Intro to HBase via R

Aaron Benz

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Part I: Intro to HBase

Welcome to a brief introduction to HBase by way of R. This tutorial is aimed at explaining how you can use R through the rhbase package. However, it will use my little custom addition to `rhbase` which is geared towards using `tidyr` principals and `data.tables`/`data.frames`. Other differences include:

1. Standardized row-key serializer (raw data type)
2. sz and usz functions only apply to the actual data instead of row-key
3. hb.put - wrapper around hb.insert for easier inputting
4. hb.pull - wrapper around hb.scan for easier retrieval

So what will you get out of this? Good question. It is broken down into three parts:

1. Getting HBase, Thrift, and rhbase installed with a brief intro into HBase
2. Inserting Data into HBase + HBase Basic Design/Modelling
3. Retrieving Data from HBase, doing calculations, and inserting calculations

So what is HBase Anyway?

Hopefully you have some bare knowledge of what HBase is, because after all, you are reading this. By no means will I attempt to explain all of HBase, but here is a brief attempt to summarize the mammoth:

Wikipedias definition: HBase is an open source, non-relational, distributed database modeled after Google's BigTable and written in Java. It is developed as part of Apache Software Foundation's Apache Hadoop project and runs on top of HDFS (Hadoop Distributed File system), providing BigTable-like capabilities for Hadoop.

From Apache HBase's Website "Use Apache HBase when you need **random, realtime read/write access** to your Big Data. This project's goal is the hosting of very large tables – **billions of rows X millions of columns** – atop clusters of commodity hardware. Apache HBase is an **open-source, distributed, versioned, non-relational database** modeled after Google's BigTable... Just as BigTable leverages the distributed data storage provided by the Google File System, Apache HBase provides BigTable-like capabilities **on top of Hadoop and HDFS**."

Clearly with those definitions you should know what HBase is now, right? If you're like me, a little more explanation is helpful. To start wrapping your head around NoSQL and HBase, here is a 5-step progression that I have found helpful:

1. A **Key-Value Store**

- At its core, that's all HBase really is. It's a map, a dictionary (python), a hash (ruby), etc...

2. **Distributed**

- HBase sits atop a Hadoop Cluster. Basically what that means from HBase's perspective is that the data in HBase is replicated out to, by default, 3 nodes in a Hadoop Cluster.

- Based on the assumption that servers go down and bad things happen
- A full implementation relies on HDFS, Zookeeper, and your HBase region master(s)

3. **Consistent**

- HBase is an immediately consistent database. That means that HBase guarantees your data to be the exact same on any of the nodes that it is replicated to.
- See CAP Theorem for more information on Consistent, Available, and Partition tolerant databases (Cassandra is a similar NoSQL Columnar Database emphasizing Availability over Consistency)

4. **Sorted**

- The Keys in this key-value store are stored alphabetically
- Designed for faster reads than writes
- Allows the concepts of "scanning" to exist

5. **Multi-Dimensional Key-Value Store** <<<<<<< HEAD

- **Remember that it is a key-value store? Well, really, its more like a key-column-value store, or a Map of Maps**

- Remember how it is a key-value store. Well, really, its more like a key-column-value store, or a Map of Maps >>>>>>> 91bf20b9969f42dc30bf1b630c84e825e989b0aa
- This is what is referred to as "columnar" or "wide rows"
- For any given key, it allows you to store any amount of information
- Schema-less - your key-column-value combination can be defined at any time and does not naturally conform to any schema

HBase Frame of Mind

- First there is a HBase **table**, which is exactly what you would think it is... a table <<<<<<< HEAD
- Within a table are **column families**, which are basically just a subgroup of your table. Best practice is to limit the number and size of these. So, if you are new to HBase, just specify one column family, which is all that is necessary in many cases.
- All data is then accessed via a **rowkey**, which is essentially your indexing mechanism (enter row-key or range of row-keys, and BLAM, data). This is also your key in "key-column-value" as depicted earlier
- Within a given row, there can be potentially millions of columns. This is the concept of **wide rows**. Although it can certainly be used for many things, time-series data is a good use case as it allows you to store time values as column names, and then the variable value correlating to a particular timestamp is in a cell (the variable name would be in the row key). This concept is often hard to grasp the first time, so I have provided some visuals to help explain it. Many people's breakthrough on this concept is often when they realize that values are/can be stored as columns.
- **Schemaless**. You do not need to add columns in advance, you can simply do it on the fly. However, you should keep record or develop a scheme of how you are storing data as the actual retrieval will be made very difficult if you have no idea whats in there.

