Relational Databases and SQL Basics

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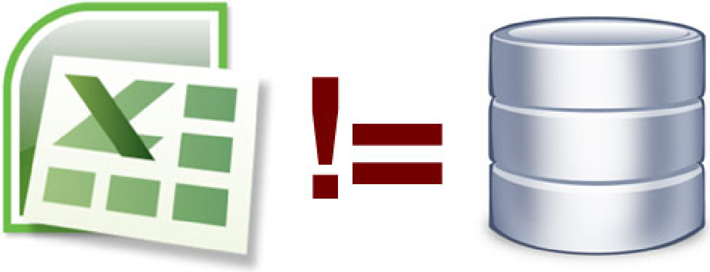
Motivations

"Excel is the World's Most Used Database"



Motivations

There are limitations on the types (and size) of data that programming languages and stat analyis packages can handle well:

- Extremely large data sets are difficult to manage. Memory (RAM) and disk space is an issue
- Concurrency is an issue. One user at a time access.
- Persistence of data between analysis sessions is a problem. How do you maintain data ?

Advantages of RDBMS

Relational Database Management Systems, (RDBMS), are designed to do all of these things well.

- Fast access to arbitrary parts of large data warehouses
- Powerful ways to summarize and cross-tabulate data
- Store data in more optimal and organized ways than the rectangular grid model of spreadsheets and R data frames
- Concurrent access from multiple clients running on multiple hosts while enforcing security constraints on access to the data

Taken from `http://cran.r-project.org/doc/manuals/R-data.html#Relational-databases`

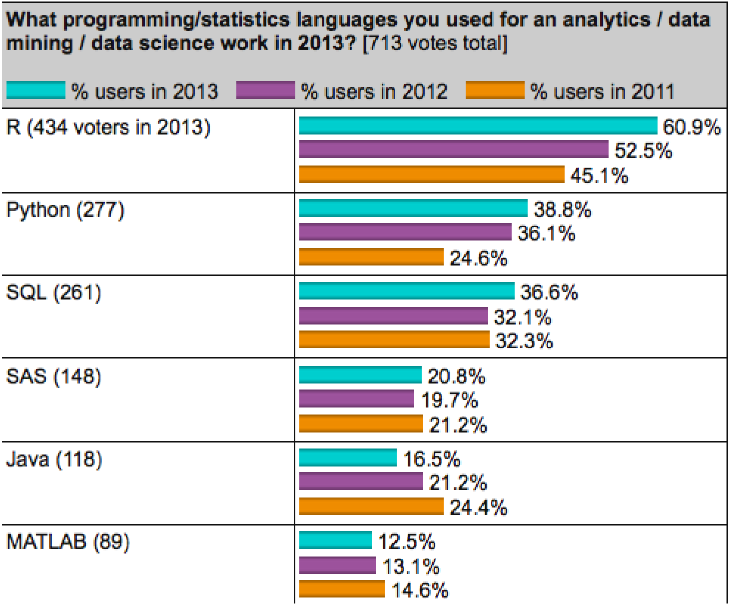
Advantages of RDBMS

Databases are useful when the size and organization of the data is large, complex, or requires security, (e.g. patient data, proprietary information).

- Commonly used in areas such as bioinformatics, medical records, machine learning, text mining, search algorithms
- Users search, extract, and collate data from the RDBMS and then do statistical analyses on the extracted info.
- You can create your own databases. Take a class - Coursera and Edx have free courses.

Some Examples

Here are some popular RDBMS packages. Some are free - some aren't.



Taken from `http://www.kdnuggets.com/2013/08/languages-for-analytics-data-mining-data-science.html`

Databse Jobs

There are different jobs for databases and users of SQL. The traditional ones are:

- **Database Administrator (DBA)** - Responsible for installing, configuring and maintaining a database management system (DBMS). Often tied to a specific platform such as Oracle, MySQL, DB2, SQL Server and others.
- **Datbase Architect** - Prepare and map out how the databases should look.
- **Database Designer/Database Architect** - Researches data requirements for specific applications or users, and designs database structures and application capabilities to match.
- **Database Developer** - Works with generic and proprietary APIs to build applications that interact with DBMSs (also platform specific, as with DBA roles).

