

Big Data Processing Made Easy

Balaswamy Vaddeman



Beginning Apache Pig

Big Data Processing Made Easy



Balaswamy Vaddeman

Apress[®]

Beginning Apache Pig: Big Data Processing Made Easy

Balaswamy Vaddeman Hyderabad, Andhra Pradesh, India

ISBN-13 (pbk): 978-1-4842-2336-9

ISBN-13 (electronic): 978-1-4842-2337-6

DOI 10.1007/978-1-4842-2337-6

Library of Congress Control Number: 2016961514

Copyright © 2016 by Balaswamy Vaddeman

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

Trademarked names, logos, and images may appear in this book. Rather than use a trademark symbol with every occurrence of a trademarked name, logo, or image we use the names, logos, and images only in an editorial fashion and to the benefit of the trademark owner, with no intention of infringement of the trademark.

The use in this publication of trade names, trademarks, service marks, and similar terms, even if they are not identified as such, is not to be taken as an expression of opinion as to whether or not they are subject to proprietary rights.

While the advice and information in this book are believed to be true and accurate at the date of publication, neither the authors nor the editors nor the publisher can accept any legal responsibility for any errors or omissions that may be made. The publisher makes no warranty, express or implied, with respect to the material contained herein.

Managing Director: Welmoed Spahr Lead Editor: Celestin Suresh John Technical Reviewer: Manoj R. Patil Editorial Board: Steve Anglin, Pramila Balan, Laura Berendson, Aaron Black, Louise Corrigan, Jonathan Gennick, Robert Hutchinson, Celestin Suresh John, Nikhil Karkal, James Markham, Susan McDermott, Matthew Moodie, Natalie Pao, Gwenan Spearing Coordinating Editor: Prachi Mehta Copy Editor: Kim Wimpsett Compositor: SPi Global Indexer: SPi Global Artist: SPi Global

Distributed to the book trade worldwide by Springer Science+Business Media New York, 233 Spring Street, 6th Floor, New York, NY 10013. Phone 1-800-SPRINGER, fax (201) 348-4505, e-mail orders-ny@springer-sbm.com, or visit www.springeronline.com. Apress Media, LLC is a California LLC and the sole member (owner) is Springer Science + Business Media Finance Inc (SSBM Finance Inc). SSBM Finance Inc is a **Delaware** corporation.

For information on translations, please e-mail rights@apress.com, or visit www.apress.com.

Apress and friends of ED books may be purchased in bulk for academic, corporate, or promotional use. eBook versions and licenses are also available for most titles. For more information, reference our Special Bulk Sales–eBook Licensing web page at www.apress.com/bulk-sales.

Any source code or other supplementary materials referenced by the author in this text are available to readers at www.apress.com. For detailed information about how to locate your book's source code, go to www.apress.com/source-code/. Readers can also access source code at SpringerLink in the Supplementary Material section for each chapter.

Printed on acid-free paper

The six most important people in my life: The late Kammari Rangaswamy (Teacher) The late Niranjanamma (Mother) Devaiah (Father) Radha (Wife) Sai Nirupam (Son) Nitya Maithreyi (Daughter)

Contents at a Glance

About the Author	xix
About the Technical Reviewer	xxi
Acknowledgments	xxiii
Chapter 1: MapReduce and Its Abstractions	1
Chapter 2: Data Types	21
Chapter 3: Grunt	33
Chapter 4: Pig Latin Fundamentals	41
Chapter 5: Joins and Functions	69
Chapter 6: Creating and Scheduling Workflows Using Apache Oozie	
Chapter 7: HCatalog	103
Chapter 8: Pig Latin in Hue	115
Chapter 9: Pig Latin Scripts in Apache Falcon	123
Chapter 10: Macros	137
Chapter 11: User-Defined Functions	147
Chapter 12: Writing Eval Functions	157
Chapter 13: Writing Load and Store Functions	171
Chapter 14: Troubleshooting	187
Chapter 15: Data Formats	201