- **Data modeling: Based off query patterns and stored directly. Cross-table joins are a BAD thing (Spark can help with this, but that does not mean you should design your data model to do any kind of joins). Essentially you are sacrificing complex querying for huge speed gains.**

- Tables are organized by **column families**, which is basically just another container for your data. Best practice is to limit the number and size of these. So, if you are new to HBase, just pretend you only have 1 as in many cases that is all that is necessary.
- All data is then accessed via a **rowkey**, which is essentially your indexing mechanism (enter row-key or range of row-keys, and BLAM, data). This is also your key in "key-column-value" as depicted earlier
- Within a given row, there can be potentially millions of columns. This is the concept of **wide rows**. Although it can certainly be used for many things, time-series data is a good use case as it allows you to store time values as column names, and then the variable value correlating to a particular timestamp is in a cell (the variable name would be in the row key). This concept is often hard to grasp the first time, so I have provided some visuals to help explain it. Many people's breakthrough on this concept is often when they realize that values are/can be stored as columns.
- **Schemaless*. You do not need to add columns in advance ever, you can simply do it on the fly. However, is advised that you keep record or develop a scheme of how you are storing data as the actual retrieval will be made very difficult if you have no idea whats in there.
- Data modeling: **Based off query patterns and stored directly**. Cross-table joins are a BAD thing (Spark can help with this, but that does not mean your design should implementjoins). Essentially you are sacrificing complex querying for huge speed gains. >>>>>>> 91bf20b9969f42dc30bf1b630c84e825e989b0aa

Hopefully that helped, and if not, there is plenty of information out there about HBase and what it does. Here are a few links:

- Apache HBase
- Wikipedia
- Hortonworks

Installing HBase and rhbase

In order to use this stuff, you have to install HBase, Thrift, and the rhbase package. The basic instructions are found here, but if you are trying to get up and running as soon as possible, here are a few helpful hints:

1. Install Thrift following this guide
2. Update PKG_CONFIG_PATH: export PKG_CONFIG_PATH=$PKG_CONFIG_PATH:/usr/local/lib/pkgconfig/
3. Verify pkg-config path is correct: pkg-config –cflags Thrift , returns: -I/usr/local/include/Thrift
4. Copy Thrift library sudo cp /usr/local/lib/libThrift-0.8.0.so /usr/lib/

- **Under this implementation I would advise using Thrift 0.8.0 as the latest version might include some bugs as it relates to this build**

5. Install HBase following Apache's quick start guide

6. Start up HBase and Thrift

```
[hbase-root]/bin/start-hbase.sh
[hbase-root]/bin/hbase Thrift start
```

7. Now download and install the package with devtools (or get a tarball copy here)

Test it out

Provided HBase, Thrift, and `rhbase` are now installed correctly and are running, the code below should run successfully.

```
library(rhbase)
library(data.table)
hb.init()
```

```
## <pointer: 0x3a5d5b0>
## attr(,"class")
## [1] "hb.client.connection"
```

Understanding Our Sample Data

The data that is being supplied in this tutorial is time-series data taken from airport support vehicles (like a baggage truck) from various airports over a small period of time. The data is stored hierarchically as: Airport_Day_VehicleID_Variable. You can retrieve a list of all of the data simply by loading it from the `rhbase` package:

```
data(baggage_trucks)
str(baggage_trucks[1:3])
```

```
## List of 3
##  $ JFK_20140306_1CKPH7747ZK277944_gear :Classes 'data.table' and 'data.frame':   126 obs. of  2 varia
##   ..$ date_time: num [1:126] 1.39e+09 1.39e+09 1.39e+09 1.39e+09 1.39e+09 ...
##   ..$ gear     : num [1:126] 1 2 3 4 3 2 1 2 3 4 ...
##   ..- attr(*, ".internal.selfref")=<externalptr>
##  $ JFK_20140306_1CKPH7747ZK277944_rpm  :Classes 'data.table' and 'data.frame':   13770 obs. of  2 va
##   ..$ date_time: num [1:13770] 1.39e+09 1.39e+09 1.39e+09 1.39e+09 1.39e+09 ...
##   ..$ rpm      : num [1:13770] 1012 1229 1460 1758 1706 ...
##   ..- attr(*, ".internal.selfref")=<externalptr>
##  $ JFK_20140306_1CKPH7747ZK277944_speed:Classes 'data.table' and 'data.frame':   13793 obs. of  2 va
##   ..$ date_time: num [1:13793] 1.39e+09 1.39e+09 1.39e+09 1.39e+09 1.39e+09 ...
##   ..$ speed    : num [1:13793] 16.9 17.3 17.6 17.7 18.1 ...
##   ..- attr(*, ".internal.selfref")=<externalptr>
```

The three variables are ***gear***, ***speed*** (mph), and **rpm** (revolutions per minute of engine). With these variables, the goal is to calculate the fuel rate of a vehicle. For more information about the data use `?baggage_trucks`.