Database Jobs

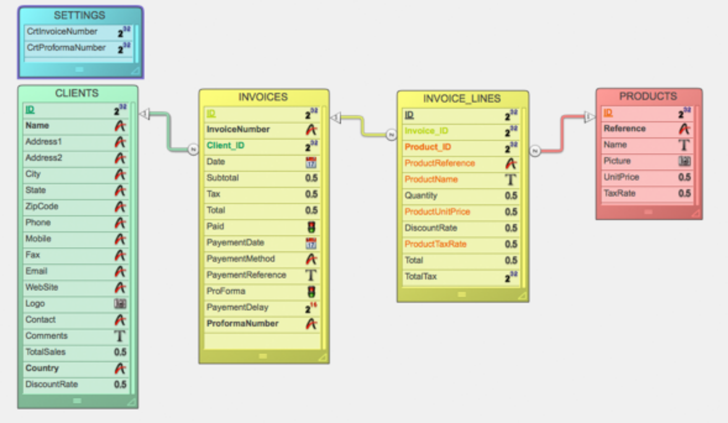
But there are newer career directions that rely upon a knowlege of SQL such as Data Scientist and Business Intellligence Analyst. Here is a set of job skill requirements from a job posting at Coursera.

Your skills

- 3+ years of industry experience in a relevant role
- Demonstrated aptitude for independent research based on past project
- Strong applied statistics and data visualization skills
- Proficient with relational databases and SQL
- Proficient with at least one scripting language (e.g. Python)
- Proficient with at least one statistical software package (e.g. R, MatLab, or NumPy, SciPy, Pandas)
- Communicates technical concepts clearly and concisely in oral and written form
- B.S., M.S., or PhD. in Applied Mathematics, Statistics, Computer Science, Economics, Operations Research, or related technical field

Data is organized in *schemas* which describe the objects, (tables). Tables are stored in a database.

A single database can contain one or more tables. The schema of the table describes the nature of the columns (e.g. numeric, character, integer, etc)



R concepts vs. Database concepts

R Concept	Database Concept
multiple related yet separate dataframes	Database
namespaces (sort of)	schema
data frame	table
variable (column)	column (attribute)
observation (row)	row(tuple)
subset(), [ ], transform, filter, select etc	SQL

Table : See https://goo.gl/YNC5ML

Introducing SQL

- Databases can be created and maintained locally on your computer or they can exist on a remote server. As long as you know the address of the server, and have permission, you can query the remote database.
- SQL, (Structured Query Language), is a language based on relational algebra that allows us to search and extract data. SQL includes capabilities to do data insert, query, update, delete, schema creation, and modification.
- SQL Server might support a slightly different SQL command set than MySQL or Postgres. These differences can ususally be addressed with minor adjustments in the query.

Introducing SQL

- S.Q.L is generally pronounced “sequel” or like “Ess Queue El”.
- Declarative - Write simple queries to extract data. You don’t need to know how that happens behind the scenes.
- SQL can be sent to a database interactively via a command line or GUI client but more common to happen from within a high level programming language such as R,Java,Python,C,C++,SAS, etc.
- Supported by all major RDBMS

Introducing SQL

There are two types of command sets in SQL: 1) DDL (Data Definition Language) and 2) DML (Data Manipulation Language)

- Data Definition Language
  - Create Table
  - Drop Table
  - Alter Table
- Data Manipulation Language
  - Select
  - Insert
  - Delete
  - Update

Typical Scenarios

There are two scenarios, (at least), that are common when working with databases:

- Users search for and extract data to an intermediate file, (e.g. a .csv file) after which they import it into their favorite analysis package.
- Users search for and extract data from within a program they have written. This is useful if repeated sampling is necessary based on some computation as the program executes.

SQLite

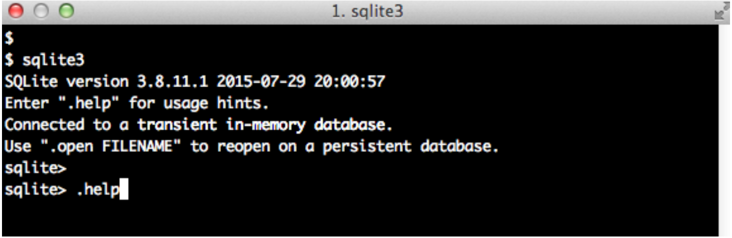
For this presentation we will use SQLite because it is free, lighweight, yet powerful. It comes preinstalled on Apple OSX and can be installed on Windows.

Go to `http://www.sqlite.org/download.html` to download the package. It is command line based although there are GUI front ends available.

SQLite

SQLite comes with a command line shell utility. On an Apple it is already installed by default. You just launch a terminal and type "sqlite3" to get it up and running.

If you are a Windows user then you will need to download and install the SQLITE shell as indicated above but once you get it installed it behaves the same as the client shell on Apple



SQLite GUI

There are various Graphical User Interfaces available for SQLite that try to make the process of creating and managing databases easier.

These are helpful to get you up and running with databases and I don't mind if you use them although you should over time gravitate towards the shell / command line because it offers more flexiblity.

DB Browser for SQLite

http://sqlitebrowser.org/

What is a Database ?