Chapter 16: Optimization	209
Chapter 17: Hadoop Ecosystem Tools	225
Appendix A: Built-in Functions	249
Appendix B: Apache Pig in Apache Ambari	257
Appendix C: HBaseStorage and ORCStorage Options	261
Index	265

Contents

About the Author	xix
About the Technical Reviewer	xxi
Acknowledgments	xxiii
Chapter 1: MapReduce and Its Abstractions	1
Small Data Processing	
Relational Database Management Systems	3
Data Warehouse Systems	3
Parallel Computing	4
GFS and MapReduce	4
Apache Hadoop	4
Problems with MapReduce	
Cascading	13
Apache Hive	
Apache Pig	
Summary	
Chapter 2: Data Types	21
Simple Data Types	
int	
long	22
float	22
double	23
chararray	23

boolean	23
bytearray	23
datetime	23
biginteger	24
bigdecimal	24
Summary of Simple Data Types	24
Complex Data Types	24
map	25
tuple	26
bag	26
Summary of Complex Data Types	27
Schema	28
Casting	28
Casting Error	29
Comparison Operators	29
Identifiers	30
Boolean Operators	31
Summary	31
Chapter 3: Grunt	
Invoking the Grunt Shell	
Commands	
The fs Command	
The sh Command	
Utility Commands	
-	
help history	
quit	
•	
kill	37

set	37
clear	
exec	
run	
Summary of Commands	39
Auto-completion	40
Summary	40
Chapter 4: Pig Latin Fundamentals	
Running Pig Latin Code	
Grunt Shell	
Pig -e	42
Pig -f	42
Embed Pig Code in a Java Program	42
Ние	44
Pig Operators and Commands	44
Load	45
store	47
dump	48
version	48
Foreach Generate	48
filter	50
Limit	51
Assert	51
SPLIT	52
SAMPLE	53
FLATTEN	53
import	54
define	
distinct	55

CONTENTS

RANK	
Union	
ORDER BY	
GROUP	
Stream	61
MAPREDUCE	
CUBE	
Parameter Substitution	65
-param	65
-paramfile	
Summary	67
Chapter 5: Joins and Functions	69
Join Operators	70
Equi Joins	
cogroup	72
CROSS	73
Functions	74
String Functions	74
Mathematical Functions	
Date Functions	
EVAL Functions	
Complex Data Type Functions	
Load/Store Functions	
Summary	87
Chapter 6: Creating and Scheduling Workflows Using	
Apache Oozie	89
Types of Oozie Jobs	89
Workflow	

Using a Pig Latin Script as Part of a Workflow	91
Writing job.properties	91
workflow.xml	91
Uploading Files to HDFS	93
Submit the Oozie Workflow	93
Scheduling a Pig Script	
Writing the job.properties File	94
Writing coordinator.xml	94
Upload Files to HDFS	96
Submitting Coordinator	96
Bundle	
oozie pig Command	
Command-Line Interface	
Job Submitting, Running, and Suspending	98
Killing Job	98
Retrieving Logs	98
Information About a Job	98
Oozie User Interface	
Developing Oozie Applications Using Hue	100
Summary	100
Chapter 7: HCatalog	103
Features of HCatalog	103
Command-Line Interface	
show Command	
Data Definition Language Commands	
dfs and set Commands	

WebHCatalog	107
Executing Pig Latin Code	108
Running a Pig Latin Script from a File	108
HCatLoader Example	109
Writing the Job Status to a Directory	
HCatLoader and HCatStorer	110
Reading Data from HCatalog	110
Writing Data to HCatalog	110
Running Code	111
Data Type Mapping	112
Summary	113
Chapter 8: Pig Latin in Hue	115
Pig Module	115
My Scripts	116
Pig Helper	117
Auto-suggestion	117
UDF Usage in Script	118
Query History	118
File Browser	119
Job Browser	121
Summary	122
Chapter 9: Pig Latin Scripts in Apache Falcon	123
cluster	
Interfaces	
Locations	
feed	126
Feed Types	
Frequency	

