huge impact, so get in the habit of always following this best practice.

6. Please note that the `batting_hof` table excludes players admitted to the Hall of Fame based on their pitching record. With the exception of Babe Ruth — who would likely have made the Hall of Fame as a pitcher if he hadn't been the most dominant hitter of all time — most pitchers have very poor offensive skills and so are relegated back with the rest of the crowd

A Pig join is outwardly similar to the join portion of a SQL SELECT statement, but notice that although you can place simple expressions in the join expression, you can make no further manipulations to the data whatsoever in that statement. Pig's design philosophy is that each statement corresponds to a specific data transformation, making it very easy to reason about how the script will run; this makes the typical Pig script more long-winded than corresponding SQL statements but clearer for both human and robot to understand.

Pattern in Use

- *Where You'll Use It* — Any time only some records have matches but you want to preserve the whole. All products from the manufacturing line paired with each incident report about a product (keeping products with no incident report). All customers that took a test drive matched with the past cars they bought from you (but not discarding the new customer records)
- *Standard Snippet* — `FOREACH (JOIN aa BY key LEFT OUTER, bb BY key) GENERATE a::key..a::last_field,b::second_field...;`
- *Hello, SQL Users* — Right joins are much more common in Pig, because you want the table size to determine the order they're listed in
- *Important to Know* — Records with NULL keys are dropped even in an outer join
- *Output Count* — At least as many records as the `OUTER` table has, expanded by the number of ways to pair records from each table for a key. Like any join, output size can be explosively higher
- *Data Flow* — Pipelinable: it's composed onto the end of the preceding map or reduce, and if it stands alone becomes a map-only job.

Joining Tables that do not have a Foreign-Key Relationship

All of the joins we've done so far have been on nice clean values designed in advance to match records among tables. In SQL parlance, the career_stats and batting_hof tables both had player_id as a primary key (a column of unique, non-null values tied to each record's identity). The team_id field in the bat_seasons and park_team_years tables points into the teams table as a foreign key: an indexable column whose only values are primary keys in another table, and which may have nulls or duplicates. But sometimes you must match records among tables that do not have a polished mapping of values. In that case, it can be useful to use an outer join as the first pass to unify what records you can before you bring out the brass knuckles or big guns for what remains.

Suppose we wanted to plot where each major-league player grew up — perhaps as an answer in itself as a browsable map, or to allocate territories for talent scouts, or to see

whether the quiet wide spaces of country living or the fast competition of growing up in the city better fosters the future career of a high performer. While the people table lists the city, state and country of birth for most players, we must geolocate those place names — determine their longitude and latitude — in order to plot or analyze them.

There are geolocation services on the web, but they are imperfect, rate-limited and costly for commercial use [7]. Meanwhile the freely-available geonames database gives geocoordinates and other information on more than seven million points of interest across the globe, so for informal work it can make a lot of sense to opportunistically decorate whatever records match and then decide what to do with the rest.

```
geolocated_somewhat = JOIN
  people BY (birth_city, birth_state, birth_country),
  places BY (city, admin_1, country_id)
```

In the important sense, this worked quite well: XXX% of records found a match. (Question do we talk about the problems of multiple matches on name here, or do we quietly handle it?)

Experienced database hands might now suggest doing a join using some sort of fuzzy-match or some sort of other fuzzy equality. However, in map-reduce the only kind of join you can do is an "equi-join" — one that uses key equality to match records. Unless an operation is *transitive* — that is, unless `a joinsto b` and `b joinsto c` guarantees `a joinsto c`, a plain join won't work, which rules out approximate string matches; joins on range criteria (where keys are related through inequalities (x < y)); graph distance; geographic nearness; and edit distance. You also can't use a plain join on an *OR* condition: "match stadiums and places if the placename and state are equal or the city and state are equal", "match records if the postal code from table A matches any of the component zip codes of place B". Much of the middle part of this book centers on what to do when there *is* a clear way to group related records in context, but which is more complicated than key equality.

Exercise: are either city dwellers or country folk over-represented among major leaguers? Selecting only places with very high or very low population in the geonames table might serve as a sufficient measure of urban-ness; or you could use census data and the methods we cover in the geographic data analysis chapter to form a more nuanced indicator. The hard part will be to baseline the data for population: the question is how the urban vs rural proportion of ballplayers compares to the proportion of the general populace, but that distribution has changed dramatically over our period of interest. The US has seen a steady increase from a rural majority pre-1920 to a four-fifths majority of city dwellers today.

7. Put another way, "Accurate, cheap, fast: choose any two

Pattern in Use

- *Where You'll Use It* — Any time you're geolocating records, sure, but the lessons here hold any time you're combining messy data with canonical records
- *Hello, SQL Users* — No fuzzy matches, no string distance, no inequalities. There's no built-in `SOUNDEX` UDF, but that would be legal as it produces a scalar value to test with equality
- *Important to Know* — Watch out for an embarrassment of riches — there are many towns named "Springfield".

Joining on an Integer Table to Fill Holes in a List

In some cases you want to ensure that there is an output row for each potential value of a key. For example, a histogram of career hits will show that Pete Rose (4256 hits) and Ty Cobb (4189 hits) have so many more hits than the third-most player (Hank Aaron, 3771 hits) there are gaps in the output bins.

To fill the gaps, generate a list of all the potential keys, then generate your (possibly holey) result table, and do a join of the keys list (LEFT OUTER) with results. In some cases, this requires one job to enumerate the keys and a separate job to calculate the results. For our purposes here, we can simply use the integer table. (We told you it was surprisingly useful!)