Note: Credit to Spencer Herath for creating the sample data set of imaginary trucks whizzing around an invisible airport.

Part II: Getting Data Into HBase with R

Ok, now it's time to talk about actually putting some stuffing in the elephant.

HBase Table Design

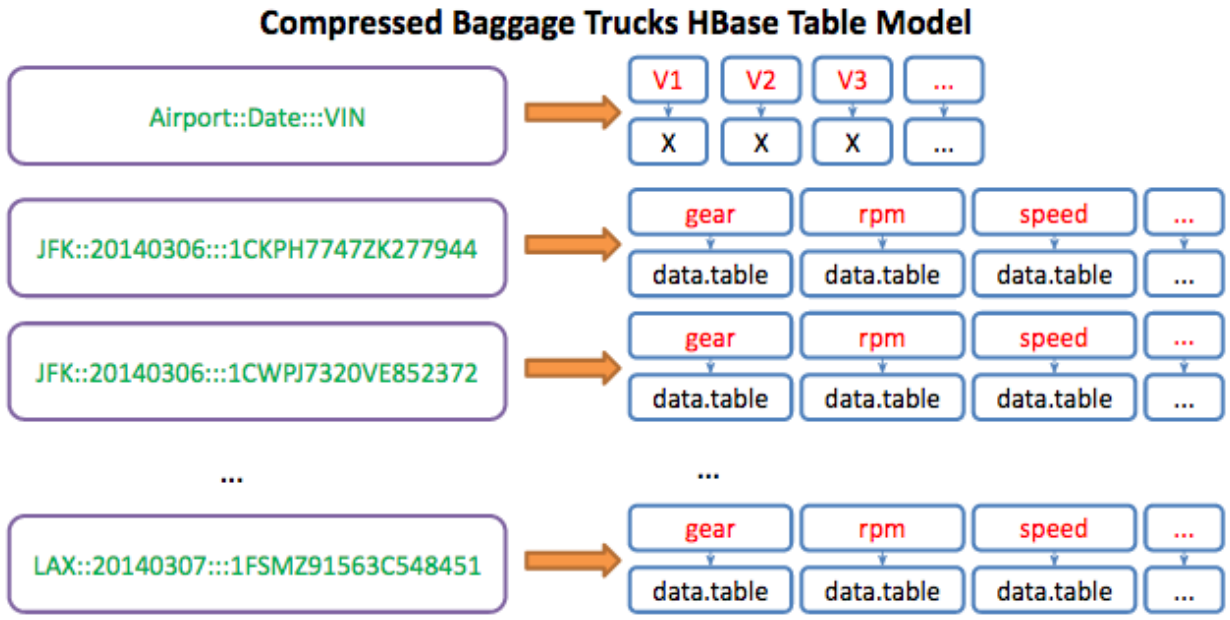
<<<<<<< HEAD It's important that the design of the HBase table suits the desired query pattern(s). A NoSQL Columnar frame of mind is always ***Design Your Tables For Your Query Pattern***. Unlike a relational store, each table that is built is traditionally designed for one single type of query pattern (document stores like Solr or Elastic Search can offer a backwards indexing solution. Overall, this can make a data modeling experience "simpler" in concept). To recap slightly, this frame of mind implies that: ======= It's important that the HBase table is designed to fit your query pattern(s) exactly. A NoSQL Columnar frame of mind is always ***Design Your Tables For Your Query Pattern***. Unlike a relational store, each table that is built is traditionally designed for one single type of query pattern (document stores like Solr or Elastic Search can offer a backwards indexing solution. Overall, this can make a data modeling experience "simpler" in concept). A good way to think about NoSQL is that **in one fetch, you want to retrieve all of the data neccessary to make a business decision**. To recap slightly, this frame of mind implies that: >>>>>>> 91bf20b9969f42dc30bf1b630c84e825e989b0aa

- Joins are BAD
- Avoid lookups as much as possible
- Do all data transformations on the incoming stream versus the outgoing

Remember, the goal is to get the data out and delivered as soon as possible, so take special precaution to insure that the data and the query patterns are designed for the end format, not the raw format.

