Comparative Study: R, PostgreSQL, MongoDB

Daniel Dittenhafer

Monday, November 3, 2014

Introduction

This study compares the basic data storage and querying capability of R, PostgreSQL and MongoDB using a common data set as described in the next section. Commentary regarding advantages and disadvantages, as well as specific experiences with the scenario data set are presented. Finally, a recommended technology is put forward with supporting points. An appendix including comparable sample code is provided as well.

Data Set Use Case

The data set used in this comparative study was obtained from the U.S. Department of Housing and Urban Development (HUD). It contains fair market rent (FMR) data points for counties and metropolitan statistical areas through-out the United States of America. The FMR data points are required to be published by HUD as part of Section 8 of the United States Housing Act of 1937.

FMR data is used by programs operating under Section 8 including the Housing Choice Voucher, the Moderate Rehabilitation, and the project-based voucher programs. External to these programs, this data set can be used to better understand differences in housing costs around the United States, and if compared to other years, how costs are changing over time.

Advantages / Disadvantages

R The R runtime provides several functions for saving and loading data in the RData format. The save function will persist one or more variables to a specified file in either ASCII or binary format, and likewise the load function will deserialize the data from a given file into the R runtime's environment.

The RData format and associated functions are quite useful for importing and/or sharing small data sets, as well as preserving work from day to day. Mid-sized data sets (< 8GB) could be serialized using these functions as well, wherein the compress option might be a significant benefit.

Beyond the use cases described above, the RData format is unlikely to be useful for larger data sets (8+GB). The R runtime wants to place any data loaded from RData files into the environment's memory space. Depending on your operating system some of this may be swapped to disk, but nonetheless working memory is now limited due to the presence of the loaded data.

Simultaneous access by multiple users could also be a problem. Once a data set is loaded from a given file, another user could also load the same data from the file, for example if the file is shared on a network drive. Sharing changes presents a problem though. The entire data set would need to be serialized back to the file and notifications broadcast to colleagues of the need to reload the file (thereby losing any changes they had made).

In terms of security, if an unauthorized user were to acquire an RData file, there is no inherent permissions management to prevent them from accessing and/or updating the data.

For the Fair Market Rents data set, R's read.table function did not handle some of the encoding used in place names even when both the latin1 and UTF-8 options were specified for the encoding parameter.

A portion of the data was able to be loaded. Once loaded, R's querying and data analytic capabilities shined.

PostgreSQL PostgreSQL is an open source relational database management system (RDBMS) which stores data in databases and tables hosted through a separate data service typically on a separate server.

PostgreSQL is well suited for persisting data sets ranging from kilobytes to terabytes. According to the PostgreSQL website, a given database in not limited in size, and a given table within a database can be as large as 32TB. Since the data is hosted on a central server, sharing across multiple users is much simpler than the RData scenario. Each user can connect and query the data independently, and PostgreSQL manages the access (security) as well as any updates that might be committed.

Once data is in a PostgreSQL database, sharing the data within an organization is very straight forward. Any user with permission can connect and query from a wide range of client applications. Sharing the data outside an organization is much more difficult. The data could be exported to a CSV file for example, though depending on the size of the data set, this might not be feasible. Alternatively, a web application interface might be developed to enable external access while maintaining security for other data sources.

For the Fair Market Rent data set, PostgreSQL pgAdmin's import utility was used to load the data from the CSV file into a staging table very smoothly, including the handling of latin1 encoded characters, without issue. The staging table had to be predefined and created within a pre-created database before the import utility was used. See the Appendix - PostreSQL Code section for details regarding the database design and normalization after the raw data was loaded.

Although not strictly necessary, normalizing the data, such as state and county names, into look-up tables is considered best practice in RDBMS database design. Normalization requires several extra steps that might not be necessary for all data sets. In the case of the Fair Market Rent data, the normalization process revealed some missing data (a FIPS and county code) for Cumberland County, ME as shown in the following screenshot.