If we prepare a histogram of career hits, similar to the one above for seasons, you'll find that Pete Rose (4256 hits) and Ty Cobb (4189 hits) have so many more hits than the third-most player (Hank Aaron, 3771 hits) there are gaps in the output bins. To make it so that every bin has an entry, do an outer join on the integer table. (See, we told you the integers table was surprisingly useful.)

```
-- SQL Equivalent:
SET @H_binsize = 10;
SELECT bin, H, IFNULL(n_H,0)
  FROM      (SELECT @H_binsize * idx AS bin FROM numbers WHERE idx <= 430) nums
  LEFT JOIN (SELECT @H_binsize*CEIL(H/@H_binsize) AS H, COUNT(*) AS n_H
    FROM bat_career bat GROUP BY H) hist
  ON hist.H = nums.bin
  ORDER BY bin DESC
;
```

Regular old histogram of career hits, bin size 100

```
H_vals = FOREACH (GROUP bat_seasons BY player_id) GENERATE
  100*ROUND(SUM(bat_seasons.H)/100.0) AS bin;
H_hist_0 = FOREACH (GROUP H_vals BY bin) GENERATE
  group AS bin, COUNT_STAR(H_vals) AS ct;
```

Generate a list of all the bins we want to keep, then perform a LEFT JOIN of bins with histogram counts. Missing rows will have a null ct value, which we can convert to zero.

```
H_bins = FOREACH (FILTER numbers_10k BY num0 <= 43) GENERATE 100*num0  AS bin;

H_hist = FOREACH (JOIN H_bins BY bin LEFT OUTER, H_hist_0 BY bin) GENERATE
  H_bins::bin,
  ct,                   -- leaves missing values as null
  (ct IS NULL ? 0 : ct)  -- converts missing values to zero
;
```

Pattern in Use

- *Where You'll Use It* — Whenever you know the values you want (whether they're integers, model numbers, dates, etc) and always want a corresponding row in the output table

Selecting Only Records That Lack a Match in Another Table (anti-join)

A common use of a JOIN is to perform an effective filter on a large number of values — the big brother of the pattern in section (REF). In this case (known as an *anti-join*), we don't want to keep the selection table around afterwards

```
-- Project just the fields we need
allstars_p  = FOREACH allstars GENERATE player_id, year_id;

-- An outer join of the two will leave both matches and non-matches.
scrub_seasons_jn = JOIN
  bat_seasons BY (player_id, year_id) LEFT OUTER,
  allstars_p  BY (player_id, year_id);

-- ...and the non-matches will have Nulls in all the allstars slots
scrub_seasons_jn_f = FILTER scrub_seasons_jn
  BY allstars_p::player_id IS NULL;
```

Once the matches have been eliminated, pick off the first table's fields. The double-colon in *bat_seasons::* makes clear which table's field we mean. The fieldname-ellipsis *bat_seasons::player_id..bat_seasons::RBI* selects all the fields in bat_seasons from player_id to RBI, which is to say all of them.

```
scrub_seasons_jn   = FOREACH scrub_seasons_jn_f
  GENERATE bat_seasons::player_id..bat_seasons::RBI;
```

Selecting Only Records That Posess a Match in Another Table (semi-join)

A semi-join is the counterpart to an anti-join: you want to find records that *do* have a match in another table, but not keep the fields from that table around.

Let's use the same example — player seasons where they made the all-star team — but only look for seasons that *were* all-stars. You might think you could do this with a join:

```
-- Don't do this... produces duplicates!
bats_g    = JOIN allstar BY (player_id, year_id), bats BY (player_id, year_id);
badness   = FOREACH bats_g GENERATE bats::player_id .. bats::HR;
```

The result is wrong, and even a diligent spot-check will probably fail to notice. You see, from 1959-1962 there were multiple All-Star games (!), and so players who appeared in both have two rows in the All-Star table. In turn, each singular row in the `bat_season` table became two rows in the result for players in those years. We've broken the contract of leaving the original table unchanged.

This is the biggest thing people coming from a SQL background need to change about their thinking. In SQL, the JOIN rules all. In Pig, GROUP and COGROUP rule the land, and nearly every other structural operation is some piece of syntactic sugar on top of those. So when going gets rough with a JOIN, remember that it's just a convenience and ask yourself whether a COGROUP would work better. In this case it does:

```
-- Players with no entry in the allstars_p table have an empty allstars_p bag
allstar_seasons_cg = COGROUP
  bat_seasons BY (player_id, year_id),
  allstars_p  BY (player_id, year_id);
```

Now select all cogrouped rows where there was an all-star record, and project just the records from the original table.

```
-- One row in the batting table => One row in the result
allstar_seasons = FOREACH
  (FILTER allstar_seasons_cg BY (COUNT_STAR(allstars_p) > 0L))
  GENERATE FLATTEN(bat_seasons);
```

The `JOIN` version was equivent to flattening both bags (`GENERATE FLATTEN(bat_seasons), FLATTEN(allstars_p)`) and then removing the fields we had just flattened. In the `COGROUP` version, neither the incorrect duplicate rows nor the unnecessary columns are created.

An Alternative to Anti-Join: use a COGROUP

As a lesson on the virtues of JOINs and COGROUPs, let's examine an alternate version of the anti-join introduced above (REF).

```
-- Players with no entry in the allstars_p table have an empty allstars_p bag
bats_ast_cg = COGROUP
  bat_seasons BY (player_id, year_id),
  allstars_p BY (player_id, year_id);
```

Select all cogrouped rows where there were no all-star records, and project the batting table fields.

```
scrub_seasons_cg = FOREACH
  (FILTER bats_ast_cg BY (COUNT_STAR(allstars_p) == 0L))
  GENERATE FLATTEN(bat_seasons);
```

There are three opportunities for optimization here. Though these tables are far to small to warrant optimization, it's a good teachable moment for when to (not) optimize.