	Late Arrival	
	Cluster	
	process	128
	cluster	
	Failures	
	feed	
	workflow	
	CLI	129
	entity	
	Web Interface	130
	Search	
	Create an Entity	
	Notifications	
	Mirror	
	Data Replication Using the Falcon Web Ul	131
	Create Cluster Entities	
	Create Mirror Job	
	Pig Scripts in Apache Falcon	134
	Oozie Workflow	
	Pig Script	
	Summary	136
ì	Chapter 10: Macros	
	Structure	
	Macro Use Case	
	Macro Types	
	Internal Macro	
	External Macro	

CONTENTS

	dryrun	141
	Macro Chaining	141
	Macro Rules	142
	Define Before Usage	142
	Valid Macro Chaining	143
	No Macro Within Nested Block	143
	No Grunt Shell Commands	143
	Invisible Relations	143
	Macro Examples	144
	Macro Without Input Parameters Is Possible	144
	Macro Without Returning Anything Is Possible	144
	Summary	145
	Chapter 11: User-Defined Functions	147
	User-Defined Functions	148
	Java	
	JavaScript	
	Other Languages	
	Other Libraries	154
	PiggyBank	
	Apache DataFu	155
	Summary	155
ì	Chapter 12: Writing Eval Functions	157
	MapReduce and Pig Features	
	Accessing the Distributed Cache	
	Accessing Counters	
	Reporting Progress	
	Output Schema and Input Schema in UDF	
	Examples of Output and Input Schemas	
	· · · · · · · · · · · · · · · · · · ·	

162
162
168
168
169
171
171
174
177
178
183
185
185
186
187
187
188
188
188
193
195
197

CONTENTS

U	ounters	198
S	ummary	199
C	hapter 15: Data Formats	201
C	ompression	201
Se	equence File	202
Pa	arquet	203
	Parquet File Processing Using Apache Pig	204
0	RC	205
	Index	207
	ACID	207
	Predicate Pushdown	
	Data Types	207
	Benefits	
Si	ummary	208
C	hapter 16: Optimization	209
	hapter 16: Optimization	
	• •	209
	dvanced Joins	209 209
	dvanced Joins Small Files	
	dvanced Joins Small Files User-Defined Join Using the Distributed Cache	
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys	
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys Sorted Data	
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys Sorted Data est Practices	209 209 210 212 212 212 213 213
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys Sorted Data est Practices Choose Your Required Fields Early	209 209 210 212 212 212 213 213 213 213
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys Sorted Data est Practices Choose Your Required Fields Early Define the Appropriate Schema	209 209 210 212 212 212 213 213 213 213 213
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys Sorted Data est Practices Choose Your Required Fields Early Define the Appropriate Schema Filter Data	209 209 210 212 212 213 213 213 213 214 214
A	dvanced Joins Small Files User-Defined Join Using the Distributed Cache Big Keys Sorted Data est Practices Choose Your Required Fields Early Define the Appropriate Schema Filter Data Store Reusable Data	209 209 210 212 212 213 213 213 213 214 214 214

Combine Small Inputs	215
Prefer a Two-Way Join over Multiway Joins	216
Better Execution Engine	
Parallelism	
Job Statistics	
Rules	
Partition Filter Optimizer	218
Merge foreach	218
Constant Calculator	219
Cluster Optimization	
Disk Space	219
Separate Setup for Zookeeper	
Scheduler	220
Name Node Heap Size	220
Other Memory Settings	221
Summary	
Chapter 17: Hadoop Ecosystem Tools	225
Apache Zookeeper	
Terminology	
Applications	226
Command-Line Interface	
Four-Letter Commands	229
Measuring Time	230
Cascading	
Defining a Source	230
Defining a Sink	232
Pipes	233
Types of Operations	

