

Unit 8: Databases and Big Data

October 7, 2017

References:

- [SCF tutorial on “Working with large datasets in SQL, R, and Python”](#)
- Murrell: Introduction to Data Technologies
- Adler: R in a Nutshell
- [Spark Programming Guide](#)

I’ve also pulled material from a variety of other sources, some mentioned in context below.

Note that for a lot of the demo code I ran the code separately outside of *knitr* and this document because of the time involved in working with large datasets.

1 A few preparatory notes

1.1 An editorial on ‘big data’

Big data is trendy these days.

Personally, I think some of the hype is justified and some is hype. Large datasets allow us to address questions that we can’t with smaller datasets, and they allow us to consider more sophisticated (e.g., nonlinear) relationships than we might with a small dataset. But they do not directly help with the problem of correlation not being causation. Having medical data on every American still doesn’t tell me if higher salt intake causes hypertension. Internet transaction data does not tell me if one website feature causes increased viewership or sales. One either needs to carry out a designed experiment or think carefully about how to infer causation from observational data. Nor does big data help with the problem that an ad hoc ‘sample’ is not a statistical sample and does not provide the ability to directly infer properties of a population. A well-chosen smaller dataset may be much more informative than a much larger, more ad hoc dataset. However, having big

datasets might allow you to select from the dataset in a way that helps get at causation or in a way that allows you to construct a population-representative sample. Finally, having a big dataset also allows you to do a large number of statistical analyses and tests, so multiple testing is a big issue. With enough analyses, something will look interesting just by chance in the noise of the data, even if there is no underlying reality to it.

Here's a **different way to summarize it**.

Different people define the 'big' in big data differently. One definition involves the actual size of the data, and in some cases the speed with which it is collected. Our efforts here will focus on dataset sizes that are large for traditional statistical work but would probably not be thought of as large in some contexts such as Google or the US National Security Agency (NSA). Another definition of 'big data' has more to do with how pervasive data and empirical analyses backed by data are in society and not necessarily how large the actual dataset size is.

1.2 Logistics and data size

One of the main drawbacks with R in working with big data is that all objects are stored in memory, so you can't directly work with datasets that are more than 1-20 Gb or so, depending on the memory on your machine.

The techniques and tools discussed in this Unit (apart from the section on MapReduce/Spark) are designed for datasets in the range of gigabytes to tens of gigabytes, though they may scale to larger if you have a machine with a lot of memory or simply have enough disk space and are willing to wait. If you have 10s of gigabytes of data, you'll be better off if your machine has 10s of GBs of memory, as discussed in this Unit.

If you're scaling to 100s of GBs, terabytes or petabytes, tools such as Spark may be your best bet, or possibly carefully-administered databases.

Note: in handling big data files, it's best to have the data on the local disk of the machine you are using to reduce traffic and delays from moving data over the network.

1.3 What we already know about handling big data!

UNIX operations are generally very fast, so if you can manipulate your data via UNIX commands and piping, that will allow you to do a lot. We've already seen UNIX commands for extracting columns. And various commands such as *grep*, *head*, *tail*, etc. allow you to pick out rows based on certain criteria. As some of you have done in problem sets, one can use *awk* to extract rows. So basic shell scripting may allow you to reduce your data to a more manageable size.

And don't forget simple things. If you have a dataset with 30 columns that takes up 10 Gb but you only need 5 of the columns, get rid of the rest and work with the smaller dataset. Or you might

be able to get the same information from a random sample of your large dataset as you would from doing the analysis on the full dataset. Strategies like this will often allow you to stick with the tools you already know.

Also, remember that we can often store data more compactly in binary formats than in flat text (e.g., csv) files.

2 Databases

This material is drawn from the tutorial on “Working with large datasets in SQL, R, and Python”, though I won’t hold you responsible for all of the database/SQL material in that tutorial, only what appears here in this Unit.

2.1 Overview

Basically, standard SQL databases are *relational* databases that are a collection of rectangular format datasets (*tables*, also called *relations*), with each table similar to R or Pandas data frames, in that a table is made up of columns, which are called *fields* or *attributes*, each containing a single *type* (numeric, character, date, currency, enumerated (i.e., categorical), ...) and rows or records containing the observations for one entity. Some of the tables in a given database will generally have fields in common so it makes sense to merge (i.e., join) information from multiple tables. E.g., you might have a database with a table of student information, a table of teacher information and a table of school information, and you might join student information with information about the teacher(s) who taught the students. Databases are set up to allow for fast querying and merging (called joins in database terminology).

Formally, databases are stored on disk, while R and Python store datasets in memory. This would suggest that databases will be slow to access their data but will be able to store more data than can be loaded into an R or Python session. However, databases can be quite fast due in part to disk caching by the operating system as well as careful implementation of good algorithms for database operations. For more information about disk caching see the tutorial.

2.2 Interacting with a database

You can interact with databases in a variety of database systems (*DBMS*=database management system). Some popular systems are SQLite, MySQL, PostgreSQL, Oracle and Microsoft Access. We’ll concentrate on accessing data in a database rather than management of databases. SQL is the Structured Query Language and is a special-purpose high-level language for managing databases and making queries. Variations on SQL are used in many different DBMS.

Queries are the way that the user gets information (often simply subsets of tables or information merged across tables). The result of an SQL query is in general another table, though in some cases it might have only one row and/or one column.

Many DBMS have a client-server model. Clients connect to the server, with some authentication, and make requests (i.e., queries).

There are often multiple ways to interact with a DBMS, including directly using command line tools provided by the DBMS or via Python or R, among others.

We'll concentrate on SQLite (because it is simple to use on a single machine). SQLite is quite nice in terms of being self-contained - there is no server-client model, just a single file on your hard drive that stores the database and to which you can connect to using the SQLite shell, R, Python, etc. However, it does not have some useful functionality that other DBMS have. For example, you can't use ALTER TABLE to modify column types or drop columns.

2.3 Database schema and normalization

To truly leverage the conceptual and computational power of a database you'll want to have your data in a normalized form, which means spreading your data across multiple tables in such a way that you don't repeat information unnecessarily.

The schema is the metadata about the tables in the database and the fields (and their types) in those tables.

Let's consider this using an educational example. Suppose we have a school with multiple teachers teaching multiple classes and multiple students taking multiple classes. If we put this all in one table organized per student, the data might have the following fields:

- student ID
- student grade level
- student name
- class 1
- class 2
- ...
- class n
- grade in class 1
- grade in class 2

- ...
- grade in class n
- teacher ID 1
- teacher ID 2
- ...
- teacher ID n
- teacher department 1
- teacher department 2
- ...
- teacher department n
- teacher age 1
- teacher age 2
- ...
- teacher age n

There are a lot of problems with this.

1. 'n' needs to be the maximum number of classes a student might take. If one ambitious student takes many classes, there will be a lot of empty data slots.
2. All the information about individual teachers (department, age, etc.) is repeated many times, meaning we use more storage than we need to.
3. If we want to look at the data on a per teacher basis, this is very poorly organized for that.
4. If one wants to change certain information (such as the age of a teacher) one needs to do it in many locations, which can result in errors and is inefficient.

It would get even worse if there was a field related to teachers for which a given teacher could have multiple values (e.g., teachers could be in multiple departments). This would lead to even more redundancy - each student-class-teacher combination would be crossed with all of the departments for the teacher (so-called multivalued dependency in database theory).

An alternative organization of the data would be to have each row represent the enrollment of a student in a class.

- student ID
- student name
- class
- grade in class
- student grade level
- teacher ID
- teacher department
- teacher age

This has some advantages relative to our original organization in terms of not having empty data slots, but it doesn't solve the other three issues above.

Instead, a natural way to order this database is with the following tables.

- Student
 - ID
 - name
 - grade_level
- Teacher
 - ID
 - name
 - department
 - age
- Class
 - ID
 - topic
 - class_size
 - teacher_ID

- ClassAssignment
 - student_ID
 - class_ID
 - grade

Then we do queries to pull information from multiple tables. We do the joins based on *keys*, which are the fields in each table that allow us to match rows from different tables.

(That said, if all anticipated uses of a database will end up recombining the same set of tables, we may want to have a denormalized schema in which those tables are actually combined in the database. It is possible to be too pure about normalization! We can also create a virtual table, called a *view*, as discussed later.)

2.3.1 Keys

A *key* is a field or collection of fields that give(s) a unique value for every row/observation. A table in a database should then have a *primary key* that is the main unique identifier used by the DBMS. *Foreign keys* are columns in one table that give the value of the primary key in another table. When information from multiple tables is joined together, the matching of a row from one table to a row in another table is generally done by equating the primary key in one table with a foreign key in a different table.

In our educational example, the primary keys would presumably be: *Student.ID*, *Teacher.ID*, *Class.ID*, and for ClassAssignment two fields: *{ClassAssignment.studentID, ClassAssignment.class_ID}*.

Some examples of foreign keys would be:

- student_ID as the foreign key in ClassAssignment for joining with Student on Student.ID
- teacher_ID as the foreign key in Class for joining with Teacher based on Teacher.ID
- class_ID as the foreign key in ClassAssignment for joining with Class based on Class.ID

2.3.2 Queries that join data across multiple tables

Suppose we want a result that has the grades of all students in 9th grade. For this we need information from the Student table (to determine grade level) and information from the ClassAssignment table (to determine the class grade). More specifically we need a query that joins *Student* with *ClassAssignment* based on *Student.ID* and *ClassAssignment.student_ID* and filters the rows based on *Student.grade_level*:

```
SELECT Student.ID, grade FROM Student, ClassAssignment WHERE
```

```
Student.ID = ClassAssignment.student_ID and Student.grade_level  
= 9;
```

Note that the query is a *join* (specifically an *inner join*), which is like *merge()* in R. We don't specifically use the JOIN keyword, but one could do these queries explicitly using JOIN, as we'll see later.