- You'll notice that we projected off the extraneous fields from the allstars table before the map. Pig is sometimes smart enough to eliminate fields we don't need early. There's two ways to see if it did so. The surest way is to consult the tree that EXPLAIN produces. If you make the program use `allstars` and not `allstars_p`, you'll see that the extra fields are present. The other way is to look at how much data comes to the reducer with and without the projection. If there is less data using `allstars_p` than `allstars`, the explicit projection is required.
- The EXPLAIN output also shows that co-group version has a simpler map-reduce plan, raising the question of whether it's more performant.
- Usually we put the smaller table (allstars) on the right in a join or cogroup. However, although the allstars table is smaller, it has larger cardinality (barely): `(player_id, team_id)` is a primary key for the bat_seasons table. So the order is likely to be irrelevant.

But "more performant" or "possibly more performant" doesn't mean "use it instead".

Eliminating extra fields is almost always worth it, but the explicit projection means extra lines of code and it means an extra alias for the reader to understand. On the other hand, the explicit projection reassures the experienced reader that the projection is for-sure-no-doubt-about-it taking place. That's actually why we chose to be explicit here: we find that the more-complicated script gives the reader less to think about.

In contrast, any SQL user will immediately recognize the join formulation of this as an anti-join. Introducing a RIGHT OUTER join or choosing the cogroup version disrupts that familiarity. Choose the version you find most readable, and then find out if you care whether it's more performant; the simpler explain graph or the smaller left-hand join table *do not* necessarily imply a faster dataflow. For this particular shape of data, even at much larger scale we'd be surprised to learn that either of the latter two optimizations mattered.

CHAPTER 8

Analytic Patterns: Ordering Operations

Sorting All Records in Total Order

We're only going to look at players able to make solid contributions over several years, which we'll define as playing for five or more seasons and 2000 or more plate appearances (enough to show statistical significance), and a OPS of 0.650 (an acceptable-but-not-allstar level) or better.

Career Epochs.

```
career_epochs = FILTER career_epochs BY
  ((PA_all >= 2000) AND (n_seasons >= 5) AND (OPS_all >= 0.650));

career_young = ORDER career_epochs BY OPS_young DESC;
career_prime = ORDER career_epochs BY OPS_prime DESC;
career_older = ORDER career_epochs BY OPS_older DESC;
```

You'll spot Ted Williams (willite01) as one of the top three young players, top three prime players, and top three old players. Ted Williams was pretty awesome.

Sorting by Multiple Fields

Sorting on Multiple fields is as easy as adding them in order with commas. Sort by number of older seasons, breaking ties by number of prime seasons:

```
career_older = ORDER career_epochs
  BY n_older DESC, n_prime DESC;
```

Whereever reasonable, "stabilize" your sorts by adding enough columns to make the ordering unique. This ensures the output will remain the same from run to run, a best practice for testing and maintainability.

```
career_older = ORDER career_epochs
  BY n_older DESC, n_prime DESC, player_id ASC; -- makes sure that ties are always broken the same
```

Sorting on an Expression (You Can't)

Which players have aged the best — made the biggest leap in performance from their prime years to their older years? You might thing the following would work, but you cannot use an expression in an `ORDER..BY` statement:

```
by_diff_older = ORDER career_epochs BY (OPS_older-OPS_prime) DESC; -- fails!
```

Instead, generate a new field, sort on it, then project it away. Though it's cumbersome to type, there's no significant performance impact.

```
by_diff_older = FOREACH career_epochs
  GENERATE OPS_older - OPS_prime AS diff, player_id..;
by_diff_older = FOREACH (ORDER by_diff_older BY diff DESC, player_id)
  GENERATE player_id..;
```

If you browse through that table, you'll get a sense that current-era players seem to be over-represented. This is just a simple whiff of a question, but more nuanced analyses do show an increase in longevity of peak performance. Part of that is due to better training, nutrition, and medical care — and part of that is likely due to systemic abuse of performance-enhancing drugs.

Sorting Case-insensitive Strings

There's no intrinsic way to sort case-insensitive; instead, just force a lower-case field to sort on. We don't have an interesting table with mixed-case records in the baseball dataset, but most UNIX-based computers come with a dictionary in the `/usr/share` directory tree. Here's how to sort that ignoring case:

Case-insensitive Sort.

```
dict        = LOAD '/usr/share/dict/words' AS (word:chararray);
sortable    = FOREACH dict GENERATE LOWER(word) AS l_word, *;
dict_nocase = FOREACH (ORDER sortable BY l_word, word) GENERATE word;
dict_case   = ORDER dict BY word DESC;
```

Note that we sorted on `l_word` *and* `word`: this stabilizes the sort, ensuring that even though `Polish` and `polish` tie in case-insensitivity those ties will always be resolved the same way.

Dealing with Nulls When Sorting

When the sort field has nulls, Pig sorts them as least-most by default: they will appear as the first rows for `DESC` order and as the last rows for `ASC` order. To float Nulls to the front or back, project a dummy field having the favoritism you want to impose, and name it first in the `ORDER..BY` clause.

Handling Nulls When Sorting.

```
nulls_sort_demo = FOREACH career_epochs
  GENERATE (OPS_older IS NULL ? 0 : 1) AS has_older_epoch, player_id..;
nulls_then_vals = FOREACH (ORDER nulls_sort_demo BY
  has_older_epoch ASC,  OPS_all DESC, player_id)
  GENERATE player_id..;
vals_then_nulls = FOREACH (ORDER nulls_sort_demo BY
  has_older_epoch DESC, OPS_all DESC, player_id)
  GENERATE player_id..;
```

Floating Values to the Top or Bottom of the Sort Order

Use the dummy field trick any time you want to float records to the top or bottom of the sort order based on a criterion. This moves all players whose careers start in 1985 or later to the top, but otherwise sorts on number of older seasons:

Floating Values to the Top of the Sort Order.

```
post1985_vs_earlier = FOREACH career_epochs
  GENERATE (beg_year >= 1985 ? 1 : 0) AS is_1985, player_id..;
post1985_vs_earlier = FOREACH (ORDER post1985_vs_earlier BY is_1985 DESC, n_older DESC, player_id)
  GENERATE player_id..;
```

Pattern in Use

- *Standard Snippet* — `ORDER tbl BY mykey;`
- *Hello, SQL Users*
  - — Usually this is part of a `SELECT` statement; in Pig it stands alone
  - — You can't put an expression in the `BY` clause
- *Important to Know* — Pound-for-pound, unless followed by a `LIMIT` statement this is one of the most expensive operations you can perform, requiring two to three jobs and a full reduce
- *Output Count* — Unchanged
- *Records* — Unchanged
- *Data Flow* — Map-only on a sample of the data; Map and Reduce to perform the sort. In some cases, if Pig isn't confident that it will sample correctly, an extra Map-only to perform the pipelinable operations before the sample

Sorting Records within a Group

This operation is straightforward enough and so useful we've been applying it all this chapter, but it's time to be properly introduced and clarify a couple points.

Sort records within a group using ORDER BY within a nested FOREACH. Here's a snippet to list the top four players for each team-season, in decreasing order by plate appearances.

```
players_PA = FOREACH bat_seasons GENERATE team_id, year_id, player_id, name_first, name_last, PA;
team_playerslist_by_PA = FOREACH (GROUP players_PA BY (team_id, year_id)) {
  players_o_1 = ORDER players_PA BY PA DESC, player_id;
  players_o = LIMIT players_o_1 4;
  GENERATE group.team_id, group.year_id,
    players_o.(player_id, name_first, name_last, PA) AS players_o;
};
```

Ordering a group in the nested block immediately following a structural operation does not require extra operations, since Pig is able to simply specify those fields as secondary sort keys. Basically, as long as it happens first in the reduce operation it's free (though if you're nervous, look for the line "Secondary sort: true" in the output of EXPLAIN). Messing with a bag before the `ORDER..BY` causes Pig to instead sort it in-memory using quicksort, but will not cause another map-reduce job. That's good news unless some bags are so huge they challenge available RAM or CPU, which won't be subtle.

If you depend on having a certain sorting, specify it explicitly, even when you notice that a `GROUP..BY` or some other operation seems to leave it in that desired order. It gives a valuable signal to anyone reading your code, and a necessary defense against some future optimization deranging that order [1]

Once sorted, the bag's order is preserved by projections, by most functions that iterate over a bag, and by the nested pipeline operations FILTER, FOREACH, and LIMIT. The return values of nested structural operations CROSS, ORDER..BY and DISTINCT do not follow the same order as their input; neither do structural functions such as CountEach (in-bag histogram) or the set operations (REF) described at the end of the chapter. (Note that though their outputs are dis-arranged these of course don't mess with the order of their inputs: everything in Pig is immutable once created.)

```
team_playerslist_by_PA_2 = FOREACH team_playerslist_by_PA {
  -- will not have same order, even though contents will be identical
  disordered    = DISTINCT players_o;
  -- this ORDER BY does _not_ come for free, though it's not terribly costly
  alt_order     = ORDER players_o BY player_id;
  -- these are all iterative and so will share the same order of descending PA
  still_ordered = FILTER players_o BY PA > 10;
  pa_only       = players_o.PA;
  pretty        = FOREACH players_o GENERATE
    CONCAT((chararray)PA, ':', name_first, ' ', name_last);
  GENERATE team_id, year_id,
    disordered, alt_order,
```

1. That's not too hypothetical: there are cases where you could more efficiently group by binning the items directly in a Map rather than sorting

```
    still_ordered, pa_only, BagToString(pretty, '|');
};
```

The lines *Global sort: false // Secondary sort: true* in the explain output indicate that pig is indeed relying on the free secondary sort, rather than quicksorting the bag itself in the reducer.

Pattern in Use

- *Where You'll Use It* — Extracting top records from a group (see next). Preceding many UDFs that depend on ordering. To make your output readable. To stabilize results.
- *Hello, SQL Users* — This is not directly analogous to the `ORDER BY` part of a `SELECT` statement, as it is done to the inner bag. For users of Oracle and other databases, this is similar to a sort within a windowed query.
- *Important to Know* — If it can be applied to the records coming from the mapper, it's free. Verify by looking for `Secondary sort: true` in the output of `EXPLAIN`
- *Output Count* — Unchanged
- *Records* — Unchanged

Select Rows with the Top-K Values for a Field

On its own, `LIMIT` will return the first records it finds. What if you want to *rank* the records — sort by some criteria — so you don't just return the first ones, but the *top* ones?

Use the `ORDER` operator before a `LIMIT` to guarantee this "top *K*" ordering. This technique also applies a clever optimization (reservoir sampling, see TODO ref) that sharply limits the amount of data sent to the reducers.

Let's say you wanted to select the top 20 seasons by number of hits:

```
TODO: Pig code
```

In SQL, this would be:

```
SELECT H FROM bat_season WHERE PA > 60 AND year_id > 1900 ORDER BY H  DESC LIMIT 10
```

There are two useful optimizations to make when the number of records you will keep (*K*) is much smaller than the number of records in the table (*N*). The first one, which Pig does for you, is to only retain the top K records at each Mapper; this is a great demonstration of where a Combiner is useful: After each intermediate merge/sort on the Map side and the Reduce side, the Combiner discards all but the top K records.

We've cheated on the theme of this chapter (pipeline-only operations) — sharp eyes will note that `ORDER … LIMIT` will in fact trigger a reduce operation. We still feel that top-*K* belongs with the other data elimination pattern, though, so we've included it here.