- A database is a set of named relations which are also known as tables. Think of an Excel WorkBook that contains one or more WorkSheets.
- Each Worksheet can be related to another Worksheet via formulas,etc.
- In RDBMS we create a database name and THEN create tables within the database.
- We can specify things like what are the uniquely identifying aspects of the table (for example a unique student id.)
- This enables us to “link” between tables if necessary. We aren’t obligated to do that but many SQL commands will span multiple tables.

Creating a Database

Let's say we have .csv file containing info on three species of iris flowers, (Setosa, Virginica, and Versicolor). Columns 1-4 are numeric values representing sepal length, sepal width, petal length, petal width. Column 5 is species.

You can download this file from
`http://steviep42.bitbucket.org/YOUTUBE.DIR/iris.csv`

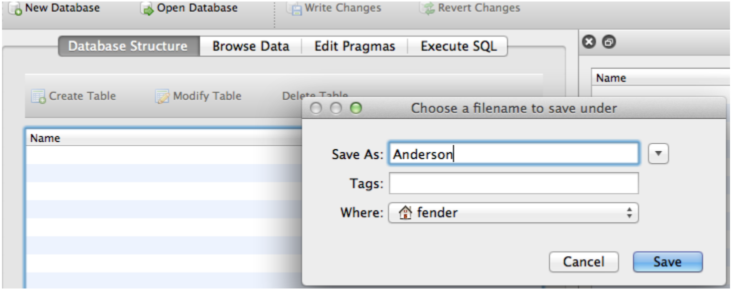
```
$ head iris.csv
5.1,3.5,1.4,0.2,setosa
4.9,3,1.4,0.2,setosa
4.7,3.2,1.3,0.2,setosa
4.6,3.1,1.5,0.2,setosa
5,3.6,1.4,0.2,setosa
5.4,3.9,1.7,0.4,setosa
4.6,3.4,1.4,0.3,setosa
```

We could read this into R or Excel and work with it there but let's see what SQLite can do for us.

Create a Database and a Single Table - GUI

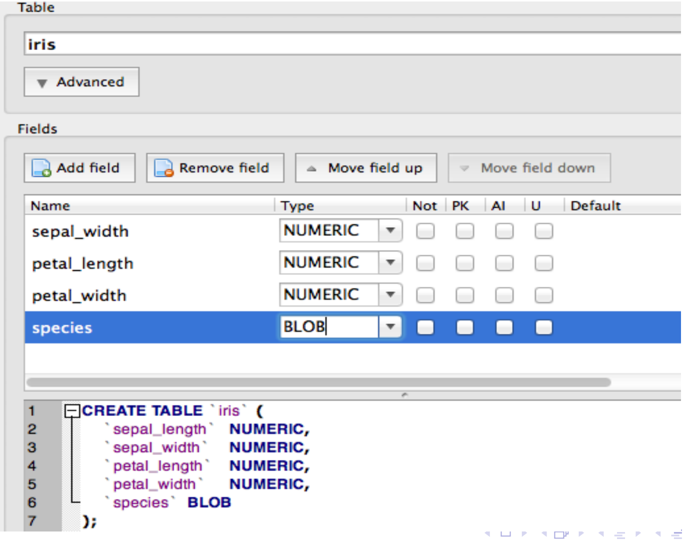
This data actually comes from the Edgar Anderson data set which is famous in statistics.

We will use the GUI to create a database called "Anderson" and then create a single table called "iris" to host the data.



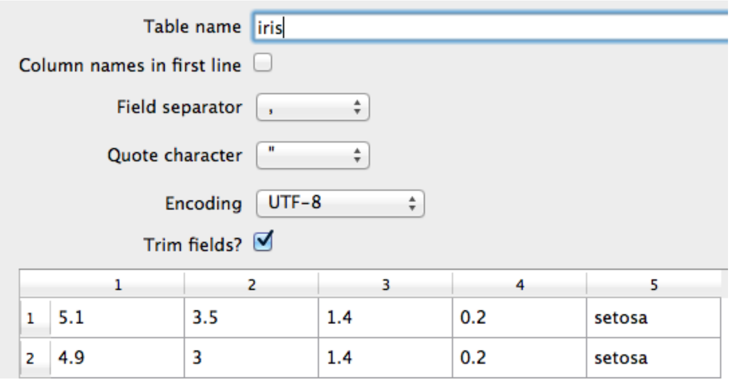
Create a Database and a Single Table - GUI

After we give the name “Anderson” to the database then we’ll create a table called “iris” to host the information in the .csv file.