Apache Spark	237
Core	
SQL	
Apache Tez	245
Presto	245
Architecture	
Connectors	
Pushdown Operations	
Summary	247
Appendix A: Built-in Functions	249
Appendix B: Apache Pig in Apache Ambari	257
Modifying Properties	258
Service Check	258
Installing Pig	259
Pig Status	259
Check All Available Services	
Summary	260
Appendix C: HBaseStorage and ORCStorage Options	261
HBaseStorage	
Row-Based Conditions	
Timestamp-Based Conditions	
Other Conditions	
OrcStorage	263
Index	

About the Author



Balaswamy Vaddeman is a thinker, blogger, and serious and self-motivated big data evangelist with 10 years of experience in IT and 5 years of experience in the big data space. His big data experience covers multiple areas such as analytical applications, product development, consulting, training, book reviews, hackathons, and mentoring. He has proven himself while delivering analytical applications in the retail, banking, and finance domains in three aspects (development, administration, and architecture) of Hadoop-related technologies. At a startup company, he developed a Hadoop-based product that was used for delivering analytical applications without writing code.

In 2013 Balaswamy won the Hadoop Hackathon event for Hyderabad conducted by Cloudwick Technologies. Being the top contributor at

Stackoverflow.com, he helped countless people on big data topics at multiple web sites such as Stackoverflow.com and Quora.com. With so much passion on big data, he became an independent trainer and consultant so he could train hundreds of people and set up big data teams in several companies.

About the Technical Reviewer



Manoj R. Patil is a big data architect at TatvaSoft, an IT services and consulting firm. He has a bachelor's of engineering degree from COEP in Pune, India. He is a proven and highly skilled business intelligence professional with 17 years of information technology experience. He is a seasoned BI and big data consultant with exposure to all the leading platforms such as Java EE, .NET, LAMP, and so on. In addition to authoring a book on Pentaho and big data, he believes in knowledge sharing, keeps himself busy in corporate training, and is a passionate teacher. He can be reached at on Twitter @manojrpatil and at https:// in.linkedin.com/in/manojrpatil on LinkedIn.

Manoj would like to thank his family, especially his two beautiful daughters, Ayushee and Ananyaa, for their patience during the review process.

Acknowledgments

Writing a book requires a great team. Fortunately, I had a great team for my first project. I am deeply indebted to them for making this project reality.

I would like to thank the publisher, Apress, for providing this opportunity.

Special thanks to Celestin Suresh John for building confidence in me in the initial stages of this project.

Special thanks to Subha Srikant for your valuable feedback. This project would have not been in this shape without you. In fact, I have learned many things from you that could be useful for my future projects also.

Thank you, Manoj R. Patil, for providing valuable technical feedback. Your contribution added a lot of value to this project.

Thank you, Dinesh Kumar, for your valuable time.

Last but not least, thank you, Prachi Mehta, for your prompt coordination.

CHAPTER 1

MapReduce and Its Abstractions

In this chapter, you will learn about the technologies that existed before Apache Hadoop, about how Hadoop has addressed the limitations of those technologies, and about the new developments since Hadoop was released.

Data consists of facts collected for analysis. Every business collects data to understand their business and to take action accordingly. In fact, businesses will fall behind their competition if they do not act upon data in a timely manner. Because the number of applications, devices, and users is increasing, data is growing exponentially. Terabytes and petabytes of data have become the norm. Therefore, you need better data management tools for this large amount of data.

Data can be classified into these three types:

- Small data: Data is considered small data if it can be measured in gigabytes.
- *Big data*: Big data is characterized by volume, velocity, and variety. *Volume* refers to the size of data, such as terabytes and more. *Velocity* refers to the age of data, such as real-time, near-real-time, and streaming data. *Variety* talks about types of data; there are mainly three types of data: structured, semistructured, and unstructured.
- *Fast data*: Fast data is a type of big data that is useful for the real-time presentation of data. Because of the huge demand for real-time or near-real-time data, fast data is evolving in a separate and unique space.