<<<<<<< HEAD Currently the data in its raw format is **organized by variable, by vehicle, and by date.** Because this is archived data, additionally compression to a binary blob(byte array) is achievable. If properly done, it will drastically reduce the size of the data set and immensely increase the speed at which it is retrieved (because the dataset sits in just one blob as opposed to many cells). However, the approach should be cautious of the memory limitations that might exist; the size and number of blobs has to be manageable. That is, data needs to be retrieved in manageable partitions that contain all of the necessary variables to perform a fuel usage calculation. With those concepts in mind, the query pattern should be able to take on specific airports and date ranges, along with whatever variables that are desired. Thus: ======= Currently the data in its raw format is **by variable by vehicle by date.** Additionally, because this is archived data, additionally compression to a binary blob (byte array) is achievable, drastically reducing the size of the data set while immensely increasing the speed at which it is retrieved (because its just in one blob as opposed to many cells). However, the approach should be cautious of the memory limitations that might exist; the size and number of blobs has to be manageable. That is, data needs to be retrieved in manageable partitions that contain all of the necessary variables to perform a fuel usage calculation. With those concepts in mind, the query pattern should be able to take on specific airports and date ranges, along with whatever variables that are desired. Thus: >>>>>>> 91bf20b9969f42dc30bf1b630c84e825e989b0aa

- row-key = airport::day::vin
- column = variable
- value = specific data.table



Create HBase Table Now that the data model is defined, a table must be created to use it. In this case, we create a table called `Test` with a column family called `test`:

```
## [1] TRUE
```

```
hostLoc = '127.0.0.1'  #Give your server IP
port = 9090  #Default port for Thrift service
hb.init()
```

```
## <pointer: 0x2d96320>
## attr(,"class")
## [1] "hb.client.connection"
```

```
hb.list.tables()
```

```
## $Test_Text
##       maxversions compression inmemory bloomfiltertype bloomfiltervecsize
## test:           3        NONE    FALSE            NONE                  0
##       bloomfilternbhashes blockcache timetolive
## test:                   0      FALSE 2147483647
```

```
TABLE_NAME = "Test"
COLUMN_FAMILY = "test"
hb.new.table(TABLE_NAME, COLUMN_FAMILY)
```

```
## [1] TRUE
```

Input Data into HBase

Now that the HBase table is created, all that is left is actually putting the `baggage_trucks` data into HBase. This can be done with the convenient `hb.put` function:

```
require(magrittr,quietly = T)
require(tidyr,quietly = T,warn.conflicts = F)
data(baggage_trucks)
dt_names <- names(baggage_trucks) %>%
  data.frame() %>%
  tidyr::separate(".",c("airport","date","vin","variable"))
dt_names <- dt_names %>% unite(rowkey,airport,date,vin, sep = "::")
head(dt_names)
```

```
##                              rowkey variable
## 1 JFK::20140306::1CKPH7747ZK277944     gear
## 2 JFK::20140306::1CKPH7747ZK277944      rpm
## 3 JFK::20140306::1CKPH7747ZK277944    speed
## 4 JFK::20140306::1CWPJ7320VE852372     gear
## 5 JFK::20140306::1CWPJ7320VE852372      rpm
## 6 JFK::20140306::1CWPJ7320VE852372    speed
```

How `hb.put` Works The design of `hb.put` is meant to be relatively simple and flexible. For a given table and column family, `hb.put` allows the creation of a list of "columns" and a list of "values" for each "row-key." This option is very useful and designed for inputting multiple columns into the same row-key (an uncompressed time-series use case). Additionally, `hb.put` allows the insertion of data using a 1-1-1 ratio like this example will do.

```
hb.put(table_name = TABLE_NAME,column_family = COLUMN_FAMILY, rowkey = dt_names$rowkey, column = dt_name
```

```
## [1] TRUE
```

And just like that, data is in HBase. Before proceeding further, it is important to understand how data was put into HBase, as this is actually a modification from the original rhbase package. The row-keys are turned into byte arrays using the `charToRaw` method, essentially turning the character row-key into a raw binary data type. The data.tables are turned into byte arrays using R's native serializer. If you would like to use your own serializer for the actual data, input the data as raw (maybe because its already serialized), etc..., simply specify `sz =` "raw", "character", or custom function in `hb.put`, OR specify it in the original `hb.init` function. Note: the row-key serializer is not editable at the moment. The change to this branch was separating the serialization method for the row-keys from the values.

Examples Retrieving Data Now that data is inserted, here are some brief examples worth reviewing to understand how data can be retrieved from HBase with this package.