Create a Database and a Single Table - GUI

Now we can import the iris.csv file into the table we just created



Creating a Database and a Single Table - Shell

If we wanted to create a database and table using the SQLite command shell we would do it as follows. Here is how:

```
$ sqlite3 iris.db   # Creates a database called "iris"
SQLite version 3.7.13 2012-07-17 17:46:21
Enter ".help" for instructions
Enter SQL statements terminated with a ";"
sqlite>
```

This creates a database called "iris". If the database were pre-existing then SQLite would simply load it in.

Creating a Database and a Single Table - Shell

Next we create one or more tables to host the data in the iris.csv file. The table is a template describing the column names as well as what type they are (e.g. numeric, double, character, date, etc).

```
sqlite> create table iris (sepal_length numeric(5,1),
   ...> sepal_width numeric(5,1),
   ...> petal_length numeric(5,1),
   ...> petal_width numeric(5,1),
   ...> species varchar(10));
sqlite>
```

We created it on the fly though tables can be created from within a programming language such as Python, R, C++, Java, Perl, etc.

Creating a Database and a Single Table - Shell

To verify our work let's issue the *schema* command:

```
sqlite> .schema
CREATE TABLE iris (sepal_length numeric(5,1),
sepal_width numeric(5,1),
petal_length numeric(5,1),
petal_width numeric(5,1),
species varchar(10));
```

So now let's import the data:

```
sqlite> .header on
sqlite> .mode csv
sqlite> .import iris.csv iris
```

Introducing SQL

The SELECT statement is the most frequently used SQL command.

It is basically three clauses: 1) FROM, 2) WHERE, 3) SELECT although they do not necessarily appear in that order

```
SELECT (what column attributes, data to return)
FROM  (relations between database table(s) )
WHERE (some condition is met)
```

Basic SQL Examples

So now we can start having fun.

```
sqlite> select count(*) from iris;
count(*)
150

sqlite> select count(*) as total_iris from iris;
total_iris
150

sqlite> .header off
sqlite> select count(*) from iris where species = "versicolor";
50

sqlite> select species, sepal_length from iris
        where sepal_length >= 7.8;
virginica|7.9
```

We don't have to know a lot about SQL to leverage it's power. Just a few commands will help us.

SQL Overview

SQL uses the SELECT statement to search and extract data. A general format is given here.

```
SELECT column or computations
       FROM table
       WHERE condition
       GROUP BY columns
       HAVING conditions
       ORDER BY column (ascending or descending)
       LIMIT offset, count;
```

Not all of these specifiers are necessary.

SQL	Result
SELECT * from iris	Extracts all rows and columns
SELECT sepal_width, petal_width from iris	A two column result

SQL Overview

SELECT * FROM iris WHERE species = 'setosa' LIMIT 5
Gets all Setosa records but list only the first 5 records

SELECT * FROM iris WHERE species = 'setosa' AND sepal_width >4.0
Gets all Setosa or Versicolor records with sepal_width greater than 4.0

SELECT * FROM iris WHERE (species = 'setosa' OR species = 'versicolor') AND sepal_width >3.3 LIMIT 5
Gets all setosa or versicolor records whose sepal_width is >than 3.3. Display only 5 records.

SELECT species, sepal_width, sepal_length from iris where sepal_width >3.5 ORDER BY species
Gets species, sepal_width, sepal_length where sepal_width is greater than 3.5 Result is then ordered by species alphabetically.

SQL Examples

```
sqlite> SELECT * FROM iris WHERE species = 'setosa' LIMIT 5;
5.1|3.5|1.4|0.2|setosa
4.9|3|1.4|0.2|setosa
4.7|3.2|1.3|0.2|setosa
4.6|3.1|1.5|0.2|setosa
5|3.6|1.4|0.2|setosa

sqlite> SELECT * FROM iris WHERE species = 'setosa' AND sepal_width > 4.0 ;
5.7|4.4|1.5|0.4|setosa
5.2|4.1|1.5|0.1|setosa
5.5|4.2|1.4|0.2|setosa

sqlite> SELECT * FROM iris WHERE (species = 'setosa' OR species = 'versicolor')
        AND sepal_width > 3.3 LIMIT 5;
5.1|3.5|1.4|0.2|setosa
5|3.6|1.4|0.2|setosa
5.4|3.9|1.7|0.4|setosa
4.6|3.4|1.4|0.3|setosa
5|3.4|1.5|0.2|setosa

sqlite> select * from iris where species like '%osa%' limit 1;
5.1|3.5|1.4|0.2|setosa
```

SQL Aggregation Functions

SQL provides some aggregate functions. These are basic though can be used to compute more sophisticated quantities. However do not try to use SQL as a substitute for R, SAS, or SPSS.