2.4 Stack Overflow metadata example

I've obtained data from [Stack Overflow](#), the popular website for asking coding questions, and placed it into a normalized database. The SQLite version has metadata (i.e., it lacks the actual text of the questions and answers) on all of the questions and answers posted in 2016.

We'll explore SQL functionality using this example database.

Now let's consider the Stack Overflow data. Each question may have multiple answers and each question may have multiple (topic) tags.

If we tried to put this into a single table, the fields could look like this if we have one row per question:

- question ID
- ID of user submitting question
- question title
- tag 1
- tag 2
- ...
- tag n
- answer 1 ID
- ID of user submitting answer 1
- age of user submitting answer 1
- name of user submitting answer 1
- answer 2 ID
- ID of user submitting answer 2

- age of user submitting answer 2
- name of user submitting answer 2
- ...

or like this if we have one row per question-answer pair:

- question ID
- ID of user submitting question
- question title
- tag 1
- tag 2
- ...
- tag n
- answer ID
- ID of user submitting answer
- age of user submitting answer
- name of user submitting answer

As we've discussed neither of those schema is particularly desirable.

Challenge: How would you devise a schema to normalize the data. I.e., what set of tables do you think we should create?

You can view one reasonable schema in the file *normalized_example.png*. The lines between tables indicate the relationship of foreign keys in one table to primary keys in another table. The schema in the actual databases of Stack Overflow data we'll use in this tutorial is similar to but not identical to that.

You can download a copy of the SQLite version of the Stack Overflow 2016 database from <http://www.stat.berkeley.edu/share/paciorek/stackoverflow-2016.db>.

2.5 Accessing databases in R

The *DBI* package provides a front-end for manipulating databases from a variety of DBMS (SQLite, MySQL, PostgreSQL, among others). Basically, you tell the package what DBMS is being used on the back-end, link to the actual database, and then you can use the standard functions in the package regardless of the back-end. This is a similar style to how one uses *foreach* for parallelization.

With SQLite, R processes make calls against the stand-alone SQLite database (.db) file, so there are no SQLite-specific processes. With a client-server DBMS like PostgreSQL, R processes call out to separate Postgres processes; these are started from the overall Postgres background process

You can access and navigate an SQLite database from R as follows.

```
library(RSQLite)
drv <- dbDriver("SQLite")
dir <- '../data' # relative or absolute path to where the .db file is
dbFilename <- 'stackoverflow-2016.db'
db <- dbConnect(drv, dbname = file.path(dir, dbFilename))
# simple query to get 5 rows from a table
dbGetQuery(db, "select * from questions limit 5")
```

##	questionid	creationdate	score	viewcount
## 1	34552550	2016-01-01 00:00:03	0	108
## 2	34552551	2016-01-01 00:00:07	1	151
## 3	34552552	2016-01-01 00:00:39	2	1942
## 4	34552554	2016-01-01 00:00:50	0	153
## 5	34552555	2016-01-01 00:00:51	-1	54
##				
## 1				Scope
## 2				Rails - Unknown Attribute - Unable to add a new field to a form or
## 3				Selenium Firefox webdriver won't load a blank page after changing Fire
## 4				Android Studio st
## 5				Java: reference to non-final local variables
##	ownerid			
## 1	5684416			
## 2	2457617			
## 3	5732525			
## 4	5735112			

```
## 5 4646288
```

We can easily see the tables and their fields:

```
dbListTables(db)

## [1] "answers"          "maxRepByQuestion" "questions"
## [4] "questionsAugment" "questions_tags"   "users"

dbListFields(db, "questions")

## [1] "questionid"      "creationdate" "score"          "viewcount"
## [5] "title"           "ownerid"

dbListFields(db, "answers")

## [1] "answerid"        "questionid"    "creationdate" "score"
## [5] "ownerid"
```

Here's how to make a basic SQL query. One can either make the query and get the results in one go or make the query and separately fetch the results. Here we've selected the first five rows (and all columns, based on the * wildcard) and brought them into R as a data frame.

```
results <- dbGetQuery(db, 'select * from questions limit 5')
class(results)

## [1] "data.frame"

query <- dbSendQuery(db, "select * from questions")
results2 <- fetch(query, 5)
identical(results, results2)

## [1] TRUE

dbClearResult(query) # clear to prepare for another query
```

To disconnect from the database:

```
dbDisconnect (db)
```

2.6 Basic SQL for choosing rows and columns from a table

SQL is a declarative language that tells the database system what results you want. The system then parses the SQL syntax and determines how to implement the query.

Here are some examples using the Stack Overflow database.

```
## find the largest viewcounts in the questions table
dbGetQuery (db,
'select distinct viewcount from questions order by viewcount desc limit 10')

##      viewcount
## 1      196469
## 2      174790
## 3      134399
## 4      129874
## 5      129624
## 6      127764
## 7      126752
## 8      112000
## 9      109422
## 10     106995

## now get the questions that are viewed the most
dbGetQuery (db, 'select * from questions where viewcount > 100000')

##      questionid      creationdate  score  viewcount
## 1      34579099 2016-01-03 16:55:16      8      129624
## 2      34814368 2016-01-15 15:24:36     206      134399
## 3      35062852 2016-01-28 13:28:39     730      112000
## 4      35429801 2016-02-16 10:21:09     400      100125
## 5      35588699 2016-02-23 21:37:06      57      126752
## 6      35890257 2016-03-09 11:25:05      51      129874
## 7      35990995 2016-03-14 15:01:17     104      127764
## 8      36668374 2016-04-16 18:57:19      20      196469
## 9      37280274 2016-05-17 15:21:49      23      106995
```

```

## 10    37806538 2016-06-14 08:16:21    223    174790
## 11    37937984 2016-06-21 07:23:00    202    109422
##
## 1
## 2
## 3
## 4
## 5
## 6
## 7
## 8
## 9
## 10 Code signing is required for product type 'Application' in SDK 'iOS 10'
## 11
##      ownerid
## 1    3656666
## 2    3319176
## 3    2761509
## 4    5881764
## 5    2896963
## 6    1118886
## 7    1629278
## 8    1707976
## 9    4043633
## 10   1554347
## 11   2670370

```

Let's lay out the various verbs in SQL. Here's the form of a standard query (though the ORDER BY is often omitted and sorting is computationally expensive):

```

SELECT <column(s)> FROM <table> WHERE <condition(s) on column(s)>
ORDER BY <column(s)>

```

SQL keywords are often written in ALL CAPITALS though I won't necessarily do that here.

And here is a table of some important keywords:

Table 1. Basic SQL keywords.

Keyword	Usage
SELECT	select columns
FROM	which table to operate on
WHERE	filter (choose) rows satisfying certain conditions
LIKE, IN, <, >, ==, etc.	used as part of conditions
ORDER BY	sort based on columns

For comparisons in a WHERE clause, some common syntax for setting conditions includes LIKE (for patterns), =, >, <, >=, <=, !=.

Some other keywords are: DISTINCT, ON, JOIN, GROUP BY, AS, USING, UNION, INTERSECT, SIMILAR TO.

Question: how would we find the youngest users in the database?

2.7 Simple SQL joins

It turns out that the syntax of using multiple tables we've seen can be viewed formally as a table join and could also be implemented using the JOIN keyword.

The syntax generally looks like this (again the WHERE and ORDER BY are optional):

```
SELECT <column(s)> FROM <table1> JOIN <table2> ON <columns to match on>
WHERE <condition(s) on column(s)> ORDER BY <column(s)>
```

Let's see some joins using the different syntax on the Stack Overflow database. In particular let's select only the questions with the tag "python".

Here's a join using similar syntax to what we saw above, without using the JOIN keyword.

```
result1 <- dbGetQuery(db, "select * from questions, questions_tags
    where questions.questionid = questions_tags.questionid and
    tag = 'python'")
```

And here's how we do it with an explicit JOIN:

```
result2 <- dbGetQuery(db, "select * from questions join questions_tags
    on questions.questionid = questions_tags.questionid
    where tag = 'python'")

head(result1)

##      questionid      creationdate score viewcount
```

```
## 1      34553559 2016-01-01 04:34:34      3      96
## 2      34556493 2016-01-01 13:22:06      2      30
## 3      34557898 2016-01-01 16:36:04      3     143
## 4      34560088 2016-01-01 21:10:32      1     126
## 5      34560213 2016-01-01 21:25:26      1     127
## 6      34560740 2016-01-01 22:37:36      0     455
##
## 1
## 2
## 3
## 4
## 5 How to set the type of a pyqtSignal (variable of class X) that takes a
## 6 Flask: Peewee model_to_

##  ownerid questionid  tag
## 1   845642    34553559 python
## 2  4458602    34556493 python
## 3  2927983    34557898 python
## 4  5736692    34560088 python
## 5  5636400    34560213 python
## 6  3262998    34560740 python

identical(result1, result2)

## [1] TRUE
```

Here's a three-way join (using both types of syntax) with some additional use of aliases to abbreviate table names. What does this query ask for?

```
result1 <- dbGetQuery(db, "select * from
    questions Q, questions_tags T, users U where
    Q.questionid = T.questionid and
    Q.ownerid = U.userid and
    tag = 'python' and
    age < 18")

result2 <- dbGetQuery(db, "select * from
    questions Q
```

```
join questions_tags T on Q.questionid = T.questionid
join users U on Q.ownerid = U.userid
where tag = 'python' and
age < 18")
```

```
identical(result1, result2)
```

Challenge: Write a query that would return all the answers to questions with the Python tag.