1. Retrieving only from 03/06/2014 onward for LAX and for just the "Speed" variable:

```
hb.pull(TABLE_NAME, COLUMN_FAMILY, start = "LAX::20140306", end = "LAXa", columns = "speed", batchsize =
```

```
##                              rowkey column_family column       values
## 1: LAX::20140306::1CHMP60486H283129          test  speed <data.table>
```

```
## 2: LAX::20140306::1FAJL35763D392894          test  speed <data.table>
## 3: LAX::20140306::1FJAL1998VS238734          test  speed <data.table>
## 4: LAX::20140306::1FSMZ91563C548451          test  speed <data.table>
## 5: LAX::20140307::1CHMP60486H283129          test  speed <data.table>
## 6: LAX::20140307::1FAJL35763D392894          test  speed <data.table>
## 7: LAX::20140307::1FJAL1998VS238734          test  speed <data.table>
## 8: LAX::20140307::1FSMZ91563C548451          test  speed <data.table>
```

2. Retrieving everything between the start of 03/07/2014 and the start of 03/08/2014:

```
hb.pull(TABLE_NAME, COLUMN_FAMILY, start = "LAX::20140307", end = "LAX::20140308",batchsize = 100)
```

```
##                               rowkey column_family column       values
##  1: LAX::20140307::1CHMP60486H283129          test   gear <data.table>
##  2: LAX::20140307::1CHMP60486H283129          test    rpm <data.table>
##  3: LAX::20140307::1CHMP60486H283129          test  speed <data.table>
##  4: LAX::20140307::1FAJL35763D392894          test   gear <data.table>
##  5: LAX::20140307::1FAJL35763D392894          test    rpm <data.table>
##  6: LAX::20140307::1FAJL35763D392894          test  speed <data.table>
##  7: LAX::20140307::1FJAL1998VS238734          test   gear <data.table>
##  8: LAX::20140307::1FJAL1998VS238734          test    rpm <data.table>
##  9: LAX::20140307::1FJAL1998VS238734          test  speed <data.table>
## 10: LAX::20140307::1FSMZ91563C548451          test   gear <data.table>
## 11: LAX::20140307::1FSMZ91563C548451          test    rpm <data.table>
## 12: LAX::20140307::1FSMZ91563C548451          test  speed <data.table>
```

Part III: Retrieve and Store

Ok, so now that data is in HBase, lets:

1. **Retrieve Data with rhbase**
2. **Manipulate Data using Tidyr + data.table + timeseriesr**
3. **Perform Calculations with timeseriesr**
4. **Store Our Results using rhbase**

Retrieving Data with rhbase

From the HBase input tutorial, we stored data.tables via byte arrays in HBase (from hbase_input document). But what about getting it out? By using `hb.pull`, we will be able to pull our desired HBase data.

Going back to the use case at hand, our goal is to measure the total fuel consumption of these trucks present in the data. To do so, we need to call gear, rpm, and speed (the three variables we put in HBase) and apply a custom fuel calculator in R. However, as mentioned previously, we need to be careful about how we bring data in, as too much data at one time could easily lead to memory problems.

Based on how we modeled our data, we are going to **retrieve ALL variables for ALL VINs by EACH day for EACH airport**. We can do this in HBase with the `scan` function. Recalling the description of HBase, all of the keys or row-keys are sorted alphabetically. This means that all of the data for 1 airport is stored next to each other. Additionally, because of our row-key, all of the data is sorted by Airport by Date. A scan operation will allow us to get back all of the data for one airport for one day in essentially one iop.

That is, with one "scan" we can get all of the data because its located next to each other. So how can we do this in R?

We begin with a list of our airports:

```
airports <- c("JFK","LAX")
```

Then we create a list of all the dates we want, which in this case is between the 6th and 8th of March 2014.

```
start_dates <- paste0("2014030", 6:7)
end_dates <- paste0("2014030", 7:8)
```

Now lets create a function that will allow us to pull back all of the variables one VIN one Day at a time (this is done to demonstrate responsible memory management.)

```
library(data.table)
rk_generator <- function(start, end, ...){
  function(x){
    data.table(start = paste(x,start, ...), end = paste(x,end,...))
  }
}

march <- rk_generator(start_dates, end_dates, sep = "::")
```

The functional `march` allows us to have all of the time stamps we want for each airport. For example:

```
march(airports[1])
```

```
##            start           end
## 1: JFK::20140306 JFK::20140307
## 2: JFK::20140307 JFK::20140308
```

Don't you just love how easy R is? This output will feed our function to call HBase for each day for each airport.

Pull Data, Merge, and Calculate

1. Bring in some data for 1 day
2. Merge the data together to do a proper fuel calculation of `gal_per_hr`, average speed, and time in use
3. Visualize some of the results:

```
a_day <- march(airports[1])[1]
```

OK, time to bring in some data:

```
library(rhbase)
library(magrittr)
hb.init()
```

```
## <pointer: 0x39403f0>
## attr(,"class")
## [1] "hb.client.connection"
```

```
data <- hb.pull("Test","test",start = a_day[[1]], end = a_day[[2]], columns = c("gear","rpm","speed"))
data[1:6]
```

```
##                              rowkey column_family column       values
## 1: JFK::20140306::1CKPH7747ZK277944          test   gear <data.table>
## 2: JFK::20140306::1CKPH7747ZK277944          test    rpm <data.table>
## 3: JFK::20140306::1CKPH7747ZK277944          test  speed <data.table>
## 4: JFK::20140306::1CWPJ7320VE852372          test   gear <data.table>
## 5: JFK::20140306::1CWPJ7320VE852372          test    rpm <data.table>
## 6: JFK::20140306::1CWPJ7320VE852372          test  speed <data.table>
```

And just like that, boom, data!!!!!