TASK	SQL Aggregate Function
Count number of occurences	COUNT()
Compute the sum	SUM()
Get the mean	AVG()
Get the minimum	MIN()
Get the maximum	MAX()
Get the variance	VAR_SAMP()
Get the standard deviation	STDDEV_SAMP()

SQL Examples

```
sqlite> select avg(sepal_length), avg(sepal_width) from iris;
5.84333333333333|3.05733333333333

sqlite> select round(avg(sepal_length),2), round(avg(sepal_width),2) from iris;
5.84|3.06

sqlite> select round(avg(sepal_length),2),round(avg(sepal_width),2)
        from iris group by species;
5.01|3.43
5.94|2.77
6.59|2.97

# But we need the species names here too

sqlite> select species, round(avg(sepal_length),2), round(avg(sepal_width),2)
        from iris group by species;
setosa|5.01|3.43
versicolor|5.94|2.77
virginica|6.59|2.97
```

The "as" operator

The "as" operator can cause some initial confusion until you see a few examples. At its most basic we use it to name columns in the output. To see the result you need to turn headers on in sqlite

```
sqlite> .headers on
sqlite> select species,avg(sepal_length) from iris;
species|avg(sepal_length)
virginica|5.84333333333333

sqlite> select species,avg(sepal_length) as mean_sepal_length from iris;
species|mean_sepal_length
virginica|5.84333333333333

sqlite> select species as Iris_Species,avg(sepal_length) as mean_sepal_length
        from iris;
Iris_Species|mean_sepal_length
virginica|5.84333333333333
```

The "as" operator

Let's say that we want the average sepal length across all three species but only for records where the sepal length is greater than 2.8.

```
sqlite> select species,avg(sepal_length) from iris where avg(sepal_length) > 2.8;
Error: misuse of aggregate: avg()

# Not quite what we wanted. Where are the other two species ?

sqlite> select species,avg(sepal_length) from iris group by species;
species|avg(sepal_length)
setosa|5.006
versicolor|5.936
virginica|6.588

# Better but still not what we want

sqlite> select species,avg(sepal_length) as mean from iris where mean > 2.8;
Error: misuse of aggregate: avg()
```

The "as" operator

```
sqlite> select species, round(avg(sepal_width),2) as mean
        from iris group by species HAVING mean > 2.8;
species|mean
setosa,3.43
virginica,2.97

# If we remove the requirement for the mean to be > 2.8

sqlite> select species, round(avg(sepal_width),2) as mean
        from iris group by species;
species|mean
setosa|3.43
versicolor|2.77
virginica|2.97

# Let's sort the result by the mean in ascending order

sqlite> select species, round(avg(sepal_width),2) as mean
        from iris group by species order by mean asc;
species|mean
versicolor|2.77
virginica|2.97
setosa|3.43
```

Insertions

We can also insert new records into the database. Usually this is done from a program or script which loads many records at once. However, you can load records one at a time if you wish.

```
sqlite> insert into iris values (5.1,3.5,1.4,0.2,"setosa");
sqlite> insert into iris values (4.9,3.5,1.4,0.2,"setosa");
```

We can also update or delete existing records based on some condition. An example:

```
sqlite> delete from iris where species = 'versicolor';
sqlite> select count(*) from iris where species = 'versicolor';
0
```

Access from within R

We can also access databases from within R. There are different ways to do this. Let's say we have a pre-existing database such as the one we just created - iris.db

```
> library(RSQLite)   # You will have to install this package
> (alltables <- dbListTables(con))
[1] "iris"

> (res <- dbGetQuery(con, "select count(*) from iris"))
  count(*)
1      150
> (res <- dbGetQuery(con, "select * from iris where sepal_length > 3.0 limit 5"))
  sepal_length sepal_width petal_length petal_width species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa
4          4.6         3.1          1.5         0.2  setosa
5          5.0         3.6          1.4         0.2  setosa
```

Access from within R

There is the “sqldf” package that allows you to query data frames as if they were database tables. You don’t need to have a pre-existing relational database to use SQL on the data frame.

```
> library(sqldf)
> data(mpg, package = "ggplot2") # Get the mpg data frame from ggplot2
> head(mpg,2)
  manufacturer model displ year cyl      trans drv cty hwy fl   class
1         audi    a4   1.8 1999   4   auto(l5)   f  18  29  p compact
2         audi    a4   1.8 1999   4 manual(m5)   f  21  29  p compact

> sqldf("select * from mpg where hwy > 35 and cty > 20")
  manufacturer      model displ year cyl      trans drv cty hwy fl      class
1        honda      civic   1.8 2008   4   auto(l5)   f  25  36  r subcompact
2        honda      civic   1.8 2008   4   auto(l5)   f  24  36  c subcompact
3       toyota    corolla   1.8 2008   4 manual(m5)   f  28  37  r    compact
4   volkswagen      jetta   1.9 1999   4 manual(m5)   f  33  44  d    compact
5   volkswagen new beetle   1.9 1999   4 manual(m5)   f  35  44  d subcompact
6   volkswagen new beetle   1.9 1999   4   auto(l4)   f  29  41  d subcompact
```