Finding Records Associated with Maximum Values

For each player, find their best significant season by OPS:

```
  -- For each season by a player, select the team they played the most games for.
  -- In SQL, this is fairly clumsy (involving a self-join and then elimination of
  -- ties) In Pig, we can ORDER BY within a foreach and then pluck the first
  -- element of the bag.

SELECT bat.player_id, bat.year_id, bat.team_id, MAX(batmax.Gmax), MAX(batmax.stints), MAX(team_ids
  FROM       batting bat
  INNER JOIN (SELECT player_id, year_id, COUNT(*) AS stints, MAX(G) AS Gmax, GROUP_CONCAT(team_id)
  ON bat.player_id = batmax.player_id AND bat.year_id = batmax.year_id AND bat.G = batmax.Gmax
  GROUP BY player_id, year_id
  -- WHERE stints > 1
  ;

  -- About 7% of seasons have more than one stint; only about 2% of seasons have
  -- more than one stint and more than a half-season's worth of games
SELECT COUNT(*), SUM(mt1stint), SUM(mt1stint)/COUNT(*) FROM (SELECT player_id, year_id, IF(COUNT(*
```

TOP(topN, sort_column_idx, bag_of_tuples) must have an explicit field — can't use an expression

Leaderboard By Season-and-league

GROUP BY year_id, lg_id

There is no good way to find the tuples associated with the minimum value. EXERCISE: make a "BTM" UDF, having the same signature as the "TOP" operation, to return the lowest-n tuples from a bag.

Top K Records within a table using ORDER..LIMIT

Most hr in a season Describe pigs optimization of order..limit

- Pulling a Section from the Middle of a Result Set: rank and filter? Modify the quantile/median code?
- Hard in SQL but easy in Pig: Finding Rows Containing Per-Group Minimum or Maximum Value, Displaying One Set of Values While Sorting by Another: - can only ORDER BY an explicit field. In SQL you can omit the sort expression from the table (use expression to sort by)

- Sorting a Result Set (when can you count on reducer order?)

Shuffle a set of records

To shuffle a set of records, we're going to apply the *Assign a unique ID* pattern to generate an arbitrary key (one that is decoupled from the records' content), and then use that to order the records.

```
DEFINE Hasher datafu.pig.hash.Hasher('sip24-32', 'rand');

vals = LOAD '$rawd/geo/census/us_city_pops.tsv' USING PigStorage('\t', '-tagSplit')
  AS (split_info:chararray, city:chararray, state:chararray, pop:int);

vals_rk = RANK vals;
vals_ided = FOREACH vals_rk {
  line_info = CONCAT((chararray)split_info, '#', (chararray)rank_vals);
  GENERATE Hasher((chararray)line_info) AS rand_id, *; -- $2..;
  };

vals_shuffled = FOREACH (ORDER vals_ided BY rand_id) GENERATE $1..;
DESCRIBE vals_shuffled;

STORE_TABLE('vals_shuffled', vals_shuffled);
```

This follows the general plot of *Assign a Unique ID*: enable a hash function UDF; load the files so that each input split has a stable handle; and number each line within the split. The important difference here is that the hash function we generated accepts a seed that we can mix in to each record. If you supply a constant to the constructor (see the documentation) then the records will be put into an effectively random order, but the same random order each time. By supplying the string `'rand'` as the argument, the UDF will use a different seed on each run. What's nice about this approach is that although the ordering is different from run to run, it does not exhibit the anti-pattern of changing from task attempt to task attempt. The seed is generated once and then used everywhere. Rather than creating a new random number for each row, you use the hash to define an effectively random ordering, and the seed to choose which random ordering to apply.

CHAPTER 9

Analytic Patterns: Finding Duplicate and Unique Records

Handling Duplicates

Eliminating Duplicate Records from a Table

The park_teams table has a row for every season. To find every distinct pair of team and home ballpark, use the DISTINCT operator. This is equivalent to the SQL statement `SELECT DISTINCT player_id, team_id from batting;`.

```
tm_pk_pairs_many = FOREACH park_teams GENERATE team_id, park_id;
tm_pk_pairs = DISTINCT tm_pk_pairs_many;
-- -- ALT     ALT01
-- -- ANA     ANA01
-- -- ARI     PHO01
-- -- ATL     ATL01
-- -- ATL     ATL02
```

Don't fall in the trap of using a GROUP statement to find distinct values:

```
dont_do_this = FOREACH (GROUP tm_pk_pairs_many BY (team_id, park_id)) GENERATE
  group.team_id, group.park_id;
```

The DISTINCT operation is able to use a combiner, eliminating duplicates at the mapper before shipping them to the reducer. This is a big win when there are frequent duplicates, especially if duplicates are likely to occur near each other. For example, duplicates in web logs (from refreshes, callbacks, etc) will be sparse globally, but found often in the same log file.

The combiner may impose a minor penalty when there are very few or very sparse duplicates. In that case, you should still use DISTINCT, but disable combiners with the `pig.exec.nocombiner=true` setting.

Eliminating Duplicate Records from a Group

Eliminate duplicates from a group with the DISTINCT operator inside a nested foreach. Instead of finding every distinct (team, home ballpark) pair as we just did, let's find the list of distinct home ballparks for each team:

```
team_parkslist = FOREACH (GROUP park_teams BY team_id) {
  parks = DISTINCT park_teams.park_id;
  GENERATE group AS team_id, BagToString(parks, '|');
};

EXPLAIN team_parkslist;

-- -- CL1     CHI02|CIN01|CLE01
-- -- CL2     CLE02
-- -- CL3     CLE03|CLE09|GEA01|NEW03
-- -- CL4     CHI08|CLE03|CLE05|CLL01|DET01|IND06|PHI09|ROC02|ROC03|STL05

SELECT team_id, GROUP_CONCAT(DISTINCT park_id ORDER BY park_id) AS park_ids
  FROM park_team_years
  GROUP BY team_id
  ORDER BY team_id, park_id DESC
  ;
```

Eliminating All But One Duplicate Based on a Key

The DataFu `DistinctBy` UDF selects a single record for each key in a bag.