1431 2300511125	2300511125	1074	730	869	1421	1492	5	23	11125	Cumberland	METRO388	Portland,	Casco town
1432	2300512300	1074	730	869	1421	1492		23	12300	Cumberland	METRO388	Portland,	Chebeague Island town
1433 2300515430	2300515430	1074	730	869	1421	1492	5	23	15430	Cumberland	METRO388	Portland,	Cumberland town

MongoDB MongoDB is an open source NoSQL document data store. As such, no pre-defined schemas are needed in order to import data and importing raw data from a CSV or JSON data file into a MongoDB collection generally requires less preparation than with PostgreSQL (the schema definition and database/table creation).

Like many NoSQL data stores, MongoDB is built to handle large data sets (as large as 128TB in MongoDB's case), but it is also quite useful for managing smaller data sets such as our Fair Market Rent data.

Like PostgreSQL, MongoDB provides security mechanisms for authenticating and authorizing client users. Also like PostgreSQL and R, MongoDB supports querying across all fields and producing aggregations from the data (many NoSQL solutions, such as HBASE, don't support this).

As part of the schemaless design of MongoDB, normalization is typically not applied to raw data. In MongoDB, references between documents are mostly manual, though there is a concept of DBRef which appears to offer similar functionality as traditional RDBMS foreign key relationships. Some data scenarios, including our Fair Market Rent scenario, don't absolutely require normalization, but others benefit from the data typing and relationship enforcement that an RDBMS provides.

For the Fair Market Rent data set, the mongoimport.exe utility was used for data import. As mentioned previously, the data was in a Latin 1 encoding, which MongoDB doesn't support. The utility did the best it could and imported all rows which didn't have Latin 1 specific encoding. The data set was reimported after converting it to UTF-8 (via Notepad++) and mongoimport performed as expected and imported all rows without issue.

Recommendation

For smaller data sets, particularly those that load into R cleanly using the read.table function, RData seems to be the best option for storing and quickly reloading data. With that said, based on the experiences with the Fair Market Rent data set and character encoding, MongoDB is the clear stand-out for its ease of import, the power it offers for querying and sharing data within a organization, and its ability to scale out as future data needs require.

Appendix

Data Set Description The specific data set used is the 2015 Fair Market Rent Country Level Data File: http://www.huduser.org/portal/datasets/fmr/fmr2015f/FY2015F_4050_Final.xls

The data set was downloaded in Microsoft Excel format (XLS) and saved to CSV format to enable easier access by the various technologies used throughout this study.

Data Set	Number of	Area	Attribute	Number of	Missing
Characteristics	Observations		Characteristics	Attributes	Values?
Multivariate	4,769	Business	Categorical, Integer, String	18	Yes

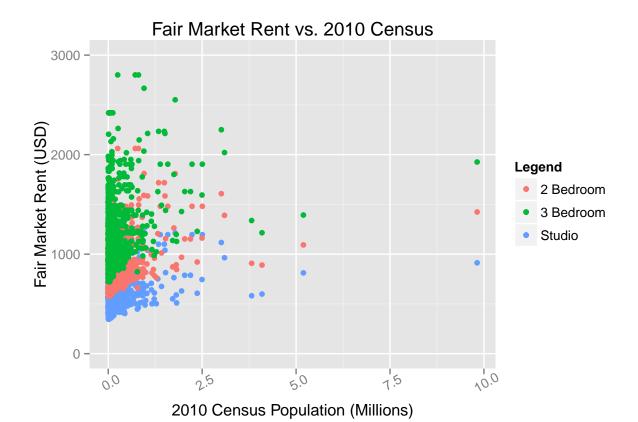
Attribute Information The following table lists the data types and a brief description of the fields contained in the data set used in this comparative study.

Field	Data Type	Description
fips2000	integer	2000 Census 10-digit state, county, metro code
fips2010	integer	2010 Census 10-digit state, county, metro code
fmr2	integer	2 bedroom fair market rent
fmr0	integer	0 bedroom (studio) fair market rent
fmr1	integer	1 bedroom fair market rent
fmr3	integer	3 bedroom fair market rent
fmr4	integer	4 bedroom fair market rent
county	integer	County number
State	integer	State number
CouSub	integer	County Sub number
countyname	string	County Name
Metro_code	string	METROxxxxxMxxxxx for metropolitan areas and NCNTYxxxxxNxxxxx for nonmetropolitan counties
Areaname	string	Area name
$county_town_name$	string	Locality name to which the pop 2010 field is relevant
pop2010	integer	Population of locality from 2010 Census
state_alpha	string	2 character abbreviation for State
fmr_type	integer	Percentile of FMR