Small Data Processing

Many tools and technologies are available for processing small data. You can use languages such as Python, Perl, and Java, and you can use relational database management systems (RDBMSs) such as Oracle, MySQL, and Postgres. You can even use data warehousing tools and extract/transform/load (ETL) tools. In this section, I will discuss how small data processing is done.

Electronic supplementary material The online version of this chapter

⁽doi:10.1007/978-1-4842-2337-6_1) contains supplementary material, which is available to authorized users.

Assume you have the following text in a file called fruits:

Apple, grape Apple, grape, pear Apple, orange

Let's write a program in a shell script that first filters out the word *pear* and then counts the number of words in the file. Here's the code:

```
cat fruits|tr ',' '\n'|grep -v -i 'pear'|sort -f|uniq -c -i
```

This code is explained in the following paragraphs.

In this code, tr (for "translate" or "transliterate") is a Unix program that takes two inputs and replaces the first set of characters with the second set of characters. In the previous program, the tr program replaces each comma (,) with a new line character (\n). grep is a command used for searching for specific text. So, the previous program performs an inverse search on the word *pear* using the -v option and ignores the case using -i.

The sort command produces data in sorted order. The -f option ignores case while sorting.

uniq is a Unix program that combines adjacent lines from the input file for reporting purposes. In the previous program, uniq takes sorted words from the sort command output and generates the word count. The -c option is for the count, and the -i option is for ignoring case.

The program produces the following output:

Apple 3 Grape 2 Orange 1

You can divide program functionality into two stages; first is tokenize and filtering, and second is aggregation. Sort is supporting functionality of aggregation. Figure 1-1 shows the program flow.



Figure 1-1. Program flow

The previous program can be run on a single machine and on small data. Such simple programs can be used to perform simple operations such as searching and sorting on one file at a time. However, writing complex queries involving multiple files and multiple conditions requires better data processing tools. Database management systems (DBMS) and RDBMS technologies were developed to address querying problems with structured data.

Relational Database Management Systems

RDBMSs were developed based on the relational model founded by E. F. Codd. There are many commercial RDBMS products such as Oracle, SQL Server, and DB2. Many open source RDBMSs such as MySQL, Postgres, and SQLite are also popular. RDBMSs store data in tables, and you can define relations between tables.

Here are some advantages of RDBMSs:

- RDBMS products come with sophisticated query languages that can easily retrieve data from multiple tables with multiple conditions.
- The query language used in RDBMSs is called Structured Query Language (SQL); it provides easy data definition, manipulation, and control.
- RDBMSs also support transactions.
- RDBMSs support low-latency queries so users can access databases interactively, and they are also useful for online transaction processing (OLTP).

RDBMSs have these disadvantages:

- As data is stored in table format, RDBMSs support only structured data.
- You need to define a schema at the time of loading data.
- RDBMSs can scale only to gigabytes of data, and they are mainly designed for frequent updates.

Because the data size in today's organizations has grown exponentially, RDBMSs have not been able to scale with respect to data size. Processing terabytes of data can take days.

Having terabytes of data has become the norm for almost all businesses. And new data types like semistructured and unstructured have arrived. Semistructured data has a partial structure like in web server log files, and it needs to be parsed like Extensible Markup Language (XML) in order to analyze it. Unstructured data does not have any structure; this includes images, videos, and e-books.

Data Warehouse Systems

Data warehouse systems were introduced to address the problems of RDBMSs. Data warehouse systems such as Teradata are able to scale up to terabytes of data, and they are mainly used for OLAP use cases.

Data warehousing systems have these disadvantages:

- Data warehouse systems are a costly solution.
- They still cannot process other data types such as semistructured and unstructured data.
- They cannot scale to petabytes and beyond.