It has the nice feature of being order-preserving: only the first record for a key is output, and all records that make it to the output follow the same relative ordering they had in the input bag,

This gives us a clean way to retrieve the distinct teams a player served in, along with the first and last year of their tenure:define DistinctBy

```
DEFINE DistinctByYear datafu.pig.bags.DistinctBy('0');

pltmyrs = FOREACH bat_seasons GENERATE player_id, year_id, team_id;
player_teams = FOREACH (GROUP pltmyrs BY player_id) {
  -- TODO does this use secondary sort, or cause a POSort?
  pltmyrs_o = ORDER pltmyrs.(team_id, year_id) BY team_id;
  pltmyrs = DistinctByYear(pltmyrs);
  GENERATE player_id, BagToString(pltmyrs, '|');
};
```

The key is specified with a string argument in the DEFINE statement, naming the positional index(es) of the key's fields as a comma-separated list.

Selecting Records with Unique (or with Duplicate) Values for a Key

The DISTINCT operation is useful when you want to eliminate duplicates based on the whole record. But to instead find only rows having a unique record for its key, or to find only rows having multiple records for its key, do a GROUP BY and then filter on the size of the resulting bag.

On a broadcast a couple years ago, announcer Tim McCarver paused from his regular delivery of the obvious and the officious to note that second baseman Asdrubal Cabrera "is the only player in the majors with that first name". This raises the question: how many other people in the history of baseball similarly are uniquely yclept [1]? Let's create a table for the biography site awarding players the "Asdrubal" badge if they are the only one in possession of their first name.

```
uniquely_yclept_g = GROUP   people BY name_first;
uniquely_yclept_f = FILTER  uniquely_yclept_g BY COUNT_STAR(people) == 1;
uniquely_yclept   = FOREACH uniquely_yclept_f GENERATE
  group AS name_first,
  FLATTEN(people.(name_last, player_id, beg_date, end_date));
```

This approach should be getting familiar. We group on the key (name_first) and eliminate all rows posessing more than one record for the key. Since there is only one element in the bag, the `FLATTEN` statement just acts to push the bag's fields up into the record itself.

There are some amazing names in this list. You might be familiar with Honus Wagner, Eppa Rixey, Boog Powell or Yogi Berra, some of the more famous in the list. But have you heard recounted the diamond exploits of Firpo Mayberry, Zoilo Versalles, Pi Schwert or Bevo LeBourveau? Mul Holland, Sixto Lezcano, Welcome Gaston and Mox McQuery are names that really should come attached to a film noir detective; the villains could choose among Mysterious Walker, The Only Nolan, or Phenomenal Smith for their name. For a good night's sleep on the couch, tell your spouse that your next child must be named for Urban Shocker, Twink Twining, Pussy Tebeau, Bris Lord, Boob Fowler, Crazy Schmit, Creepy Crespi, Cuddles Marshall, Vinegar Bend Mizell, or Buttercup Dickerson.

Set Operations

Set operations — intersection, union, set difference and so forth — are a valuable strategic formulation for the structural operations we've been learning. In terms of set operations, "Which users both clicked on ad for shirts and bought a shirt?" becomes "find the intersection of shirt-ad-clickers set with the shirt-buyers set". "What patients either were ill but did not test positive, or tested positive but were not ill?" becomes "find the

1. yclept /iklept/: by the name of; called.

symmetric difference of the actually-ill patients and the tested-positive patients". The relational logic that powers traditional database engines is, at its core, the algebra of sets. We've actually met many of the set operations in certain alternate guises, but set operations are so important it's worth calling them out specifically.

When we say *set*, we mean an unordered collection of distinct elements. Those elements could be full records, or they could be key fields in a record — allowing us to intersect the shirt-ad-clickers and the shirt-buyers while carrying along information about the ad they clicked on and the shirt they bought.

In the next several sections, you'll learn how to combine sets in the following ways:

- *Distinct Union* (`A  B`) — all distinct elements that are in *A* or in *B*.
- *Set Intersection* (`A  B`) — all distinct elements that are in *A* and also in *B*.
- *Set Difference* (`A - B`) — all distinct elements that are in *A* but are *not* in *B*.
- *Symmetric Difference* (`a ^ b`) — all distinct elements that are in *A* or in *B* but not both. Put another way, it's all distinct elements that are in *A* but not *B* as well as all distinct elements that are in *B* but not *A*.
- *Set Equality* (`A == B`) — every element in *A* is also in *B*. The result of the set equality operation is a boolean true or false, as opposed to a set as in the above operations.

The following table may help. The rows correspond to the kind of elements that are in both A and B; A but not B; and B but not A. Under the column for each operator, only the kinds of elements marked *T* will be present in the result.

Set Operation Membership.

```
                        Union   Inters  Diff    Diff    Sym.Diff
          A       B     AB   AB   a-b     b-a     a^b
A B       T       T      T       T       -       -       -
A -       T       -      T       -       T       -       T
- B       -       T      T       -       -       T       T
```

The mechanics of working with sets depends on whether the set elements are represented as records in a bag or as rows in a full table. Set operations on bags are particularly straightforward thanks to the purpose-built UDFs in the Datafu package. Set operations on tables are done using a certain `COGROUP`-and-`FILTER` combination — wordier, but no more difficult. Let's start with the patterns that implement set operations on full tables.

Set Operations on Full Tables

To demonstrate full-table set operations, we can relate the set of major US cities [2] with the set of US cities that have hosted a significant number (more than 50) of major-league games. To prove a point about set operations with duplicates, we will leave in the duplicates from the team cities (the Mets and Yankees both claim NY).