Field	Data Type	Description
metro	binary	1 = Metro, 0 = non-metro county

R Code The following R code demonstrates loading the data set from CSV format, manipulating to ensure proper data typing, and serializing to/from the RData format.

```
# Load the data into a data.frame
csv_file <- file.path(projRoot, "Week10", "Data", "FY2015F_4050_Final.csv")</pre>
csv <- read.table(csv_file, header=TRUE, sep=",",</pre>
                   fill=TRUE, stringsAsFactors=FALSE, encoding="latin1")
# Data types and scaling
dfFmrData <- data.frame(csv)</pre>
dfFmrData$fmr0 <- as.numeric(csv$fmr0)</pre>
dfFmrData$fmr1 <- as.numeric(csv$fmr1)</pre>
dfFmrData$fmr2 <- as.numeric(csv$fmr2)</pre>
dfFmrData$fmr3 <- as.numeric(csv$fmr3)</pre>
dfFmrData$fmr4 <- as.numeric(csv$fmr4)</pre>
dfFmrData$state_alpha <- as.factor(csv$state_alpha)</pre>
dfFmrData$metro <- as.numeric(csv$metro)</pre>
dfFmrData$pop2010 <- as.numeric(csv$pop2010) / 1000000
# Save to RData format
savePath <- file.path(projRoot, "Week10", "Data", "FMR_FY2015_Final.RData")</pre>
save(dfFmrData, file=savePath)
# Load from RData format
load(savePath)
```



fips2000 fips2010 fmr2 ## fmr0 Length: 3363 Length:3363 ## Min. 40 Min. ## Class : character Class : character 1st Qu.: 642 1st Qu.: 452 Median: 721 ## Mode :character Mode :character Median: 511 : 825 ## Mean Mean : 577 3rd Qu.: 944 3rd Qu.: 674 ## ## Max. :2062 :1291 Max. ## NA's :48 NA's :48 ## fmr1 fmr3 fmr4 county : 429 : 724 : 776 Length:3363 ## Min. Min. Min. 1st Qu.: 497 1st Qu.: 858 1st Qu.: 951 Class : character ##

Median: 574 Median: 971 Median:1135 Mode : character ## ## Mean : 651 Mean :1090 Mean :1239 ## 3rd Qu.: 773 3rd Qu.:1256 3rd Qu.:1459 :1635 :2801 :3386 ## Max. Max. Max. NA's :49 NA's :49 NA's :49 ##

State CouSub countyname ## Length: 3363 Length: 3363 Length:3363 ## Class :character Class :character Class : character Mode :character Mode : character Mode :character ##

##

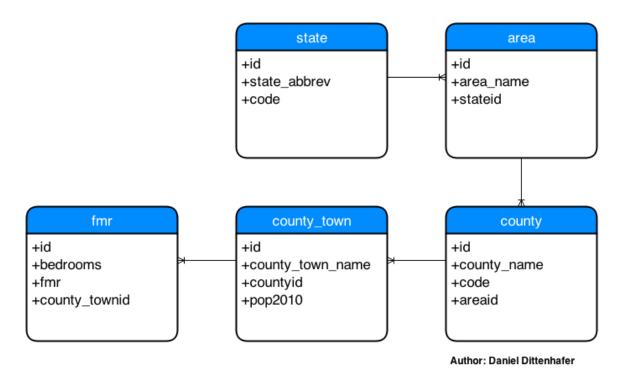
Metro_code Areaname county_town_name pop2010
Length:3363 Length:3363 Min. :0.00

```
Class :character
                       Class :character
                                           Class :character
                                                               1st Qu.:0.01
##
    Mode :character
                       Mode :character
                                           Mode :character
                                                               Median:0.02
##
                                                               Mean
                                                                     :0.08
##
                                                               3rd Qu.:0.05
##
                                                               Max.
                                                                      :9.82
##
                                                               NA's
                                                                      :51
##
     state_alpha
                     fmr_type
                                           metro
           : 351
##
    MA
                   Length:3363
                                       Min.
                                              :0.00
           : 258
##
    NH
                   Class :character
                                       1st Qu.:0.00
           : 254
                   Mode :character
                                       Median:0.00
##
    TX
##
    CT
           : 169
                                       Mean
                                              :0.43
##
    GA
           : 159
                                       3rd Qu.:1.00
           : 116
##
    MO
                                       Max.
                                              :1.00
    (Other):2056
                                       NA's
                                              :51
##
```

PostgreSQL Code The following entity relationship diagram shows the database design created during the PostgreSQL portion of this comparative study.