Challenge: Write a query that would return the users who have answered a question with the Python tag.

2.8 Grouping / stratifying

A common pattern of operation is to stratify the dataset, i.e., collect it into mutually exclusive and exhaustive subsets. One would then generally do some operation on each subset. In SQL this is done with the GROUP BY keyword.

Here's a basic example where we count the occurrences of different tags.

```
dbGetQuery(db, "select tag, count(*) as n from questions_tags
                group by tag order by n desc limit 25")
```

```
##           tag      n
## 1  javascript 290966
## 2         java 219155
## 3    android 184272
## 4         php 177969
## 5        python 171745
## 6          c# 163637
## 7         html 126851
## 8        jquery 123707
## 9          ios  95722
## 10         css  86470
## 11   angularjs  76951
## 12          c++  76260
## 13        mysql  75458
```



```
## 14      swift  61485
## 15      sql   58346
## 16    node.js  52827
## 17        r   48079
## 18    arrays  46739
## 19      json  45250
## 20 ruby-on-rails 39036
## 21    sql-server 37077
## 22        c   36080
## 23    asp.net  35610
## 24    excel   29924
## 25    angular2 28832
```

In general ‘GROUP BY’ statements will involve some aggregation operation on the subsets. Options include: COUNT, MIN, MAX, AVG, SUM.

Challenge: Write a query that will count the number of answers for each question, returning the most answered questions.

2.9 Getting unique results (DISTINCT)

A useful SQL keyword is DISTINCT, which allows you to eliminate duplicate rows from any table (or remove duplicate values when one only has a single column or set of values).

```
tagNames <- dbGetQuery(db, "select distinct tag from questions_tags")
head(tagNames)

##      tag
## 1    c#
## 2  razor
## 3  flags
## 4 javascript
## 5    rxjs
## 6  node.js

dbGetQuery(db, "select count(distinct tag) from questions_tags")

##      count(distinct tag)
## 1                    41006
```

2.10 Indexes

An index is an ordering of rows based on one or more fields. DBMS use indexes to look up values quickly, either when filtering (if the index is involved in the WHERE condition) or when doing joins (if the index is involved in the JOIN condition). So in general you want your tables to have indexes.

DBMS use indexing to provide sub-linear time lookup. Without indexes, a database needs to scan through every row sequentially, which is called linear time lookup – if there are n rows, the lookup is $O(n)$ in computational cost. With indexes, lookup may be logarithmic – $O(\log(n))$ – (if using tree-based indexes) or constant time – $O(1)$ – (if using hash-based indexes). A binary tree-based search is logarithmic; at each step through the tree you can eliminate half of the possibilities.

Here's how we create an index, with some time comparison for a simple query.

```
system.time (dbGetQuery (db,
  "select * from questions where viewcount > 10000")) # 10 seconds
system.time (dbGetQuery (db,
  "create index count_index on questions (viewcount)")) # 19 seconds
system.time (dbGetQuery (db,
  "select * from questions where viewcount > 10000")) # 3 seconds
```

In other contexts, an index can save huge amounts of time. So if you're working with a database and speed is important, check to see if there are indexes.

That being said, using indexes in a lookup is not always advantageous, as discussed in the tutorial.

2.11 Temporary tables and views

You can think of a view as a temporary table that is the result of a query and can be used in subsequent queries. In any given query you can use both views and tables. The advantage is that they provide modularity in our querying. For example, if a given operation (portion of a query) is needed repeatedly, one could abstract that as a view and then make use of that view.

Suppose we always want the age and displayname of owners of questions to be readily available. Once we have the view we can query it like a regular table.

```
## note there is a creationdate in users too, hence disambiguation
dbGetQuery (db, "create view questionsAugment as select
  questionid, questions.creationdate, score, viewcount,
  title, ownerid, age, displayname
```

```
        from questions join users
        on questions.ownerid = users.userid")

## don't be confused by the "data frame with 0 columns and 0 rows"
## message -- it just means that nothing is returned to R;
## the view HAS been created

dbGetQuery(db, "select * from questionsAugment where age < 15 limit 5")
```

One use of a view would be to create a mega table that stores all the information from multiple tables in the (unnormalized) form you might have if you simply had one data frame in R or Python.

2.12 Creating database tables

One can create tables from within the ‘sqlite’ command line interfaces (discussed in the tutorial), but often one would do this from R or Python. Here’s the syntax from R.

```
## Option 1: pass directly from CSV to database
dbWriteTable(conn = db, name = "student", value = "student.csv",
             row.names = FALSE, header = TRUE)

## Option 2: pass from data in an R data frame
## create data frame 'student' in some fashion
#student <- data.frame(...)
#student <- read.csv(...)
dbWriteTable(conn = db, name = "student", value = student,
             row.names = FALSE, append = FALSE)
```

2.13 More on joins

We've seen a bunch of joins but haven't discussed the full taxonomy of types of joins. There are various possibilities for how to do a join depending on whether there are rows in one table that do not match any rows in another table.

Inner joins: In database terminology an inner join is when the result has a row for each match of a row in one table with the rows in the second table, where the matching is done on the columns you indicate. If a row in one table corresponds to more than one row in another table, you get all of the matching rows in the second table, with the information from the first table duplicated for each of the resulting rows. For example in the Stack Overflow data, an inner join of questions and answers would pair each question with each of the answers to that question. However, questions without any answers or (if this were possible) answers without a corresponding question would not be part of the result.

Outer joins: Outer joins add additional rows from one table that do not match any rows from the other table as follows. A *left outer join* gives all the rows from the first table but only those from the second table that match a row in the first table. A *right outer join* is the converse, while a *full outer join* includes at least one copy of all rows from both tables. So a left outer join of the Stack Overflow questions and answers tables would, in addition to the matched questions and their answers, include a row for each question without any answers, as would a full outer join. In this case there should be no answers that do not correspond to question, so a right outer join should be the same as an inner join.

Cross joins: A cross join gives the Cartesian product of the two tables, namely the pairwise combination of every row from each table, analogous to `expand.grid()` in R. I.e., take a row from the first table and pair it with each row from the second table, then repeat that for all rows from the first table. Since cross joins pair each row in one table with all the rows in another table, the

resulting table can be quite large (the product of the number of rows in the two tables). In the Stack Overflow database, a cross join would pair each question with every answer in the database, regardless of whether the answer is an answer to that question.

Simply listing two or more tables separated by commas as we saw earlier is the same as a *cross join*. Alternatively, listing two or more tables separated by commas, followed by conditions that equate rows in one table to rows in another is the same as an *inner join*.

In general, inner joins can be seen as a form of cross join followed by a condition that enforces matching between the rows of the table. More broadly, here are four equivalent joins that all perform the equivalent of an inner join:

```
## explicit inner join:
select * from table1 join table2 on table1.id = table2.id
## non-explicit join without JOIN
select * from table1, table2 where table1.id = table2.id
## cross-join followed by matching
select * from table1 cross join table2 where table1.id = table2.id
## explicit inner join with 'using'
select * from table1 join table2 using(id)
```

Challenge: Create a view with one row for every question-tag pair, including questions without any tags.

Challenge: Write a query that would return the displaynames of all of the users who have **never** posted a question. The NULL keyword will come in handy – it’s like ‘NA’ in R. Hint: NULLs should be produced if you do an outer join.

2.14 SAS

SAS is quite good at handling large datasets, storing them on disk rather than in memory. I have used SAS in the past for subsetting and merging large datasets. Then I will generally extract the data I need for statistical modeling and do the analysis in R.

Here’s an example of some SAS code for reading in a CSV followed by some subsetting and merging and then output.

```
/* we can use a pipe - in this case to remove carriage returns, */
/* presumably because the CSV file was created in Windows */
filename tmp pipe "cat ~/shared/hei/gis/100w4kmgrid.csv | tr -d '\r'";
```

```

/* read in one data file */
data grid;
infile tmp
lrecl=500 trunccover dsd firstobs=2;
informat gridID x y landMask dataMask;
input gridID x y landMask dataMask;
run ;

filename tmp pipe "cat ~/shared/hei/goes/Goes_int4km.csv | tr -d '\r'";

/* read in second data file */
data match;
infile tmp
lrecl=500 trunccover dsd firstobs=2;
informat goesID gridID areaInt areaPix;
input goesID gridID areaInt areaPix;
run ;

/* need to sort before merging */
proc sort data=grid;
    by gridID;
run;
proc sort data=match;
    by gridID;
run;

/* notice some similarity to SQL */
data merged;
merge match(in=in1) grid(in=in2);
by gridID; /* key field */
if in1=1; /* also do some subsetting */
/* only keep certain fields */
keep gridID goesID x y landMask dataMask areaInt areaPix;
run;

/* do some subsetting */

```

```

data PA;    /* new dataset */
    set merged; /* original dataset */
    if x<1900000 and x>1200000 and y<2300000 and y>1900000;
run;

%let filename="/shared/hei/code/model/GOES-gridMatchPA.csv";
/* output to CSV */
PROC EXPORT DATA= WORK.PA
            OUTFILE= &filename
            DBMS=CSV REPLACE;
RUN;

```

Note that SAS is oriented towards working with data in a “data frame”-style format; i.e., rows as observations and columns as fields, with different fields of possibly different types. As you can see in the syntax above, the operations concentrate on transforming one dataset into another dataset.