Access from within R

Note that the above is equivalent to the following which is how one would usually do this within R. The advantage of using the SQL approach is that it generalizes outside of R.

```
> mpg[mpg$hwy > 35 & mpg$cty > 20,]
    manufacturer      model displ year cyl      trans drv cty hwy fl      class
106        honda      civic   1.8 2008   4   auto(l5)   f  25  36  r subcompact
107        honda      civic   1.8 2008   4   auto(l5)   f  24  36  c subcompact
197       toyota    corolla   1.8 2008   4 manual(m5)   f  28  37  r    compact
213   volkswagen      jetta   1.9 1999   4 manual(m5)   f  33  44  d    compact
222   volkswagen new beetle   1.9 1999   4 manual(m5)   f  35  44  d subcompact
223   volkswagen new beetle   1.9 1999   4   auto(l4)   f  29  41  d subcompact
```

sqldf

Behind the scenes the sqldf package creates an SQLite version of the data.

```
# How many cars have a manual transmission ?

> sqldf("select count(*) from mpg where trans like '%man%'")
  count(*)
1       77

# Here is an equivalent R expression

> nrow(mpg[grep("man",mpg$trans),])
[1] 77
```

sqldf

Find the average city MPG by manufacturer. Sort it from highest to lowest

```
> sqldf("select manufacturer,avg(cty) as mean from mpg
        group by manufacturer order by mean desc")
   manufacturer mean
1         honda 24.4
2    volkswagen 20.9
3        subaru 19.3
4       hyundai 18.6
5        toyota 18.5
6        nissan 18.1
7          audi 17.6
8       pontiac 17.0
9     chevrolet 15.0
10         ford 14.0
11         jeep 13.5
12      mercury 13.2
13        dodge 13.1
14   land rover 11.5
15      lincoln 11.3
```

sqldf

Same as

```
> tmp <- aggregate(cty~manufacturer,data=mpg,mean)
> tmp[order(tmp$cty,decreasing=T),]
   manufacturer  cty
5         honda 24.4
15   volkswagen 20.9
13       subaru 19.3
6       hyundai 18.6
14       toyota 18.5
11       nissan 18.1
1          audi 17.6
12      pontiac 17.0
2     chevrolet 15.0
4          ford 14.0
7          jeep 13.5
10      mercury 13.2
3         dodge 13.1
8    land rover 11.5
9       lincoln 11.3
```

sqldf

Use the read.csv.sql function to read in parts of really large .csv files. Here is an example using the internal mtcars dataset. We'll write it out and read it back in.

It's not a big file but provides a prototype example that could be used for huge files. We'll read in only those records corresponding to 4 cylinder cars.

```
> library(sqldf)
> write.csv(mtcars,"mtcars.csv",quote=F,row.names=F)
> mtcars2 <- read.csv.sql("mtcars.csv",sql = "select * from file where cyl = 4")
> head(mtcars2)
   mpg cyl  disp hp drat    wt  qsec vs am gear carb
1 22.8   4 108.0 93 3.85 2.320 18.61  1  1    4    1
2 24.4   4 146.7 62 3.69 3.190 20.00  1  0    4    2
3 22.8   4 140.8 95 3.92 3.150 22.90  1  0    4    2
4 32.4   4  78.7 66 4.08 2.200 19.47  1  1    4    1
5 30.4   4  75.7 52 4.93 1.615 18.52  1  1    4    2
6 33.9   4  71.1 65 4.22 1.835 19.90  1  1    4    1
```

Multiple Tables

- Up until now the database has been very simple. It contains only one table. In reality most databases have multiple tables with an identifier or key in each table that can be referenced when writing SQL statements
- When we query multiple tables using SQL we call this a “join” although one could do a “self join” on a single table.
- Joins and keys can be complicated so here we will just outline some of the basics.
- Let’s use an example where we have a database with three tables. This data relates to restaurant inspection information in San Francisco. For more info see my blog posting at `http://tinyurl.com/l4qnjbu`

Multiple Tables

SQLite databases can be dumped into a single file that can later be read by others. The dump file contains the database and schema table for all tables.

Download this file using your browser, wget, curl, or whatever command you usually use to do download files.

```
http://steviep42.bitbucket.org/YOUTUBE.DIR/restaurants_database.dmp

# Create the database and then read in the dump file
$ sqlite3 restaurants.db
SQLite version 3.7.13 2012-07-17 17:46:21
Enter ".help" for instructions
Enter SQL statements terminated with a ";"
sqlite> .read restaurants_database.dmp
```

You now have a working copy of the database and the three supporting tables as well as the data.