Manipulate Data with Tidyr + data.table + timeseriesr

OK, lets do something with that stuff. Our goal is to combine the gear, rpm, and speed data.tables by VIN. To do this, we will: 1. Split the row key to make the values meaningful with `tidyr` 2. Combine data.tables with VIN in mind 3. Clean up merged data

1. Split with `tidyr`:

```
data <- data %>%
  tidyr::separate(col = "rowkey", into = c("airport","day","vin"))
data[1:5]
```

```
##    airport      day               vin column_family column       values
## 1:     JFK 20140306 1CKPH7747ZK277944          test   gear <data.table>
## 2:     JFK 20140306 1CKPH7747ZK277944          test    rpm <data.table>
## 3:     JFK 20140306 1CKPH7747ZK277944          test  speed <data.table>
## 4:     JFK 20140306 1CWPJ7320VE852372          test   gear <data.table>
## 5:     JFK 20140306 1CWPJ7320VE852372          test    rpm <data.table>
```

2. Combine by VIN + column with rbindlist

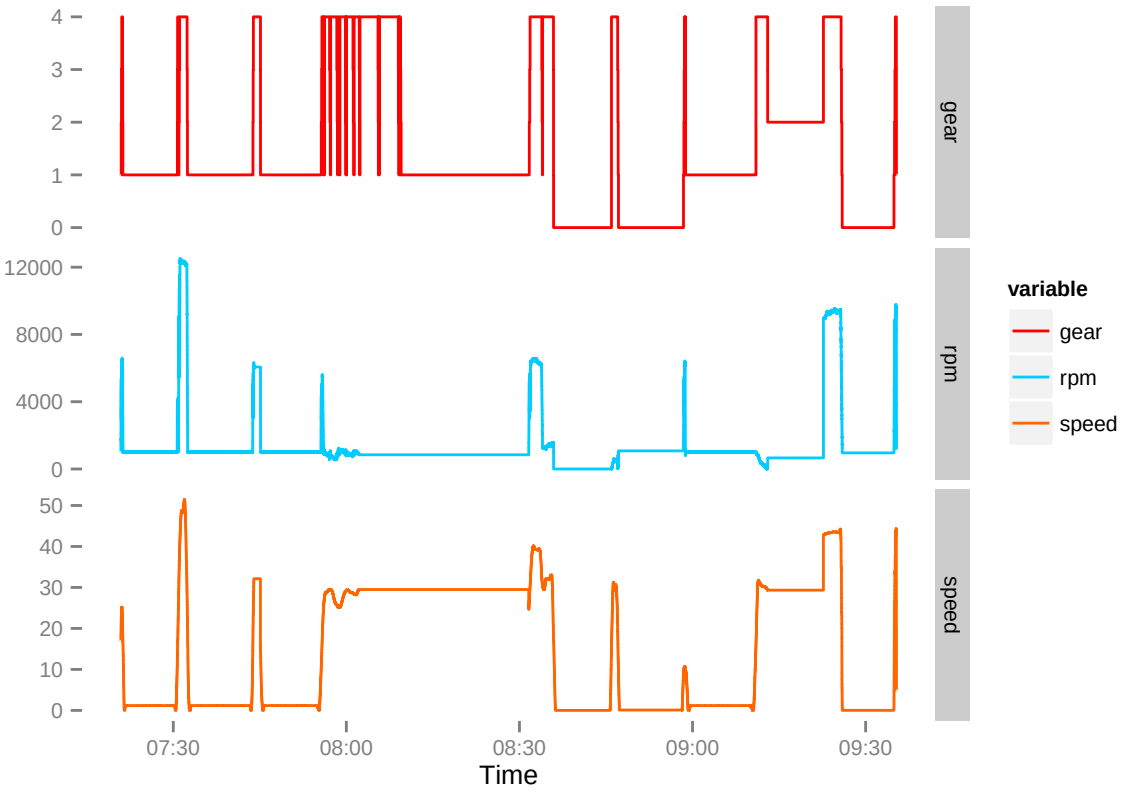
```
#rbind by variable
setkeyv(data, c("vin", "column"))

merge_em <- function(values){
  if(length(values)<=1) return(values)
  out <- values[[1]]
  for(i in 2:length(values)){
    out <- merge(out,values[[i]],all=T,by = "date_time")
  }
  out
}
data2 <- data[,list("rbinded" = list(merge_em(values))),by=c("vin","day","airport")] #data.table functi
data2$rbinded[[1]] %>% setDT
```