3 R and big data

There has been a lot of work in recent years to allow R to work with big datasets.

- The *data.table* package provides for fast operations on large data tables in memory. The *dplyr* package has also been optimized to work quickly on large data tables in memory, including operating on *data.table* objects from the *data.table* package.
- The *ff* and *bigmemory* packages provide the ability to load datasets into R without having them in memory, but rather stored in clever ways on disk that allow for fast access. Metadata is stored in R.
- The *biglm* package provides the ability to fit linear models and GLMs to big datasets, with integration with *ff* and *bigmemory*.
- Finally the *sqldf* package provides the ability to use SQL queries on R dataframes and on-the-fly when reading from CSV files. The latter can help you avoid reading in the entire dataset into memory in R if you just need a subset of it.

In this section we’ll use an example of US government data on airline delays (1987-2008) available through the ASA 2009 Data Expo at <http://stat-computing.org/dataexpo/2009/the-data.html>.

First we'll use UNIX tools to download the individual yearly CSV files and make a single CSV (~12 Gb). (See the demo code file for the bash code.) Note that it's much smaller when compressed (1.7 Gb) or if stored in a binary format.

3.1 Working quickly with big datasets in memory: `data.table`

In many cases, particularly on a machine with a lot of memory, R might be able to read the dataset into memory but computations with the dataset may be slow.

The *data.table* package provides a lot of functionality for fast manipulation: indexing, merges/joins, assignment, grouping, etc.

Let's read in the airline dataset, specifying the column classes so that *fread()* doesn't have to detect what they are. I'll also use factors since factors are represented numerically. It only takes about 5 minutes to read the data in. We'll see in the next section that this is much faster than with other approaches within R.

```
require(data.table)
dir = '/tmp'
fileName <- file.path(dir, 'AirlineDataAll.csv')

dt <- fread(fileName, colClasses=c(rep("numeric", 8), "factor",
                                   "numeric", "factor", rep("numeric", 5),
                                   rep("factor", 2), rep("numeric", 4),
                                   "factor", rep("numeric", 6)))

#Read 123534969 rows and 29 (of 29) columns from
# 11.203 GB file in 00:05:16

class(dt)
# [1] "data.table" "data.frame"
```

Now let's do some basic subsetting. We'll see that setting a key (which is how *data.table* refers to a database-style *index*) and using binary search can improve lookup speed dramatically.

```
system.time(sfo <- subset(dt, Origin == "SFO"))
## 8.8 seconds
system.time(sfoShort <- subset(dt, Origin == "SFO" & Distance < 1000))
## 12.7 seconds
```



```

system.time(setkey(dt, Origin, Distance))
## 33 seconds:
## takes some time, but will speed up later operations
tables()
##      NAME              NROW      MB
##[1,] dt          123,534,969 27334
##[2,] sfo           2,733,910   606
##[3,] sfoShort     1,707,171   379
##      COLS
##[1,] Year,Month,DayofMonth,DayOfWeek,DepTime,CRSDepTime,ArrTime,CRSArrTime
##[2,] Year,Month,DayofMonth,DayOfWeek,DepTime,CRSDepTime,ArrTime,CRSArrTime
##[3,] Year,Month,DayofMonth,DayOfWeek,DepTime,CRSDepTime,ArrTime,CRSArrTime
##      KEY
##[1,] Origin,Distance
##[2,]
##[3,]
##Total: 28,319MB

## vector scan
system.time(sfo <- subset(dt, Origin == "SFO"))
## 8.5 seconds
system.time(sfoShort <- subset(dt, Origin == "SFO" & Distance < 1000 ))
## 12.4 seconds

## binary search
system.time(sfo <- dt[.('SFO'), ])
## 0.8 seconds

```

Setting a key in *data.table* simply amounts to sorting based on the columns provided, which allows for fast lookup later using binary search algorithms, as seen with the last query. From my fairly quick look through the *data.table* documentation I don't see a way to do the subsetting based on ranges of values (e.g., flights with distance less than 1000) using the specialized functionality of *data.table*.

There's a bunch more to *data.table* and you'll have to learn a modest amount of new syntax, but if you're working with large datasets in memory, it will probably be well worth your while. Plus *data.table* objects are data frames (i.e., they inherit from data frames) so they are compatible

with R code that uses dataframes.

3.2 Working with big datasets on disk: ff and bigmemory

Note that with our 12 Gb dataset, the data took up 27 Gb of RAM on the SCF server *radagast*. Operations on the dataset would then use up additional RAM. So this would not be feasible on most machines. And of course other datasets might be so big that even *radagast* wouldn't be able to hold them in memory.

3.2.1 ff

The *ff* package stores datasets in columnar format, with one file per column, on disk, so is not limited by memory. It then provides fast access to the dataset from R.

If we need to work with a dataset in R but the dataset won't fit in memory, we can read the data into R using the *ff* package, in particular reading in as an *ffdf* object. Note the arguments are similar to those for *read.{table,csv}()*. *read.table.ffdf()* reads the data in chunks.

```
require(ff)
require(ffbase)

# I put the data file on local disk on the machine I am using
# (/tmp on radagast)
# it's good to test with a small subset before
# doing the full operations
fileName <- file.path(dir, 'test.csv')
dat <- read.csv.ffdf(file = fileName, header = TRUE,
  colClasses = c('integer', rep('factor', 3),
    rep('integer', 4), 'factor', 'integer', 'factor',
    rep('integer', 5), 'factor', 'factor', rep('integer', 4),
    'factor', rep('integer', 6)))

fileName <- '/tmp/AirlineDataAll.csv'
system.time( dat <- read.csv.ffdf(file = fileName, header = TRUE,
  colClasses = c('integer', rep('factor', 3), rep('integer', 4),
    'factor', 'integer', 'factor', rep('integer', 5), 'factor',
    'factor', rep('integer', 4), 'factor', rep('integer', 6))) )
```

```
## takes about 22 minutes

system.time(ffsave(dat, file = file.path(dir, 'AirlineDataAll')))
## takes 11 minutes
## file is saved (in a binary format) as AirlineDataAll.ffData
## with metadata in AirlineDataAll.RData

rm(dat) # pretend we are in a new R session

system.time(ffload(file.path(dir, 'AirlineDataAll')))
# this is much quicker:
# 107 seconds
```

In the above operations, we wrote a copy of the file in the ff binary format that can be read more quickly back into R than the original reading of the CSV using `ffsave()` and `ffload()`. Also note the reduced size of the binary format file compared to the original CSV. It's good to be aware of where the binary ff file is stored given that for large datasets, it will be large. With `ff` (I think *bigmemory* is different in how it handles this) it appears to be stored in `/tmp` in an R temporary directory. Note that as we work with large files we need to be more aware of the filesystem, making sure in this case that `/tmp` has enough space.

Let's look at the `ff` and `ffbase` packages to see what functions are available using `library(help=ff)`. Notice that there is an `merge.ff()`.

Note that a copy of an `ff` object does not appear to actually copy any data, but merely create another name referring to the same data object.

Next let's do a bit of exploration of the dataset. Of course in a real analysis we'd do a lot more and some of this would take some time.

```
ffload(file.path(dir, 'AirlineDataAll'))
# [1] "tmp/RtmpU5Uw6z/ffdf4e684aec7c4.ff" "tmp/RtmpU5Uw6z/ffdf4e687fb73a88"
# [3] "tmp/RtmpU5Uw6z/ffdf4e6862b1033f.ff" "tmp/RtmpU5Uw6z/ffdf4e6820053932"
# [5] "tmp/RtmpU5Uw6z/ffdf4e681e7d2235.ff" "tmp/RtmpU5Uw6z/ffdf4e686aa01c8."
# ...

dat$Dest
# ff (closed) integer length=123534969 (123534969) levels: BUR LAS LAX OAK
# ABE ABQ ACV ALB ALO AMA ANC ATL AUS AVP AZO BDL BFL BGR BHM BIL BLI BNA B
```

```

# CAK CCR CHS CID CLE CLT CMH CMI COS CPR CRP CRW CVG DAB DAL DAY DCA DEN D
# EUG EVV EWR FAI FAR FAT FLG FLL FOE FSD GCN GEG GJT GRR GSO GSP GTF HNL H
# ICT ILG ILM IND ISP JAN JAX JFK KOA LBB LEX LGA LGB LIH LIT LMT LNK MAF M
# MFR MHT MIA MKE MLB MLI MOB MRY MSN MSP MSY OGG OKC OMA ONT ORD ORF PBI P
# ...

# let's do some basic tabulation
DestTable <- sort(table.ff(dat$Dest), decreasing = TRUE)
# table is a generic, so shouldn't need explicit table.ff,
# unless dat$Dest is not see as an ff object

# takes a while

#      ORD      ATL      DFW      LAX      PHX      DEN      DTW      IAH      MSP

# 6638035 6094186 5745593 4086930 3497764 3335222 2997138 2889971 2765191 2

#      STL      EWR      LAS      CLT      LGA      BOS      PHL      PIT      SLC

# 2720250 2708414 2629198 2553157 2292800 2287186 2162968 2079567 2004414

# looks right - the busiest airports are ORD (O'Hare in Chicago) and ATL (A

dat$DepDelay[1:50]
#opening ff /tmp/RtmpU5Uw6z/ffdf4e682d8cd893.ff
# [1] 11 -1 11 -1 19 -2 -2 1 14 -1 5 16 17 1 21 3 13 -1 87 19 31 17 32
# [26] 29 26 15 5 54 0 25 -2 0 12 14 -1 2 1 16 15 44 20 15 3 21 -1 0

min.ff(dat$DepDelay, na.rm = TRUE)
# [1] -1410
max.ff(dat$DepDelay, na.rm = TRUE)
# [1] 2601

# why do I need to call min.ff and max.ff rather than min/max?

# tmp <- clone(dat$DepDelay) # make an explicit copy

```

Let's review our understanding of S3 methods. Why did I need to call `min.ff()` rather than just simply calling `min()` on the `ff` object? Could I have called `table()` instead of `table.ff()`?