Preparation for Set Operations on Full Tables.

```
parks        = load_parks();
main_parks   = FILTER parks BY n_games >=  50 AND country_id == 'US';
major_cities = load_us_city_pops();
--
bball_city_names = FOREACH main_parks   GENERATE city;
major_city_names = FOREACH major_cities GENERATE city;
```

Distinct Union

If the only contents of the tables are the set membership keys, finding the distinct union is done how it sounds: apply union, then distinct.

```
major_or_bball    = DISTINCT (UNION bball_city_names, major_city_names);
```

Distinct Union (alternative method)

For all the other set operations, or when the elements are keys within a record (rather than the full record), we will use some variation on a COGROUP to generate the result.

```
combined     = COGROUP major_cities BY city, main_parks BY city;

major_or_parks    = FOREACH combined GENERATE
  group AS city,
  FLATTEN(FirstTupleFromBag(major_cities.(state, pop_2011), ((chararray)NULL,(int)NULL))),
  main_parks.park_id AS park_ids;
```

The DataFu `FirstTupleFromBag` UDF is immensely simplifying. Since the city value is a unique key for the `major_cities` table, we know that the `major_cities` bag has only a single element. Applying `FirstTupleFromBag` turns the bag-of-one-tuple into a tuple-of-two-fields, and applying `FLATTEN` lifts the tuple-of-two-fields into top-level fields for state and for population. When the `city` key has no match in the `major_cities` table, the second argument to FirstTupleFromBag forces those fields to have `NULL` values.

As we mentioned, there are potentially many park records for each city, and so the main_parks bag can have zero, one or many records. Above, we keep the list of parks around as a single field.

2. We'll take "major city" to mean one of the top 60 incorporated places in the United States or Puerto Rico; see the "Overview of Datasets" (REF) for source information

Set Intersection

Records lie in the set intersection when neither bag is empty.

```
major_and_parks_f = FILTER combined BY
  (COUNT_STAR(major_cities) > 0L) AND (COUNT_STAR(main_parks) > 0L);
major_and_parks   = FOREACH major_and_parks_f GENERATE
  group AS city,
  FLATTEN(FirstTupleFromBag(major_cities.(state, pop_2011), ((chararray)NULL,(int)NULL))),
  main_parks.park_id AS park_ids;
```

Two notes. First, we test against `COUNT_STAR(bag)`, and not `SIZE(bag)` or `IsEmpty(bag)`. Those latter two require actually materializing the bag — all the data is sent to the reducer, and no combiners can be used. Second, since COUNT_STAR returns a value of type long, it's best to do the comparison against `0L` (a long) and not `0` (an int).

Set Difference

Records lie in A minus B when the second bag is empty, and they lie in B minus A when the first bag is empty.

```
major_minus_parks_f = FILTER combined BY (COUNT_STAR(main_parks) == 0L);
major_minus_parks   = FOREACH major_minus_parks_f GENERATE
  group AS city,
  FLATTEN(FirstTupleFromBag(major_cities.(state, pop_2011), ((chararray)NULL,(int)NULL))),
  main_parks.park_id AS park_ids;

parks_minus_major_f = FILTER combined BY (COUNT_STAR(major_cities) == 0L);
parks_minus_major   = FOREACH parks_minus_major_f GENERATE
  group AS city,
  FLATTEN(FirstTupleFromBag(major_cities.(state, pop_2011), ((chararray)NULL,(int)NULL))),
  main_parks.park_id AS park_ids;
```

Symmetric Set Difference: (A-B)+(B-A)

Records lie in the symmetric difference when one or the other bag is empty. (We don't have to test for them both being empty — there wouldn't be a row if that were the case.)

```
major_xor_parks_f   = FILTER combined BY
  (COUNT_STAR(major_cities) == 0L) OR (COUNT_STAR(main_parks) == 0L);

major_xor_parks     = FOREACH major_xor_parks_f GENERATE
  group AS city,
  FLATTEN(FirstTupleFromBag(major_cities.(state, pop_2011), ((chararray)NULL,(int)NULL))),
  main_parks.park_id AS park_ids;
```

Set Equality

Set Equality indicates whether the elements of each set are identical — here, would tell us whether the set of keys in the major_cities table and the set of keys in the main_parks table were identical.

There are several ways to determine full-table set equality, but likely the most efficient is to see whether the two sets' symmetric difference is empty. An empty symmetric difference implies that every element of *A* is in *B*, and that every element of *B* is in *A* — which is exactly what it means for two sets to be equal.

Properly testing whether a table is empty so is a bit more fiddly than you'd think. To illustrate the problem, first whip up a set that should compare as equal to the `major_cities` table, run the symmetric difference stanza from above, and then test whether the table is empty:

```
major_city_names_also = FOREACH major_cities GENERATE city;
major_xor_major = FILTER
  (COGROUP major_city_names BY city, major_city_names_also BY city)
  BY ((COUNT_STAR(major_city_names) == 0L) OR (COUNT_STAR(major_city_names_also) == 0L));

-- Does not work
major_equals_major_fail = FOREACH (GROUP major_xor_major ALL) GENERATE
   (COUNT_STAR(major_xor_major) == 0L ? 1 : 0) AS is_equal;
```

The last statement of the code block attempts to measure whether the count of records in `major_xor_major` is zero. And if the two tables were unequal, this would have worked. But `major_xor_major` is empty and so *the FOREACH has no lines to operate on*. The output file is not a `1` as you'd expect, it's an empty file.