HUD Fair Market Rents Entity Relationship Diagram

This Entity Relationship Diagram illustrates the tables and relationships for modeling HUD Fair Market Rent data in a relational database such as PostgreSQL.



Data was first imported into a staging table in PostgreSQL via the pgAdmin Import utility. After the data was imported, SQL statements were used to split the data into the appropriate tables as shown in the code segment below.

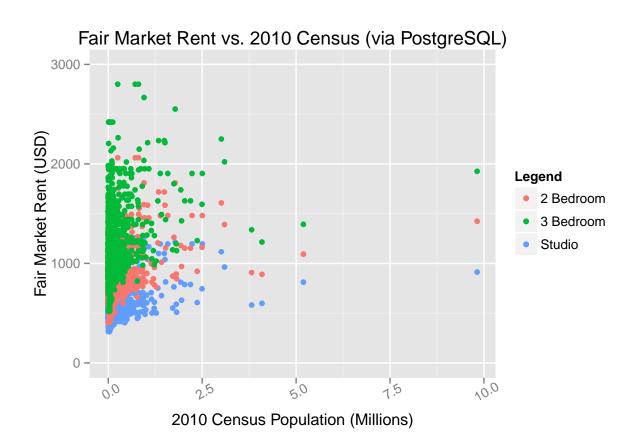
```
-- Normalize state info
INSERT INTO state (state_abbrev, code)
  SELECT DISTINCT state alpha, to number(state, '99')
 FROM staging ORDER BY state_alpha
-- Normalize area info
INSERT INTO area (area_name, stateid)
  SELECT DISTINCT areaname, s.id
       FROM staging st
        INNER JOIN state s ON s.state_abbrev = st.state_alpha
        ORDER BY areaname
-- Normalize county info
INSERT INTO county (county_name, code, areaid)
    SELECT DISTINCT countyname, to_number(county, '999'), a.id
       FROM staging st
        INNER JOIN state s ON s.state_abbrev = st.state_alpha
        INNER JOIN area a ON a.area_name = st.areaname AND a.stateid = s.id
       ORDER BY countyname
-- Normalize county town info
INSERT INTO county_town (county_town_name, countyid, pop2010)
    SELECT DISTINCT county_town_name, c.id, to_number(pop2010, '999999999')
       FROM staging st
        INNER JOIN state s ON s.state_abbrev = st.state_alpha
        INNER JOIN area a ON a.area name = st.areaname AND a.stateid = s.id
        INNER JOIN county c ON c.county_name = st.countyname AND c.areaid = a.id
        ORDER BY county_town_name
INSERT INTO fmr (bedrooms, fmr, county_townid)
   SELECT 0, to_number(fmr0, '999999'), ct.id
       FROM staging st
        INNER JOIN state s ON s.state_abbrev = st.state_alpha
        INNER JOIN area a ON a.area_name = st.areaname AND a.stateid = s.id
       INNER JOIN county c ON c.county_name = st.countyname AND c.areaid = a.id
        INNER JOIN county_town ct ON ct.county_town_name = st.county_town_name
      AND ct.countyid = c.id
INSERT INTO fmr (bedrooms, fmr, county_townid)
   SELECT 1, to_number(fmr1, '999999'), ct.id
       FROM staging st
        INNER JOIN state s ON s.state_abbrev = st.state_alpha
       INNER JOIN area a ON a.area_name = st.areaname AND a.stateid = s.id
       INNER JOIN county c ON c.county_name = st.countyname AND c.areaid = a.id
        INNER JOIN county_town ct ON ct.county_town_name = st.county_town_name
      AND ct.countyid = c.id
INSERT INTO fmr (bedrooms, fmr, county_townid)
   SELECT 2, to_number(fmr2, '999999'), ct.id
       FROM staging st
        INNER JOIN state s ON s.state_abbrev = st.state_alpha
        INNER JOIN area a ON a.area_name = st.areaname AND a.stateid = s.id
        INNER JOIN county c ON c.county_name = st.countyname AND c.areaid = a.id
```

```
INNER JOIN county_town ct ON ct.county_town_name = st.county_town_name
      AND ct.countyid = c.id
INSERT INTO fmr (bedrooms, fmr, county_townid)
    SELECT 3, to_number(fmr3, '999999'), ct.id
       FROM staging st
       INNER JOIN state s ON s.state_abbrev = st.state_alpha
       INNER JOIN area a ON a.area_name = st.areaname AND a.stateid = s.id
       INNER JOIN county c ON c.county_name = st.countyname AND c.areaid = a.id
        INNER JOIN county_town ct ON ct.county_town_name = st.county_town_name
      AND ct.countyid = c.id
INSERT INTO fmr (bedrooms, fmr, county_townid)
    SELECT 4, to_number(fmr4, '999999'), ct.id
       FROM staging st
       INNER JOIN state s ON s.state_abbrev = st.state_alpha
       INNER JOIN area a ON a.area_name = st.areaname AND a.stateid = s.id
        INNER JOIN county c ON c.county_name = st.countyname AND c.areaid = a.id
       INNER JOIN county_town ct ON ct.county_town_name = st.county_town_name
      AND ct.countyid = c.id
```