A note of caution. Debugging code involving `ff` can be a hassle because the size gets in the way in various ways. Until you're familiar with the various operations on `ff` objects, you'd be wise to try to run your code on a small test dataset loaded in as an `ff` object. Also, we want to be sure that the operations we use keep any resulting large objects in the `ff` format and use `ff` methods and not standard R functions.

3.2.2 bigmemory

The *bigmemory* package is an alternative way to work with datasets in R that are kept stored on disk rather than read entirely into memory. *bigmemory* provides a *big.matrix* class, so it appears to be limited to datasets with a single type for all the variables. However, one nice feature is that one can use *big.matrix* objects with *foreach* (one of R's parallelization tools, to be discussed soon) without passing a copy of the matrix to each worker. Rather the workers can access the matrix stored on disk.

3.2.3 sqldf

The *sqldf* package provides the ability to use SQL queries on data frames (via *sqldf()*) as well as to filter an input CSV via an SQL query (via *read.csv.sql()*), with only the result of the subsetting put in memory in R. The full input data can be stored temporarily in an SQLite database on disk.

```
require(sqldf)
dir = '/tmp'
fileName <- file.path(dir, 'AirlineDataAll.csv')
# read in file, with temporary database in memory
system.time(sfo <- read.csv.sql(fn,
  sql = "select * from file where Origin = 'SFO'",
  dbname=NULL, header = TRUE))
# read in file, with temporary database on disk
system.time(sfo <- read.csv.sql(fn,
  sql = "select * from file where Origin = 'SFO'",
  dbname=tempfile(), header = TRUE))
```

3.3 dplyr package

You should already be familiar with using *dplyr*. One very nice feature is that with *dplyr* one can work with data stored in the *data.table* format and in external databases.

```
library(dplyr)

## with database
dir <- '../data' # relative or absolute path to where the .db file is
dbFilename <- 'stackoverflow-2016.db'

db <- src_sqlite(file.path(dir, dbFilename))
questions <- tbl(db, "questions")
questions

## with data.table
dir <- '/tmp'
fileName <- file.path(dir, 'AirlineDataAll.csv')
flights <- tbl_dt(fread(fileName, colClasses=c(rep("numeric", 8), "factor",
                                                "numeric", "factor", rep("numeric", 5),
                                                rep("factor", 2), rep("numeric", 4),
                                                "factor", rep("numeric", 6))))

# now use dplyr functionality on 'flights'

flights %>% group_by(UniqueCarrier) %>%
  summarize(mnDelay = mean(DepDelay, na.rm=TRUE))

# Source: local data table [29 x 2]
#
#   UniqueCarrier mean(DepDelay, na.rm = TRUE)
#1             PS                8.928104
#2             TW                7.658251
#3             UA                9.667930
#4             WN                9.077167
#5             EA                8.674051
#6             HP                8.107790
```

```
#7          NW          6.007974
#8      PA  (1)          5.532442
#9          PI          9.560336
#10         CO          7.695967
#..         ...          ...
```

3.4 Fitting models to big datasets: biglm

The *biglm* package provides the ability to fit large linear models and GLMs. *ffbase* has a *biglm.ffdf()* function that builds on *biglm* for use with *ffdf* objects. Let's fit a basic model on the airline data. Note that we'll also fit the same model on the dataset when we use Spark at the end of the Unit.

```
require(ffbase)
require(biglm)

dir = '/tmp'
datUse <- subset(dat, ArrDelay < 60*12 & ArrDelay > (-30) &
                 !is.na(ArrDelay) & !is.na(Distance) & !is.na(DayOfWeek))
datUse$Distance <- datUse$Distance / 1000 # helps stabilize numerics
# 119971791 records

# any concern about my model?
system.time(mod <- bigglm(ArrDelay ~ Distance + DayOfWeek, data = datUse))
# 542.149 11.248 550.779
summary(mod)

coef <- summary(mod)$mat[,1]
```

Here are the results. Day 1 is Monday, so that's the baseline category for the ANOVA-like part of the model.

Large data regression model: bigglm(DepDelay ~ Distance + DayOfWeek, data =
Sample size = 119971791

	Coef	(95%	CI)	SE	p
(Intercept)	6.3662	6.3504	6.3820	0.0079	0

Distance	0.7638	0.7538	0.7737	0.0050	0
DayOfWeek2	-0.6996	-0.7197	-0.6794	0.0101	0
DayOfWeek3	0.3928	0.3727	0.4129	0.0101	0
DayOfWeek4	2.2247	2.2046	2.2449	0.0101	0
DayOfWeek5	2.8867	2.8666	2.9068	0.0101	0
DayOfWeek6	-2.4273	-2.4481	-2.4064	0.0104	0
DayOfWeek7	-0.1362	-0.1566	-0.1158	0.0102	0

Of course as good statisticians/data analysts we want to do careful assessment of our model, consideration of alternative models, etc. This is going to be harder to do with large datasets than with more manageable ones. However, one possibility is to do the diagnostic work on subsamples of the data.

Now let's consider the fact that very small substantive effects can be highly statistically significant when estimated from a large dataset. In this analysis the data are generated from $Y \sim \mathcal{N}(0 + 0.001x, 1)$, so the R^2 is essentially zero.

```
n <- 150000000 # n*4*8/1e6 Mb of RAM (~5 Gb)
# but turns out to be 11 Gb as a text file
nChunks <- 100
chunkSize <- n/nChunks

set.seed(0)

for(p in 1:nChunks) {
  x1 <- runif(chunkSize)
  x2 <- runif(chunkSize)
  x3 <- runif(chunkSize)
  y <- rnorm(chunkSize, .001*x1, 1)
  write.table(cbind(y,x1,x2,x3), file = file.path(dir, 'signif.csv'),
    sep = ',', col.names = FALSE, row.names = FALSE,
    append = TRUE, quote = FALSE)
}

fileName <- file.path(dir, 'signif.csv')
system.time( dat <- read.csv.ffdf(file = fileName,
  header = FALSE, colClasses = rep('numeric', 4)))
```



```

# 922.213  18.265 951.204 -- timing is on an older machine than radagast

names(dat) <- c('y', 'x1', 'x2', 'x3')
ffsave(dat, file = file.path(dir, 'signif'))

system.time(ffload(file.path(dir, 'signif')))
# 52.323    7.856  60.802  -- timing is on an older machine

system.time(mod <- bigglm(y ~ x1 + x2 + x3, data = dat))
# 1957.358    8.900 1966.644  -- timing is on an older machine

options(digits = 12)
summary(mod)

# R^2 on a subset (why can it be negative?)
coefs <- summary(mod)$mat[,1]
wh <- 1:1000000
1 - sum((dat$y[wh] - coefs[1] + coefs[2]*dat$x1[wh] +
  coefs[3]*dat$x2[wh] + coefs[4]*dat$x3[wh])^2) /
  sum((dat$y[wh] - mean(dat$y[wh]))^2)

```

Here are the results:

```

Large data regression model: bigglm(y ~ x1 + x2 + x3, data = dat)
Sample size = 1.5e+08

```

	Coef	(95%	CI)	SE	p
(Intercept)	-0.0001437	-0.0006601	0.0003727	0.0002582	0.5777919
x1	0.0013703	0.0008047	0.0019360	0.0002828	0.0000013
x2	0.0002371	-0.0003286	0.0008028	0.0002828	0.4018565
x3	-0.0002620	-0.0008277	0.0003037	0.0002829	0.3542728

```

### and here is the R^2 calculation (why can it be negative?)
[1] -1.111046828e-06

```

So, do I care the result is highly significant? Perhaps if I'm hunting the Higgs boson... As you have hopefully seen in statistics courses, statistical significance \neq practical significance.

4 Sparsity

A lot of statistical methods are based on sparse matrices. These include:

- Matrices representing the neighborhood structure (i.e., conditional dependence structure) of networks/graphs.
- Matrices representing autoregressive models (neighborhood structure for temporal and spatial data)
- A statistical method called the *lasso* is used in high-dimensional contexts to give sparse results (sparse parameter vector estimates, sparse covariance matrix estimates)
- There are many others (I've been lazy here in not coming up with a comprehensive list, but trust me!)

When storing and manipulating sparse matrices, there is no need to store the zeros, nor to do any computation with elements that are zero. A few of you exploited sparse matrices in PS4.

R, Matlab and Python all have functionality for storing and computing with sparse matrices. We'll see this a bit more in the linear algebra unit.

```
require(spam)
mat = matrix(rnorm(1e8), 1e4)
mat[mat > (-2)] <- 0
sMat <- as.spam(mat)
print(object.size(mat), units = 'Mb') # 762.9 Mb
print(object.size(sMat), units = 'Mb') # 26 Mb

vec <- rnorm(1e4)
system.time(mat %*% vec) # 0.385 seconds
system.time(sMat %*% vec) # 0.015 seconds
```

Here's a [blog post](#) describing the use of sparse matrix manipulations for analysis of the Netflix Prize data.