3. Clean up our data with timeseriesr. Essentially, because our timestamps for each variable were not guaranteed to match, we probably (and do) have NA values in each data set. This use of `dtreplace` will take any NA values and replace them with the last observation.

```
data2$rbinded <- data2$rbinded %>% lapply(timeseriesr::dtreplace)  %>% lapply(setDT)#fills in missing N
data2$rbinded[[1]]
```

```
##          date_time gear      rpm     speed
##     1: 1394112055    1 1012.492 16.937217
##     2: 1394112055    1 1228.810 17.264578
##     3: 1394112055    1 1459.631 17.585472
##     4: 1394112056    1 1757.546 17.743490
##     5: 1394112056    1 1705.891 18.054664
##    ---
## 14081: 1394120120    1 3762.915 19.516140
## 14082: 1394120120    1 2902.979 14.085581
## 14083: 1394120120    1 2602.196 11.170207
## 14084: 1394120121    1 1898.852  4.939276
## 14085: 1394120121    1 1150.547  4.939276
```

4. Now lets see what this baby looks like:



Perform our calculations with timeseriesr 3.Now that we have our data in memory, lets do our calculation! Below is a function to calculate `gal_per_hr` using our three variables (`rpm`, `gear`, and `speed`)

```
#I basically estimated this by looking at some relations between acceleration, vehicle weight, torque,

#calculates Fuel Usage by row, returns array of fuel usage
#engine power = torque * rpm / 5252
# The constant 5252 is the rounded value of (33,000 ft?lbf/min)/(2?? rad/rev).
```

```
#fuel usage: if Power < 0, alpha
#           : alpha + min(Pmax, engine power)
# alpha = constant idle fuel consumption rate (estimate of fuel sued to maintain engine operation)
# Pt = power = min(Pmax, torque + inertia(mass * radius^2))
gal_per_hr = function(engine_gear, engine_rpm, time, speed, alpha = .7, mass = 10000, gear_ratio = 1.2,
    torque <- c(diff(engine_rpm),0)
    torque[torque<0] <- 0
    torque <- torque * engine_gear * gear_ratio
    Pt <- torque * engine_rpm / (33000/2/pi)
    Pt[Pt>200] <- 200
    engine_power <- t
    acceleration <- c(-diff(speed),0) / c(-diff(time),1)
    #Pi = Mu(kg) * acceleration * velocity /1000
    fuel <- alpha + efficiency_parameter * Pt + acceleration_parameter * acceleration * mass*.45359/100
    fuel[fuel < alpha] <- alpha
    fuel[is.nan(fuel)] <- alpha

    return(fuel)
}
```

Actually perform that operation

```
data2$rbinded <- lapply(data2$rbinded,function(i){
                        i$gal_per_sec <- gal_per_hr(engine_gear = i$gear, engine_rpm = i$rpm, speed = i$
                        i %>% setDT
                        })
data2$rbinded[[1]]
```

```
##         date_time gear      rpm     speed  gal_per_sec
##     1: 1394112055    1 1012.492 16.937217 0.0008217549
##     2: 1394112055    1 1228.810 17.264578 0.0009034893
##     3: 1394112055    1 1459.631 17.585472 0.0010965335
##     4: 1394112056    1 1757.546 17.743490 0.0005422796
##     5: 1394112056    1 1705.891 18.054664 0.0014310010
##    ---
## 14081: 1394120120    1 3762.915 19.516140 0.0001944444
## 14082: 1394120120    1 2902.979 14.085581 0.0001944444
## 14083: 1394120120    1 2602.196 11.170207 0.0001944444
## 14084: 1394120121    1 1898.852  4.939276 0.0001944444
## 14085: 1394120121    1 1150.547  4.939276 0.0001944444
```