Multiple Tables

Let's do some exploration.

```
sqlite> select count(score) as 'number_of_inspections' from inspections;
number_of_inspections
40936

# How many scores were below 70 ?

sqlite> select count(score) as score70 from inspections where score < 70;
score70
373

# Below 80 ?

sqlite> select count(score) as score80 from inspections where score < 80;
score80
1793
```

Multiple Tables

Okay well WHO has the LOWEST numeric score overall ?

```
sqlite> select name, score from businesses, inspections
       where businesses.business_id = inspections.business_id
       order by score limit 15;

PACIFIC SUPER MARKET|42
DICK LEE PASTRY|42
MANILA MARKET & GROCERIES|44
KL1 RESTAURANT|45
NEW ASIA RESTAURANT|47
ALBORZ|47
MANILA MARKET & GROCERIES|48
PUNJAB KABAB HOUSE|49
MEE HEONG BAKERY|49
HAPPY CHINESE RESTAURANT|50
KUSINA NI TESS|50
BANGKOK NOODLES & THAI BBQ|50
BROADWAY DIM SUM|51
NEW ASIA RESTAURANT|51
HONG KEE & KIM|51
```

Multiple Tables

How many violations exist for each restaurant ?

```
sqlite> select name, count(violationid) from businesses, violations
        where businesses.business_id = violations.business_id
        group by name limit 15;

HOL N JAM LEMONADE STAND  #2|2
 HOL N JAM LEMONADE STAND #1|6
 HOL N JAM LEMONADE STAND #3|4
 NORDSTROM CAFE BISTRO|19
1-CREDE|7
100% DESSERT CAFE|11
1058 HOAGIE|5
123 DELI - LEE'S|3
1300 ON FILLMORE|1
1760|1
17TH & NOE MARKET|6
18 REASONS|4
18TH STREET COMMISSARY|3
19TH AVE SHELL|9
20 SPOT MISSION, LLC|1
```

Multiple Tables

Well that wasn't sorted. I want to know the place with the most violations

```
sqlite> select name, count(violationid) as volcnt from businesses, violations
        where businesses.business_id = violations.business_id
        group by name order by volcnt desc limit 15;

STARBUCKS COFFEE|327
PEET'S COFFEE & TEA|189
MCDONALDS|121
QUICKLY|90
KENTUCKY FRIED CHICKEN|85
ROUND TABLE PIZZA|70
SPECIALTY'S CAFE & BAKERY|68
SAN FRANCISCO SOUP COMPANY|59
BURGERMEISTER|58
TEAWAY|58
HO'S BAR & RESTAURANT INC|56
KING OF THAI NOODLE HOUSE|54
MARNEE THAI RESTAURANT|54
YOPPI YOGURT|54
NORTH BEACH PIZZA|53
```

Multiple Tables

Wait a minute. So was it one Starbuck's location that got 327 violations ? Probably not. There are multiple Starbucks. How could we find out ?

The DISTINCT function in SQL will show us how many distinct business ids there are associated with any business containing "STARBUCK" in the name.

```
sqlite> select count(distinct(business_id)) from businesses
        where name like '%STARBUCK%';
71
```

Multiple Tables

So there are 71 Starbucks in the area. The 327 violations are spread over them. But how many per each

```
sqlite> select count(distinct(business_id)) from businesses
        where name like '%STARBUCK%';
71

sqlite> select name, businesses.business_id, count(violationid) from
        businesses, violations where name like '%STARBUCK%' and
        businesses.business_id = violations.business_id group by
        businesses.business_id order by count(violationid) desc limit 10;

STARBUCKS COFFEE|2072|18
STARBUCKS COFFEE|4425|13
STARBUCKS COFFEE|19416|13
STARBUCKS COFFEE|1505|12
STARBUCKS COFFEE|2633|12
STARBUCKS COFFEE|2799|12
STARBUCKS COFFEE|2805|12
STARBUCKS COFFEE|35771|12
STARBUCKS COFFEE|2218|11
STARBUCKS COFFEE|4656|11
```

Dates

We can use SQL to extract query and data between given date ranges. We need to use a helper function that tells SQLite that we are processing a true date as opposed to a mere character string.

See https://www.sqlite.org/lang_datefunc.html for more info on dates in SQLite.