5 Using statistical concepts to deal with computational bottlenecks

As statisticians, we have a variety of statistical/probabilistic tools that can aid in dealing with big data.

1. Usually we take samples because we cannot collect data on the entire population. But we can just as well take a sample because we don't have the ability to process the data from the entire population. We can use standard uncertainty estimates to tell us how close to the true quantity we are likely to be. And we can always take a bigger sample if we're not happy with the amount of uncertainty.
2. There are a variety of ideas out there for making use of sampling to address big data challenges. One idea (due in part to Prof. Michael Jordan here in Statistics/EECS) is to compute estimates on many (relatively small) bootstrap samples from the data (cleverly creating a reduced-form version of the entire dataset from each bootstrap sample) and then combine the estimates across the samples. Here's [the arXiv paper](#) on this topic, also published as Kleiner et al. in Journal of the Royal Statistical Society (2014) 76:795.
3. Randomized algorithms: there has been a lot of attention recently to algorithms that make use of randomization. E.g., in optimizing a likelihood, you might choose the next step in the optimization based on random subset of the data rather than the full data. Or in a regression context you might choose a subset of rows of the design matrix (the matrix of covariates) and corresponding observations, weighted based on the statistical leverage [recall the discussion of regression diagnostics in a regression course] of the observations. Here's another [arXiv paper](#) that provides some ideas in this area.

6 Hadoop, MapReduce, and Spark

Here we'll talk about a fairly recent development in parallel computing. Traditionally, high-performance computing (HPC) has concentrated on techniques and tools for message passing such as MPI and on developing efficient algorithms to use these techniques.

6.1 Overview

A basic paradigm for working with big datasets is the *MapReduce* paradigm. The basic idea is to store the data in a distributed fashion across multiple nodes and try to do the computation in pieces on the data on each node. Results can also be stored in a distributed fashion.

A key benefit of this is that if you can't fit your dataset on disk on one machine you can on a cluster of machines. And your processing of the dataset can happen in parallel. This is the basic idea of *MapReduce*.

The basic steps of *MapReduce* are as follows:

- read individual data objects (e.g., records/lines from CSVs or individual data files)

- map: create key-value pairs using the inputs (more formally, the map step takes a key-value pair and returns a new key-value pair)
- reduce - for each key, do an operation on the associated values and create a result - i.e., aggregate within the values assigned to each key
- write out the {key,result} pair

A similar paradigm that is being implemented in some R packages by Hadley Wickham is the split-apply-combine strategy (<http://www.jstatsoft.org/v40/i01/paper>).

Hadoop is an infrastructure for enabling MapReduce across a network of machines. The basic idea is to hide the complexity of distributing the calculations and collecting results. Hadoop includes a file system for distributed storage (HDFS), where each piece of information is stored redundantly (on multiple machines). Calculations can then be done in a parallel fashion, often on data in place on each machine thereby limiting the amount of communication that has to be done over the network. Hadoop also monitors completion of tasks and if a node fails, it will redo the relevant tasks on another node. Hadoop is based on Java but there are projects that allow R to interact with Hadoop, in particular *RHadoop* and *RHipe*. *Rhadoop* provides the *rmr*, *rhdfs*, and *rhbase* packages. For more details on *RHadoop* see Adler and <http://blog.revolutionanalytics.com/2011/09/mapreduce-hadoop-r.html>.

Setting up a Hadoop cluster can be tricky. Hopefully if you're in a position to need to use Hadoop, it will be set up for you and you will be interacting with it as a user/data analyst.

Ok, so what is Spark? You can think of Spark as in-memory Hadoop. Spark allows one to treat the memory across multiple nodes as a big pool of memory. So just as *data.table* was faster than *ff* because we kept everything in memory, Spark should be faster than Hadoop when the data will fit in the collective memory of multiple nodes. In cases where it does not, Spark will make use of the HDFS.

6.2 MapReduce and RHadoop

Let's see some examples of the MapReduce approach using R syntax of the sort one would use with *RHadoop*. While we'll use R syntax in the second piece of code below, the basic idea of what the map and reduce functions are is not specific to R. Note that using Hadoop with R may be rather slower than actually writing Java code for Hadoop.

First, let's consider a basic word-counting example. Suppose we have many, many individual text documents distributed as individual files in the HDFS. Here's pseudo code from Wikipedia. Here in the map function, the input {key,value} pair is the name of a document and the words in the document and the output {key, value} pairs are each word and the value 1. Then the reduce

function takes each key (i.e., each word) and counts up the number of ones. The output {key, value} pair from the reduce step is the word and the count for that word.

```
function map(String name, String document):
// name (key): document name
// document (value): document contents
  for each word w in document:
    return (w, 1)

function reduce(String word, Iterator partialCounts):
// word (key): a word
// partialCounts (values): a list of aggregated partial counts
sum = 0
for each pc in partialCounts:
  sum += pc
return (word, sum)
```

Now let's consider an example where we calculate mean and standard deviation for the income of individuals in each state. Assume we have a large collection of CSVs, with each row containing information on an individual. *mapreduce()* and *keyval()* are functions in the *RHadoop* package. I'll assume we've written a separate helper function, *my_readline()*, that manipulates individual lines from the CSVs.

```
library(rmr)

mymap <- function(k, v) {
  record <- my_readline(v)
  key <- record[['state']]
  value <- record[['income']]
  keyval(key, value)
}

myreduce <- function(k, v) {
  keyval(k, c(length(v), mean(v), sd(v)))
}

incomeResults <- mapreduce(
```

```

input = "incomeData",
map = mymap,
reduce = myreduce,
combine = NULL,
input.format = 'csv',
output.format = 'csv')

from.dfs(incomeResults, format = 'csv', structured = TRUE)

```

A few additional comments. In our map function, we could exclude values or transform them in some way, including producing multiple records from a single record. And in our reduce function, we can do more complicated analysis. So one can actually do fairly sophisticated things within what may seem like a restrictive paradigm. But we are constrained such that in the map step, each record needs to be treated independently and in the reduce step each key needs to be treated independently. This allows for the parallelization.

6.3 Spark

We'll focus on Spark rather than Hadoop for the speed reasons described above and because I think Spark provides a very nice environment in which to work. Plus it comes out of the AmpLab here at Berkeley. One downside is we'll have to know a bit of Python to use it.

6.3.1 Getting set up on Spark and the HDFS

We'll use Spark on an Amazon EC2 virtual cluster. Thankfully, Spark provides a Python-based script for setting up such a cluster. Occasionally the setup process goes awry but usually it's pretty easy. We need our Amazon authentication keys as well as public-private keypair for SSH. **Make sure you don't hard code your Amazon key information into any public file (including Github public repositories) - hackers will find the keys and use them to spin up instances, probably to mine bitcoin or send Spam; this happened in this class in 2014.**

We start by **downloading the Spark package** as a .tgz file (choosing the "source code" option) and untarring/zippping it. This all works from the VM. Also, on the SCF it's available on the Linux machines at `/usr/local/src/pd/spark-1.4.0/spark-1.4.0/ec2`.

```

export SPARK_VERSION=1.5.1
export CLUSTER_SIZE=12 # number of slave nodes
export mycluster=sparkvm-paciorek # need unique name relative to other

```

```

users

# I unzipped the Spark tarball to /usr/lib/spark via sudo on BCE
cd /usr/lib/spark/ec2

# set Amazon secret keys (manually or in my case by querying them elsewhere)
#AWS_ACCESS_KEY_ID=blah
AWS_ACCESS_KEY_ID=$(grep -i "^AWS_ACCESS_KEY_ID" ~/stat243-fall-2015-credentials | cut -d' ' -f3)
#AWS_SECRET_ACCESS_KEY=blahhhh
AWS_SECRET_ACCESS_KEY=$(grep -i "^AWS_SECRET_ACCESS_KEY" ~/stat243-fall-2015-credentials | cut -d' ' -f3)

### DO NOT HARD CODE YOUR AMAZON SECRET KEY INFORMATION INTO ANY PUBLIC
FILE, INCLUDING A GITHUB REPO !!!!! ###

# start cluster
./spark-ec2 -k chris_paciorek@yahoo.com:stat243-fall-2015 -i ~/.ssh/stat243-ec2-key.pem \
--region=us-west-2 -s ${CLUSTER_SIZE} -v ${SPARK_VERSION} launch ${mycluster}

# login to cluster
# as root
./spark-ec2 -k chris_paciorek@yahoo.com:stat243-fall-2015 -i ~/.ssh/stat243-ec2-key.pem \
--region=us-west-2 \
    login ${mycluster}
# or you can ssh in directly if you know the URL
# ssh -i ~/.ssh/stat243-fall-2015-ssh_key.pem root@ec2-54-71-204-234.us-west-2.amazonaws.com

# you can check your nodes via the EC2 management console

# to logon to one of the slaves, look at /root/ephemeral-hdfs/conf/slaves
# and ssh to that address
ssh 'head -n 1 /root/ephemeral-hdfs/conf/slaves'

```

```

# We can view system status through a web browser interface

# on master node of the EC2 cluster, do:
MASTER_IP='cat /root/ephemeral-hdfs/conf/masters'
echo ${MASTER_IP}
# Point a browser on your own machine to the result of the next command
# you'll see info about the "Spark Master", i.e., the cluster overall
echo "http://${MASTER_IP}:8080/"
# Point a browser on your own machine to the result of the next command
# you'll see info about the "Spark Stages", i.e., the status of Spark
tasks
echo "http://${MASTER_IP}:4040/"
# Point a browser on your own machine to the result of the next command
# you'll see info about the HDFS"
echo "http://${MASTER_IP}:50070/"

# when you are done and want to shutdown the cluster:
# IMPORTANT to avoid extra charges!!!
./spark-ec2 --region=us-west-2 --delete-groups destroy ${mycluster}