Using a query such as the following, R can be used to query the PostgreSQL data and produce a similar chart as in the R code shown previously.

```
require("RPostgreSQL")
## Loading required package: RPostgreSQL
## Loading required package: DBI
# PostgreSQL - connect
drv <- dbDriver("PostgreSQL")</pre>
con <- dbConnect(drv,user="postgres",password="a",dbname="proj4")</pre>
# Query the Postgres data tables
sQuery <- "SELECT ct.pop2010 / 1000000.0 AS pop2010,
                  fmr0.fmr AS fmr0,
                  fmr2.fmr AS fmr2,
                  fmr3.fmr AS fmr3 FROM county town ct
 LEFT JOIN fmr fmr0 ON fmr0.county_townid = ct.id AND fmr0.bedrooms = 0
 LEFT JOIN fmr fmr2 ON fmr2.county_townid = ct.id AND fmr2.bedrooms = 2
 LEFT JOIN fmr fmr3 ON fmr3.county_townid = ct.id AND fmr3.bedrooms = 3"
res <- dbGetQuery(con, sQuery)
g6 <- ggplot(data=res, aes(x=pop2010))</pre>
g6 <- g6 + geom_point(aes(y=fmr0, colour="Studio"))
g6 <- g6 + geom_point(aes(y=fmr2, colour="2 Bedroom"))</pre>
g6 <- g6 + geom_point(aes(y=fmr3, colour="3 Bedroom"))</pre>
g6 <- g6 + scale_fill_hue(l=40)
g6 \leftarrow g6 + ylim(0, 3000)
g6 <- g6 + theme(axis.text.x = element_text(angle=30, vjust=1))</pre>
g6 <- g6 + guides(colour = guide_legend("Legend"))
g6 <- g6 + labs(title="Fair Market Rent vs. 2010 Census (via PostgreSQL)",
```

```
x="2010 Census Population (Millions)",
y="Fair Market Rent (USD)")
g6
```



MongoDB Code For simplicity, the data was left as it was after importing via mongoimport. An example JSON document is shown below:

```
"_id" : ObjectId("5457be09fe0613e0b0d43388"),
"fips2000" : NumberLong("5601399999"),
"fips2010" : NumberLong("5601399999"),
"fmr2" : 712,
"fmr0" : 516,
"fmr1" : 526,
"fmr3": 967,
"fmr4" : 971,
"county" : 13,
"State" : 56,
"CouSub" : 99999,
"countyname": "Fremont County",
"Metro_code" : "NCNTY56013N56013",
"Areaname" : "Fremont County, WY",
"county_town_name" : "Fremont County",
"pop2010" : 40123,
```