All traditional data-processing technologies experience a couple of common problems: storage and performance.

Computing infrastructure can face the problem of node failures. Data needs to be available irrespective of node failures, and storage systems should be able to store large volumes of data.

Traditional data processing technologies used a scale-up approach to process a large volume of data. A scale-up approach adds more computing power to existing nodes, so it cannot scale to petabytes and more because the rest of computing infrastructure becomes a performance bottleneck.

Growing storage and processing needs have created a need for new technologies such as parallel computing technologies.

Parallel Computing

The following are several parallel computing technologies.

GFS and MapReduce

Google has created two parallel computing technologies to address the storage and processing problems of big data. They are Google File System (GFS) and MapReduce. GFS is a distributed file system that provides fault tolerance and high performance on commodity hardware. GFS follows a master-slave architecture. The master is called Master, and the slave is called ChunkServer in GFS. MapReduce is an algorithm based on key-value pairs used for processing a huge amount of data on commodity hardware. These are two successful parallel computing technologies that address the storage and processing limitations of big data.

Apache Hadoop

Apache Hadoop is an open source framework used for storing and processing large data sets on commodity hardware in a fault-tolerant manner.

Hadoop was written by Doug Cutting and Mark Cafarella in 2006 while working for Yahoo to improve the performance of the Nutch search engine. Cutting named it after his son's stuffed elephant toy. In 2007, it was given to the Apache Software Foundation.

Initially Hadoop was adopted by Yahoo and, later, by companies like Facebook and Microsoft. Yahoo has about 100,000 CPUs and 40,000 nodes for Hadoop. The largest Hadoop cluster has about 4,500 nodes. Yahoo runs about 850,000 Hadoop jobs every day. Unlike conventional parallel computing technologies, Hadoop follows a scale-out strategy, which makes it more scalable. In fact, Apache Hadoop had set a benchmark by sorting 1.42 terabytes per minute.

Most of Hadoop is written in Java, but it has support for many programming languages such as C, C++, Python, and Scala through its streaming module. Apache Hadoop was initially written for high throughput and batch-processing systems. RDBMS technologies were written for frequent modifications in data, whereas Hadoop has been written for frequent reads. Moore's law says the processing capability of a machine will double every two years. Kryder's law says the storage capacity of disks will grow faster than Moore's law. The cost of computing and storage devices will go down every day, and these two factors can support more scalable technologies. Apache Hadoop was designed while keeping these things in mind, and parallel computing technologies like this will become more common going forward.

The latest Apache Hadoop contains three modules, as shown in Figure 1-2. They are HDFS, MapReduce, and Yet Another Resource Negotiator (YARN).



Figure 1-2. The three components of Hadroop

HDFS

The Hadoop distributed file system is used for storing large data sets. It divides files into blocks and stores every block on at least multiple nodes. This is called a *replication factor*, and by default it is 3. HDFS is fault-tolerant because it has more than one replica for every block, so it can handle node failures without affecting data processing. A block of HDFS is the same as an operating system block, but a HDFS block size is larger, such as 64 MB or 128 MB. Unlike traditional storage systems, it is highly scalable. It does not require any special hardware and can work on commodity hardware.

Assume you have a replication factor of 3, a block size of 64 MB, and 640 MB of data needs to be uploaded into HDFS. At the time of uploading the data into HDFS, 640 MB is divided into 10 blocks with respect to block size. Every block is stored on three nodes, which would consume 1920 MB of space on a cluster.

HDFS follows a master-slave architecture. The master is called the *name node*, and the slave is called a *data node*. The data node is fault tolerant because the same block is replicated to two more nodes. The name node was a single point of failure in initial versions; in fact, Hadoop used to go down if the name node crashed. But Hadoop 2.0+ versions have high availability of the name node. If the active name node is down, the standby name node becomes active without affecting the running jobs.