Now we have done our main calculation. But we want to know the total amount of gallons each truck burned per day. We are going to use `calc_area`, which is a timeseriesr function that calculates the area under the curve. It uses a Riemann left sum approach, but other methods may be added in the future.

```
#calculates area under the curve as a total
data2$gallons <- data2$rbinded %>%
                        sapply(function(x) timeseriesr::calc_area(time_date = x$date_time, value = x$gal
#calculates the total time range in hours (data is recorded in seconds)
data2$hours <- data2$rbinded %>%
                        sapply(function(x) (max(x$date_time) - min(x$date_time))/60/60)
#calculates the average speed
data2$mph <- data2$rbinded %>%
```

```
                        sapply(function(x) mean(x$speed))
data2[,gal_per_hr := gallons/hours]
```

```
##                  vin      day airport      rbinded   gallons    hours
## 1: 1CKPH7747ZK277944 20140306     JFK <data.table> 3.1177370 2.240531
## 2: 1CWPJ7320VE852372 20140306     JFK <data.table> 0.9673207 1.033856
## 3: 1FEMY6958XU502984 20140306     JFK <data.table> 1.5951636 1.757431
## 4: 1FVTK43691G456340 20140306     JFK <data.table> 3.6247181 3.852247
## 5: 1TULD4346YD544661 20140306     JFK <data.table> 1.6412674 1.803878
##          mph gal_per_hr
## 1:  9.026001  1.3915173
## 2: 10.746364  0.9356439
## 3: 14.793853  0.9076681
## 4: 13.923766  0.9409360
## 5:  9.326923  0.9098551
```

**We have now calculated the total amount of gallons that each truck burned, the total hours it ran, miles per hour, and its average gallons per hour.* Now, lets put all of this back into HBase to move onto the day/airport.

Store Our Results Using `rhbase`

We are going to store all of the information that we collected back into the same HBase table for later use. That includes: 1. rbinded data.table (because we might want to reuse it later) 2. gallons 3. total hours in operation 4. gal_per_hr 5. average mph

To do this we need to slightly reorganize our table (hopefully in the future I/someone will add a small wrapper to take care of this) to fit the `hb.put` standards. Nonetheless, the `tidyr` package allows us to do this with ease.

```
#First, create rowkey with unite
data3 <- tidyr::unite(data2, "rowkey",airport:vin,sep = "::")

#Second, reoganize data with gather
data3 <- tidyr::gather(data3, column, value, -rowkey,convert = T)
```

```
## Warning in melt.data.table(data, measure.vars = gather_cols, variable.name
## = key_col, : All 'measure.vars are NOT of the SAME type. By order of
## hierarchy, the molten data value column will be of type 'list'. Therefore
## all measure variables that are not of type 'list' will be coerced to.
## Check the DETAILS section of ?melt.data.table for more on coercion.
```

```
data3[c(1,6,11,16,21)]
```

```
##                               rowkey     column        value
## 1: JFK::20140306::1CKPH7747ZK277944    rbinded <data.table>
## 2: JFK::20140306::1CKPH7747ZK277944    gallons     3.117737
## 3: JFK::20140306::1CKPH7747ZK277944      hours     2.240531
## 4: JFK::20140306::1CKPH7747ZK277944        mph     9.026001
## 5: JFK::20140306::1CKPH7747ZK277944 gal_per_hr     1.391517
```

Great! Now that we have it in the format we want, lets put it back in HBase

```
#Assuming the hb.init connection is still valid
hb.put("Test","test",rowkey = data3$rowkey, column = data3$column, value = data3$value)
```

```
## [1] TRUE
```

And just to test it out, lets see what happens when we pull back one of the new columns we added:

```
hb.pull("Test","test",c("gal_per_hr","rbinded"))
```

```
##                               rowkey column_family     column       values
##  1: JFK::20140306::1CKPH7747ZK277944          test gal_per_hr     1.391517
##  2: JFK::20140306::1CKPH7747ZK277944          test    rbinded <data.table>
##  3: JFK::20140306::1CWPJ7320VE852372          test gal_per_hr    0.9356439
##  4: JFK::20140306::1CWPJ7320VE852372          test    rbinded <data.table>
##  5: JFK::20140306::1FEMY6958XU502984          test gal_per_hr    0.9076681
##  6: JFK::20140306::1FEMY6958XU502984          test    rbinded <data.table>
##  7: JFK::20140306::1FVTK43691G456340          test gal_per_hr     0.940936
##  8: JFK::20140306::1FVTK43691G456340          test    rbinded <data.table>
##  9: JFK::20140306::1TULD4346YD544661          test gal_per_hr    0.9098551
## 10: JFK::20140306::1TULD4346YD544661          test    rbinded <data.table>
```

Pretty cool right?

What is great about this is that you can easily parallelize this operation across multiple cores/nodes/clusters because we broke it down into intervals (airport and date). That is, our data model and query pattern were designed for easily doing a fork and join operation. Check out the `parallel` package or even the `rmr2` package for more details of how to do that.

If you have any suggestions, comments, or questions please feel free to contact me. Also if you would like to further contribute to the `rhbase` fork or `timeseriesr` package, I welcome all aboard.