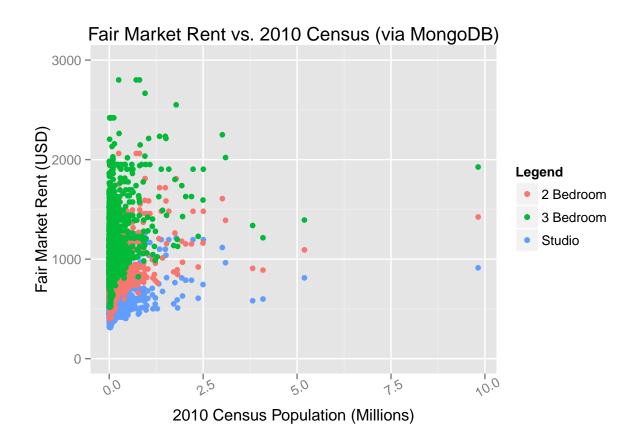
```
"state_alpha" : "WY",
    "fmr_type" : 40,
    "metro" : 0
}
```

MongoDB is accessible from many clients including R. The following code demonstrates accessing the Fair Market Rent data via the rmongodb package and producing the familiar Rent vs. Population chart as in the previous examples.

```
require (rmongodb)
```

Loading required package: rmongodb

```
# Create connection to the mongo database
mongo <- mongo.create(host=mongohost, username=user, password=pass, db=authdb)
# Get the FMR data frame
query <- "{ }"
fields <- "{ \"pop2010\": 1, \"fmr0\": 1, \"fmr2\": 1, \"fmr3\": 1}"
ns = sprintf("%s.%s", db, "fmr2015")
cursor <- mongo.find(mongo, ns, query, fields = fields)</pre>
dfFmrMongo <- mongo.cursor.to.data.frame(cursor)</pre>
# Scale the population
dfFmrMongo$pop2010 <- dfFmrMongo$pop2010 / 1000000.0
g7 <- ggplot(data=dfFmrMongo, aes(x=pop2010))
g7 <- g7 + geom_point(aes(y=fmr0, colour="Studio"))
g7 <- g7 + geom_point(aes(y=fmr2, colour="2 Bedroom"))
g7 <- g7 + geom_point(aes(y=fmr3, colour="3 Bedroom"))
g7 <- g7 + scale_fill_hue(1=30)
g7 \leftarrow g7 + ylim(0, 3000)
g7 <- g7 + theme(axis.text.x = element_text(angle=30, vjust=1))
g7 <- g7 + guides(colour = guide_legend("Legend"))
g7 <- g7 + labs(title="Fair Market Rent vs. 2010 Census (via MongoDB)",
                x="2010 Census Population (Millions)",
                y="Fair Market Rent (USD)")
g7
```



Source Code

The raw R markdown and other code used in this comparative study can be found on GitHub, in my DataAcqMgmt repository.

References

[&]quot;About." PostgreSQL: N.p., n.d. Web. 02 Nov. 2014. http://www.postgresql.org/about/.

[&]quot;Final Fair Market Rents for the Housing Choice Voucher Program and Moderate Rehabilitation Single Room Occupancy Program Fiscal Year 2015, Docket No. FR-5807-N-03; Notice of Final Fiscal Year (FY) 2015 Fair Market Rents (FMRs)," 70 Federal Register 192 (3 October 2014), pp 59786-59792.

[&]quot;MongoDB Limits and Thresholds." MongoDB Limits and Thresholds — MongoDB Manual 2.6.4. MongoDB, Inc., n.d. Web. 03 Nov. 2014. http://docs.mongodb.org/manual/reference/limits/.

[&]quot;R: Save R Objects." R: Save R Objects. R Project, n.d. Web. 02 Nov. 2014. http://stat.ethz.ch/R-manual/R-patched/library/base/html/save.html.

[&]quot;What Are the Disadvantages of Using .Rdata Files Compared to HDF5 or NetCDF?" StackOverflow.com. Stack Exchange Inc., 25 Oct. 2011. Web. 02 Nov. 2014. http://stackoverflow.com/a/7890475.