MapReduce

MapReduce is key-value programming model used for processing large data sets. It has two core functions: Map and Reduce. They are derived from functional programming languages. Both functions take a key-value pair as input and generate a key-value pair as output.

The Map task is responsible for filtering operations and preparing the data required for the Reduce tasks. The Map task will generate intermediate output and write it to the hard disk. For every key that is being generated by the Map task, a Reduce node is identified and will be sent to the key for further processing.

The Map task takes the key-value pair as input and generates the key-value pair as output.

(key1, value1) -----> Map Task-----> (Key2, Valu2)

The Reduce task is responsible for data aggregation operations such as count, max, min, average, and so on. A reduce operation will be performed on a per-key basis. Every functionality can be expressed in MapReduce.

The Reduce task takes the key and list of values as input and generates the key and value as output.

```
(key2, List (value2))-----> Reduce Task -----> (Key3, value3)
```

In addition to the Map and Reduce tasks, there is an extra stage called the *combiner* to improve the performance of MapReduce. The combiner will do partial aggregation on the Map side so that the Map stage has to write less data to disk.

You will now see how MapReduce generates a word count. Figure 1-3 depicts how MapReduce generates the fruits word count after filtering out the word *pear*.

CHAPTER 1 MAPREDUCE AND ITS ABSTRACTIONS



Figure 1-3. MapReduce generating a word count

Source and Sink are HDFS directories. When you upload data to HDFS, data is divided into chunks called *blocks*. Blocks will be processed in a parallel manner on all available nodes.

The first stage is Map, which performs filtering and data preparation after tokenization. All Map tasks (M1, M2, and M3) will do the initial numbering for words that are useful for the final aggregation. And M2 filters out the word *pear*.

The key and list of its values are retrieved from the Map output and sent to the reducer node. For example, the Apple key and its values (1, 1, 1) are sent to the reducer node R1. The reducer aggregates all values to generate the count output.

Between Map and Reduce, there is an internal stage called *shuffling* where the reducer node for the map output is identified.

You will now see how to write the same word count program using MapReduce. You first need to write a mapper class for the Map stage.

Writing a Map Class

The following is the Map program that is used for the same tokenization and data filtering as in the shell script discussed earlier:

```
import java.io.IOException;
import java.util.StringTokenizer;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.CongWritable;
import org.apache.hadoop.mapreduce.Mapper;
public class FilterMapper extends Mapper<LongWritable, Text, Text, IntWritable> {
    private final static IntWritable one = new IntWritable(1);
    private Text word = new Text();
    public void map(LongWritable offset, Text line, Context context) throws
    IOException, InterruptedException {
        //tokenize line with comma as delimiter
        StringTokenizer itr = new StringTokenizer(line.toString(),",");
        //Iterate all tokens and filter pear word
        while (itr.hasMoreTokens()) {
```

```
String strToken=itr.nextToken();
if(!strToken.equals("pear")){
//converting string data type to text data type of mapreduce
    word.set(strToken);
    context.write(word, one);//Map output
    }
}
}
```

The Map class should extend the Mapper class, which has parameters for the input key, input value, output key, and output value. You need to override the map() method. This code specifies LongWritable for the input key, Text for the input value, Text for the output key, and IntWritable for the output value.

In the map() method, you use StringTokenizer to convert a sentence into words. You are iterating words using a while loop, and you are filtering the word *pear* using an if loop. The Map stage output is written to context.

For every run of the map() method, the line offset value is the input key, the line is the input value, the word in the line will become an output key, and 1 is the output value, as shown in Figure 1-4.



Figure 1-4. M2 stage

The map() method runs once per every line. It tokenizes the line into words, and it filters the word *pear* before writing other words with the default of 1.

If the combiner is available, the combiner is run before the Reduce stage. Every Map task will have a combiner task that will produce aggregated output. Assume you have two *apple* words in the second line that is processed by the M2 map task.

The Map output without the combiner will look like Figure 1-5.



Figure 1-5. Map output without the combiner