Our integer table to the rescue! Actually we'll use her baby brother *one_line.tsv*: it has one record, with fields uno (value `1`) and zilch (value `0`). Instead of a `GROUP..ALL`, do a COGROUP of one_line on a constant value `1`. Since there is exactly one possible value for the group key, there will be exactly one row in the output.

```
one_line = LOAD '$data_dir/stats/numbers/one_line.tsv' AS (uno:int, zilch:int);

-- will be `1` (true)
major_equals_major = FOREACH (COGROUP one_line BY 1, major_xor_major BY 1)
  GENERATE (COUNT_STAR(major_xor_major) == 0L ? 1 : 0) AS is_equal;

-- will be `0` (false)
major_equals_parks = FOREACH (COGROUP one_line BY 1, major_xor_parks BY 1)
  GENERATE (COUNT_STAR(major_xor_parks) == 0L ? 1 : 0) AS is_equal;
```

TODO: clean up transition to set ops on groups

To demonstrate set operations on grouped records, let's look at the year-to-year churn of mainstay players [3] on each team.

Other applications of the procedure we follow here would include analyzing how the top-10 products on a website change over time, or identifying sensors that report values over threshold in N consecutive hours (by using an N-way COGROUP).

Constructing a Sequence of Sets

To construct a sequence of sets, perform a self-cogroup that collects the elements from each sequence key into one bag and the elements from the next key into another bag. Here, we group together the roster of players for a team's season (that is, players with a particular `team_id` and `year_id`) together with the roster of players from the following season (players with the same `team_id` and the subsequent `year_id`).

Since it's a self-cogroup, we must do a dummy projection to make new aliases (see the earlier section on self-join for details).

```
y1 = FOREACH sig_seasons GENERATE player_id, team_id, year_id;
y2 = FOREACH sig_seasons GENERATE player_id, team_id, year_id;

-- Put each team of players in context with the next year's team of players
year_to_year_players = COGROUP
  y1 BY (team_id, year_id),
  y2 BY (team_id, year_id-1)
  ;
-- Clear away the grouped-on fields
rosters = FOREACH year_to_year_players GENERATE
  group.team_id AS team_id,
  group.year_id AS year_id,
  y1.player_id  AS pl1,
  y2.player_id  AS pl2
  ;
-- The first and last years of existence don't have anything interesting to compare, so reject the
rosters = FILTER rosters BY (COUNT_STAR(pl1) == 0L OR COUNT_STAR(pl2) == 0L);
```

Set Operations Within a Group

The content of `rosters` is a table with two key columns: team and year; and two bags: the set of players from that year and the set of players from the following year.

Applying the set operations lets us describe the evolution of the team from year to year.

```
roster_changes_y2y = FOREACH rosters {
  -- Distinct Union (doesn't need pre-sorting)
  either_year  = SetUnion(pl1, pl2);
  -- The other operations require sorted bags.
```

3. using our definition of a significant season: post-1900 and 450 or more plate appearances

```
    pl1_o = ORDER pl1 BY player_id;
    pl2_o = ORDER pl2 BY player_id;

    -- Set Intersection
    stayed      = SetIntersect(pl1_o, pl2_o);
    -- Set Difference
    y1_departed = SetDifference(pl1_o, pl2_o);
    y2_arrived  = SetDifference(pl2_o, pl1_o);
    -- Symmetric Difference
    non_stayed  = DIFF(y1_departed, y2_arrived);
    -- Set Equality
    is_equal    = ( (COUNT_STAR(non_stayed) == 0L) ? 1 : 0);

    GENERATE year_id, team_id,
      either_year, stayed, y1_departed, y2_arrived, non_stayed, is_equal;
};
```

The Distinct Union (A union B, which we'll find using the DataFu `SetUnion` UDF) describes players on the roster in either year of our two-year span.

```
    either_year  = SetUnion(pl1, pl2);
```

All the DataFu set operations here tolerate inputs containing duplicates, and all of them return bags that contain no duplicates. They also each accept two or more bags, enabling you to track sequences longer than two adjacent elements.

As opposed to SetUnion, the other set operations require sorted inputs. That's not as big a deal as if we were operating on a full table, since a nested ORDER BY makes use of Hadoop's secondary sort. As long as the input and output bags fit efficiently in memory, these operations are efficient.

```
    pl1_o = ORDER pl1 BY player_id;
    pl2_o = ORDER pl2 BY player_id;
```

The Set Intersection (A intersect B, which we'll find using the DataFu SetIntersect UDF) describes the players that played in the first year and also stayed to play in the second year.

```
    stayed      = SetIntersect(pl1_o, pl2_o);
```

The Set Difference (A minus B, using the SetDifference UDF) contains the elements in the first bag that are not present in the remaining bags. The first line therefore describes players that did *not* stay for the next year, and the second describes players that newly arrived in the next year.

```
    y1_departed = SetDifference(pl1_o, pl2_o);
    y2_arrived  = SetDifference(pl2_o, pl1_o);
```

The Symmetric Difference contains all elements that are in one set or the other but not both. You can find this using either `(A minus B) union (B minus A)` — players who either departed after the first year or newly arrived in the next year — or `((A union B)`

`minus (A intersect B))` — players who were present in either season but not both seasons.

```
non_stayed  = SetUnion(y1_departed, y2_arrived);
```

Set Equality indicates whether the elements of each set are identical — here, it selects seasons where the core set of players remained the same. There's no direct function for set equality, but you can repurpose any of the set operations to serve.

If A and B each have no duplicate records, then A and B are equal if and only if

- `size(A) == size(B) AND size(A union B) == size(A)`
- `size(A) == size(B) AND size(A intersect B) == size(A)`
- `size(A) == size(B) AND size(A minus B) == 0`
- `size(symmetric difference(A,B)) == 0`

For multiple sets of distinct elements, `A, B, C...` are equal if and only if all the sets and their intersection have the same size: `size(intersect(A,B,C,...)) == size(A) == size(B) == size(C) == ...`

If you're already calculating one of the functions, use the test that reuses its result. Otherwise, prefer the A minus B test if most rows will have equal sets, and the A intersect B test if most will not or if there are multiple sets.

```
is_equal    = ( (COUNT_STAR(non_stayed) == 0L) ? 1 : 0);
```

PART III

Strategy: Practical Data Explorations