Let's determine how many inspections took place between March 27, 2014 and April 10, 2014 ?

```
sqlite> select count(*) from inspections where strftime(date) >
        strftime('20140327') and strftime(date) < strftime('20140410');
563
```

Missing Values

Frequently we have missing values in data. It might be blank or have something like "NA". We have to be on the lookout for this.

```
sqlite> select avg(score) from inspections limit 5;
51.1987736955247

sqlite> select avg(score) from inspections where score not like '%NA%';
91.952485412188

sqlite> select postal_code, avg(score) as mean from businesses,
        inspections where businesses.business_id = inspections.business_id
        and score not like '%NA%' group by postal_code order by mean
        asc limit 5;

postal_code|0.0
94014|85.6666666666667
94609|86.375
94133|87.6198514517218
94122|87.6516976998905
sqlite>
```

Summary

Use relational databases when:

- There is lots and lots of data
- When the data is complex and/or has many interrelationships
- Other people might want to work with the data but might want different subsets
- When you need to put up a website that is a front end for the data

Don't attempt to use SQL for in depth statistical analysis. In such cases use SQL to get data and then import it into SAS, Python, SPSS, R, MatLab, Java or whatever language you want to use.

Most languages have methods that allow you to query databases directly from the language if you want to do that.

Summary

SQL is powerful. With it we query databases.

- Very useful for extracting data and subsets thereof
- Can be called from most languages R, SAS, Java, Python, SPSS
- Mastering SQL, like any other language, takes effort
- Can be extended to include GIS capabilities (see GIS mods for MySQL)

Do you Really Need SQL ?

The rise of the ORMs ! Object Relational Mappers

- These are packages that allow you to communicate to databases from your language of choice (e.g. Python, Java, etc)
- You don't have to know SQL to use ORMs
- Using ORMs results in much less code tha when trying to use native SQL directly
- ORMs are good for when you don't care about the structure of the database - you just want to access it somehow

Do you Really Need SQL ?

R has some great packages that let you do "SQL-like" things without leaving R or learning SQL explicitly.

- The **data.table** and **dplyr** package are awesome !
- **data.table** is great for reading in huge files
- Both **data.table** and **dplyr** have cool ways of implementing SAC
- SAC stands for **Split-Apply-Combine**
- We **Split** data on some factor(s), **Apply** some function (e.g. mean, sd, etc) to the split data, and then combine it into a summarized/aggregated form
- I prefer **dplyr** but frequently use **data.table** to read in large files
- You can mix both packages

I will use dplyr as a "training wheels" approach to learning SQL.

Do you Really Need SQL ?

Think about common tasks associated with examining data. There are a certain number of tasks or activities:

- Filter or select observations based on values of variables
- Rename existing varibles or create new ones
- Reorder or sort data frames according to values of variables
- Group the data frame in terms of the values of factor(s)
- Summarize the data according to groups
- Merge or join data frames
- Interact with remote or local databases

Common Data Operations

Task	Explanation
filter()	Select a subset of rows from a data frame
arrange()	Reorders a data frame according to one or more keys
distinct()	Find the values of a set of variables (used with select)
mutate()	Add new columns/variables to the data frame
slice()	Select a certain range of rows/observations
summarize()	Reduce a data frame to a single row according to groups
group_by()	Reorganize a data frame according to values of a factor
join	Join data frames according to common variables

Table : Common Data Manipulation Tasks

Do you Really Need SQL ?

Let's read in some files that help illustrate the above capabilities

```
url <- "http://steviep42.bitbucket.org/YOUTUBE.DIR/flights.csv"

flights <- read.csv(url,header=T)

nrow(flights)
[1] 336776

names(flights)
 [1] "year"      "month"     "day"       "dep_time"  "dep_delay" "arr_time"
 [7] "arr_delay" "carrier"   "tailnum"   "flight"
[11] "origin"    "dest"      "air_time"  "distance"  "hour"      "minute"

filter(flights, month==1 & year==2013)  # Find all flights in Jan of 2013
[1] 27004

# This is equivalent to the more verbose code in base R:

flights[flights$month == 1 & flights$day == 1, ]
```

Do you Really Need SQL ?

arrange() works similarly to filter() except that instead of filtering or selecting rows, it reorders them.

It takes a data frame, and a set of column names (or more complicated expressions) to order by.

Here we sort first by year, then month, then day

```
head(arrange(flights, year, month, day))
year month day dep_time dep_delay arr_time arr_delay carrier tailnum flight origin d
1 2013     1   1      517         2      830        11      UA  N14228   1545    EWR
2 2013     1   1      533         4      850        20      UA  N24211   1714    LGA
3 2013     1   1      542         2      923        33      AA  N619AA   1141    JFK
4 2013     1   1      544        -1     1004       -18      B6  N804JB    725    JFK
5 2013     1   1      554        -6      812       -25      DL  N668DN    461    LGA
6 2013     1   1      554        -4      740        12      UA  N39463   1696    EWR
```

Do you Really Need SQL ?

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5 2013     1   1      554        -6      812       -25      DL  N668DN    461     LGA
6 2013     1   1      554        -4      740        12      UA  N39463   1696     EWR
```