```

Next let's get the airline dataset onto the master node and then into the HDFS. Note that the file system commands are like standard UNIX commands, but you need to do `hadoop fs -` in front of the command. At the end of this chunk we'll start the Python interface for Spark.

```

export PATH=$PATH:/root/ephemeral-hdfs/bin/

hadoop fs -mkdir /data
hadoop fs -mkdir /data/airline

df -h
mkdir /mnt/airline
cd /mnt/airline
# for in-class demo:
scp paciorek@smeagol.berkeley.edu:/scratch/users/paciorek/243/AirlineData/1
.
# scp paciorek@smeagol.berkeley.edu:/scratch/users/paciorek/243/AirlineData

```



```

# for students:
# wget http://www.stat.berkeley.edu/share/paciorek/1987-2008.csvs.tgz
# tar -xvzf 1987-2008.csvs.tgz
# or individual files, e.g., data for 1987
# wget http://www.stat.berkeley.edu/share/paciorek/1987.csv.bz2

hadoop fs -copyFromLocal /mnt/airline/*bz2 /data/airline

# check files on the HDFS, e.g.:
hadoop fs -ls /data/airline

# get numpy installed
# there is a glitch in the EC2 setup that Spark provides -- numpy is
not installed on the version of Python that Spark uses (Python 2.7).
To install numpy on both the master and worker nodes, do the following
as root on the master node.
yum install -y python27-pip python27-devel
pip-2.7 install 'numpy==1.9.2' # 1.10.1 has an issue with a warning
in median()
/root/spark-ec2/copy-dir /usr/local/lib64/python2.7/site-packages/numpy

# pyspark is in /root/spark/bin
export PATH=${PATH}:/root/spark/bin
# start Spark's Python interface as interactive session
pyspark

```

6.3.2 Using Spark for pre-processing

Now we'll do some basic manipulations with the airline dataset. We'll count the number of lines/observations in our dataset. Then we'll do a map-reduce calculation that involves counting the number of flights by airline, so airline will serve as the key.

Note that all of the various operations are OOP methods applied to either the SparkContext management object or to a Spark dataset, called a Resilient Distributed Dataset (RDD). Here *lines* and *output* are both RDDs. However the result of *collect()* is just a standard Python object.

In the last step, let's compare how long it took to grab the SFO subset relative to the performance of R earlier in this Unit.

```
from operator import add
import numpy as np

lines = sc.textFile('/data/airline')

# particularly for in-class demo - good to repartition the 3 files
to more partitions
# lines = lines.repartition(96).cache()

numLines = lines.count()

# mapper
def stratify(line):
    vals = line.split(',')
    return(vals[16], 1)

result = lines.map(stratify).reduceByKey(add).collect()
# reducer is simply the addition function

# >>> result
#[(u'Origin', 22), (u'CIC', 7281), (u'LAN', 67897), (u'LNK', 289),
(u'DAB', 86656), (u'APF', 4074), (u'ATL', 6100953), (u'BIL', 92503),
(u'JAN', 190044), (u'GTR', 7520), (u'ISO', 5945), (u'SEA', 1984077),
(u'PIT', 2072303), (u'ONT', 774679), (u'ROW', 1196), (u'PWM', 161602),
(u'FAY', 44564), (u'SAN', 1546835), (u'ADK', 589), (u'ADQ', 10327),
(u'IAD', 1336957), (u'ANI', 475), (u'CHO', 19324), (u'HRL', 116018),
(u'ACV', 23782), (u'DAY', 380459), (u'ROA', 69361), (u'VIS', 1993),
(u'PSC', 38408), (u'MDW', 1170344), (u'MRY', 67926), (u'MCO', 1967493),
(u'EKO', 12808), (u'RNO', 510023), (u'TPA', 1321652), (u'OME', 21403),
(u'DAL', 952216), (u'GJT', 34921), (u'ALB', 292764), (u'SJT', 16590),
(u'CAK', 80821), (u'TUP', 1971), (u'MKG', 396), (u'DEN', 3319905),
(u'MDT', 167293), (u'RKS', 954), (u'GSP', 200147), (u'LAW', 18019),
(u'MCN', 7203), (u'PIA', 44780), (u'ROC', 368099), (u'BQK', 6934),
```

```

(u'MSP', 2754997), (u'ACT', 21081), (u'SBA', 119959), (u'HPN', 125500),
(u'RFD', 1560), (u'CCR', 4465), (u'BWI', 1717380), (u'SJU', 461019),
(u'SAV', 185855), (u'HOU', 1205951), (u'BPT', 8452), (u'RDU', 103678
....

# this counting by key could have been done
# more easily using countByKey()

vals = [x[1] for x in result]
sum(vals) == numLines # a bit of a check
# True
[x[1] for x in result if x[0] == "SFO"] # SFO result
# [2733910]

# if don't collect, can grab a few results
output = lines.map(stratify).reduceByKey(add)
output.take(5)
#[(u'Origin', 22), (u'CIC', 7281), (u'LAN', 67897), (u'LNY', 289),
(u'DAB', 86656)]

# also, you can have interim results stored as objects
mapped = lines.map(stratify)
result = mapped.reduceByKey(add).collect()

lines.filter(lambda line: "SFO" in line.split(',')[16]).saveAsTextFile('/data/airline-SFO2')

## make sure it's all in one chunk for easier manipulation on master
lines.filter(lambda line: "SFO" in line.split(',')[16]).repartition(1).saveAsTextFile('/data/airline-SFO2')
#lines.filter(lambda line: "SFO" in line.split(',')[16]).repartition(1).
#saveAsTextFile('/data/airline-SFO2')

```

Let's consider some of the core methods we used. The [Spark programming guide](#) discusses these and a number of others.

- `map()`: take an RDD and apply a function to each element, returning an RDD
- `reduce()` and `reduceByKey()`: take an RDD and apply a reduction operation to the elements,

doing the reduction stratified by the key values for *reduceByKey()*. Reduction functions need to be associative and commutative and take 2 arguments and return 1, all so that they can be done in parallel in a straightforward way.

- *filter()*: create a subset
- *collect()*: collect results back to the master
- *cache()*: tell Spark to keep the RDD in memory for later use
- *repartition()*: rework the RDD so it is in the specified number of chunks

Question: how many chunks do you think we want the RDD split into? What might the tradeoffs be?

Here's an example where we don't have a simple commutative/associative reducer function. Instead we group all the observations for each key into a so-called iterable object. Then our second map function treats each key as an element, iterating over the observations grouped within each key.

```
def computeKeyValue(line):
    vals = line.split(',')
    # key is carrier-month-origin-destination
    keyVals = '-'.join([vals[x] for x in [8,1,16,17]])
    if vals[0] == 'Year':
        return('0', [0,0,1,1])
    cnt1 = 1
    cnt2 = 1
    # 14 and 15 are arrival and departure delays
    if vals[14] == 'NA':
        vals[14] = '0'
        cnt1 = 0
    if vals[15] == 'NA':
        vals[15] = '0'
        cnt2 = 0
    return(keyVals, [int(vals[14]), int(vals[15]), cnt1, cnt2])

def medianFun(input):
    if len(input) == 2: # input[0] should be key and input[1] set
```

```

of values
    if len(input[1]) > 0:
        # iterate over set of values
        # input[1][i][0] is arrival delay
        # input[1][i][1] is departure delay
        m1 = np.median([val[0] for val in input[1] if val[2] ==
1])
        m2 = np.median([val[1] for val in input[1] if val[3] ==
1])

        return((input[0], m1, m2)) # m1, m2))
    else:
        return((input[0], -999, -999))
else:
    return((input[0], -9999, -9999))

output = lines.map(computeKeyValue).groupByKey()
medianResults = output.map(medianFun).collect()
medianResults[0:5]
# [(u'DL-8-PHL-LAX', 85.0, 108.0), (u'OO-12-IAH-CLL', -6.0, 0.0), (u'AA-4-L
2.0, 0.0), (u'WN-8-SEA-GEG', 0.0, 0.0), (u'MQ-1-ORD-MDT', 3.0, 1.0)]

```

6.3.3 Using Spark for fitting models

Here we'll see the use of Spark to fit basic regression models in two ways. Warning: there may well be better algorithms to use and there may be better ways to implement these algorithms in Spark. But these work and give you the idea of how you can implement fitting within the constraints of a map-reduce paradigm.

Note that my first step is to repartition the data for better computational efficiency. Instead of having the data split into 22 year-specific chunks that vary in size (which is how things are initially because of the initial file structure), I'm going to split into a larger number of equal-size chunks to get better load-balancing.

Linear regression via sufficient statistics In the first algorithm we actually compute the sufficient statistics, which are simply $X^T X$ and $X^T Y$. Because the number of predictors is small, these are miniscule compared to the size of the dataset. This code has two ways of computing the

matrices. The first treats each line as an observation and sums the $X_i^\top X_i$ and $X_i Y_i$ values across all observations. The second uses a map function that can operate on an entire partition, iterating through the elements of the partition, and computing $X_k^\top X_k$ and $X_k^\top Y_k$ for each partition, k . The second way is rather faster.

```
lines = sc.textFile('/data/airline')

def screen(vals):
    vals = vals.split(',')
    return (vals[0] != 'Year' and vals[14] != 'NA' and
            vals[18] != 'NA' and vals[3] != 'NA' and
            float(vals[14]) < 720 and float(vals[14]) > (-30) )
# 0 field is Year
# 14 field is ArrDelay
# 18 field is Distance
# 3 field is DayOfWeek

lines = lines.filter(screen).repartition(192).cache()
# 192 is a multiple of the total number of cores: 24 (12 nodes * 2
cores/node)

n = lines.count()

import numpy as np
from operator import add

P = 8

#####
# calc xtx and xty
#####
def crossprod(line):
    vals = line.split(',')
    y = float(vals[14])
    dist = float(vals[18])
    dayOfWeek = int(vals[3])
```

```

xVec = np.array([0.0] * P)
xVec[0] = 1.0
xVec[1] = float(dist)/1000
if dayOfWeek > 1:
    xVec[dayOfWeek] = 1.0
xtx = np.outer(xVec, xVec)
xty = xVec * y
return(np.c_[xtx, xty])

xtxy = lines.map(crossprod).reduce(add)
# 11 minutes

# now just solve system of linear equations!!

#####
# calc xtx and xty w/ mapPartitions
#####

# dealing with x matrix via mapPartitions

def readPointBatch(iterator):
    strs = list(iterator)
    matrix = np.zeros((len(strs), P+1))
    for i in xrange(len(strs)):
        vals = strs[i].split(',')
        dist = float(vals[18])
        dayOfWeek = int(vals[3])
        xVec = np.array([0.0] * (P+1))
        xVec[8] = float(vals[14]) # y
        xVec[0] = 1.0 # int
        xVec[1] = float(dist) / 1000
        if(dayOfWeek > 1):
            xVec[dayOfWeek] = 1.0
        matrix[i] = xVec
    return([matrix.T.dot(matrix)])

```

```

xtxyBatched = lines.mapPartitions(readPointBatch).reduce(add)
# 160 seconds

mle = np.linalg.solve(xtxy[0:P,0:P], xtxy[0:P,P])

```

Linear regression via cyclic coordinate descent In the second algorithm we pretend that we don't want to compute $X^\top X$, mimicing the situation in which we have too many predictors to either store $X^\top X$ or to do linear algebra on $X^\top X$. Instead we'll have a vector of starting values for β . Then we'll cycle through each element of β and optimize that element, holding the others constant. The individual update steps look like this:

$$\beta_p^{t+1} = \frac{\sum_i r_i x_i}{\sum_i x_{ip}^2}$$

where r_i the residual not including the p th predictor: $\sum_i (y_i - \sum_{j \neq p} x_{ij} \beta_j^t)$ and based on the current parameter values.

Once again, we'll use `mapPartitions()` to do the calculations we need for each step of the optimization piecewise on each partition (I use *batch* to describe this in the code). Note that the result after 10 iterations here is not the MLE, though most of the day of week effects are all shifted by a common amount relative to the mean when compared to the MLE.

```

def readPointPartition(iterator):
    strs = list(iterator)
    matrix = np.zeros((len(strs), P+1))
    print(len(strs))
    for i in xrange(len(strs)):
        vals = strs[i].split(',')
        dist = float(vals[18])
        dayOfWeek = int(vals[3])
        xVec = np.array([0.0] * (P+1))
        xVec[8] = float(vals[14]) # y
        xVec[0] = 1.0 # int
        xVec[1] = float(dist) / 1000
        if(dayOfWeek > 1):
            xVec[dayOfWeek] = 1.0
        matrix[i] = xVec

```



```

    return([matrix])

batches = lines.mapPartitions(readPointPartition).cache()
# 3 min

def denomSumSqPartition(mat):
    return((mat*mat).sum(axis=0))

# notice I do use global variables in here
# one may be able to avoid this by using
# nested functions, if one wanted to
def getNumPartition(mat):
    beta[p] = 0
    sumXb = mat[:, 0:P].dot(beta)
    return(sum((mat[:,P] - sumXb)*mat[:,p]))

sumx2 = batches.map(denomSumSqPartition).reduce(add)

beta = np.array([0.0] * P)
p = 0

oldBeta = beta.copy() # otherwise a shallow (i.e., pointer) copy!

it = 0

tol = .001
maxIts = 10
crit = 1e16

while crit > tol and it <= maxIts:
    #for it in range(1,6):
        for p in xrange(P):
            # get numerator as product of residual and X for coordinate
            sumNum = batches.map(getNumPartition).reduce(add)
            beta[p] = sumNum / sumx2[p]
            print("Updated var " + str(p) + " in iteration ", str(it),

```

```

".")
    crit = sum(abs(beta - oldBeta))
    oldBeta = beta.copy()
    print("-"*100)
    print(beta)
    print(crit)
    print("-"*100)
    it = it+1

# 7 s per iteration; ~9 minutes for 10 iterations
beta
#array([ 6.59246803,  0.76054724, -0.92357814,  0.16881708,  2.00073749,
#        2.66270618, -2.65116571, -0.36017589])

```

We've only done linear regression here, but similar coordinate descent computations can be done for GLMs and for Lasso type problems, and probably for other types of models. In fact coordinate descent is a (the?) standard algorithm for Lasso as discussed in [this paper](#), which describes the methods in the *glmnet* package.

Linear regression via gradient descent Cycling through each coefficient has the obvious disadvantage of having to cycle through each coefficient, which would become particularly problematic in a model with more predictors. An alternative is to do gradient descent on the entire vector of coefficients at once. For this problem the update at each step looks like this

$$\beta^{t+1} = \beta^t - \alpha \nabla L(\beta^t)$$

where $\nabla L(\beta^t)$ is the gradient vector of the log-likelihood evaluated at the current value, β^t . A key issue here, which we'll discuss in detail in the Unit on optimization is the step size, α , also known as the learning rate. Here's the code for doing gradient descent on the entire set of coefficients.

```

alpha = .4

def sumVals(mat):
    return(sum(mat[:,P]))

beta = np.array([0.0] * P)

```

```

beta[0] = batches.map(sumVals).reduce(add) / n
oldBeta = beta.copy()

def getGradBatch(mat):
    sumXb = mat[:, 0:P].dot(beta)
    return( ((sumXb - mat[:,P])*((mat[:, 0:P]).T)).sum(1) )

def ssqObj(mat):
    return ( (pow(mat[:,P] - mat[:, 0:P].dot(beta), 2)).sum() )

objValue = batches.map(ssqObj).reduce(add)

nIts = 100

storeVals = np.zeros((nIts, P+2))
tol = .001
maxIts = 100
crit = 1e16

while crit > tol and it < maxIts:
    gradVec = batches.map(getGradBatch).reduce(add)
    beta = beta - alpha*gradVec / n
    crit = sum(abs(beta - oldBeta))
    objValue = batches.map(ssqObj).reduce(add)
    oldBeta = beta.copy()
    storeVals[it, 0] = pow(objValue/n, 0.5)
    storeVals[it, 1] = crit
    storeVals[it, 2:(P+2)] = beta
    print("-"*100)
    print(it)
    print(beta)
    print(crit)
    print(pow(objValue/n, 0.5))
    print("-"*100)
    it = it + 1

```

```
# 15 min
#[ 6.57348292  0.75335604 -0.9251238   0.16222806  1.98565752  2.64468325
# -2.63650861 -0.36507276]
```

Note that I'm recording the value of the objective function to make sure that it is decreasing in every iteration, as one could set the learning rate such that that does not happen.

6.3.4 Final comments

Running a batch Spark job We can run a Spark job using Python code as a batch script rather than interactively. Here's an example, which computes the value of π by Monte Carlo simulation (more on the general technique in the Unit on simulation). Assuming the script is named *piCalc.py*, we would call the script like this: `spark-submit piCalc.py 100000000 1000`

```
import sys
from pyspark import SparkContext
from numpy import random as rand
if __name__ == "__main__":
    sc = SparkContext()
    # use sys.argv to get arguments
    # for example:
    total_samples = int(sys.argv[1]) if len(sys.argv) > 1 else 1000000
    num_slices = int(sys.argv[2]) if len(sys.argv) > 2 else 2
    samples_per_slice = round(total_samples / num_slices)
    def sample(p):
        rand.seed(p)
        x, y = rand.random(samples_per_slice), rand.random(samples_per_slice)
        # x, y = rand.random(samples_per_slice),
        # rand.random(samples_per_slice)
        return sum(x*x + y*y < 1)

    count = sc.parallelize(xrange(0, num_slices), num_slices).map(sample).reduce(
a, b: a + b)
    #count = sc.parallelize(xrange(0, num_slices), num_slices).
    # map(sample).reduce(lambda a, b: a + b)
    print "Pi is roughly %f" % (4.0 * count / (num_slices*samples_per_slice))
```

This code again uses the idea that it's computationally more efficient to have each operation occur on a batch of data rather than an individual data point. So there are 1000 tasks and the total number of samples is broken up amongst those tasks. In fact, Spark has problems if the number of tasks gets too large.

Python vs. Scala/Java Spark is implemented natively in Java and Scala, so all calculations in Python involve taking Java data objects converting them to Python objects, doing the calculation, and then converting back to Java. This process is called serialization and takes time, so the speed when implementing your work in Scala (or Java) may be faster. Here's a [small bit of info](#) on that.

sparkR Finally, there is an R interface for Spark, but it's pretty new and not as widely used, so I didn't think it worth covering.