The Need for Flexibility in Distributed Computing With R

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For background on many of the motivations for these thoughts, see tessera.io

What makes R great

FLEXIBILITY

- Great for open-ended ad-hoc analysis
- “Most versatile analytics tool”
- Working with data just feels natural, data is “tangible”
- Almost anything I might want to do with my data feels quickly well within reach
- Thanks in large part to design of R for interactive analysis and a lot of packages and vis tools

However, when it comes to “big data”, we can easily lose this flexibility

Things we hear about big data

- We can rely on other systems / engineers to process / aggregate the data for us
- We can rely on other systems to apply algorithms to the data while we analyze the small results in R
- We can analyze it in RAM
- We can analyze just a subset of the data

While these are often true, they are often not, and if we concede to any of these, we lose a lot of flexibility that is **absolutely necessary** for a lot of problems

“We can rely on other systems / engineers to process / aggregate the data for us”

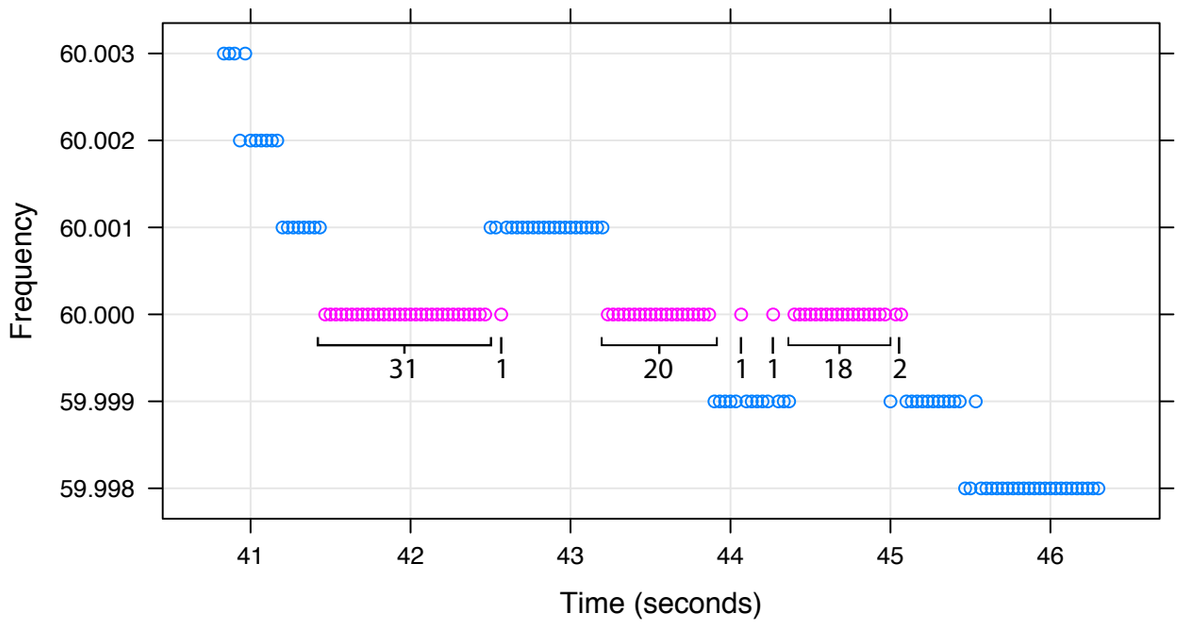
NOT FLEXIBLE

- Analyzing summaries is better than not doing anything at all
- But computing summaries without understanding what information is preserved or lost in the process goes against all statistical sense
- If the first thing you do is summarize without any investigation of the full data, what’s the point of having collected the finer-granularity data in the first place?

Example: Analysis of power grid data

- Study of a 2 TB data set of high frequency measurements at several locations on the power grid (measurements of 500 variables at 30 Hz)
- Previous approach was to study 5-minute-aggregated summary statistics (9000x reduction of the data)
- Looking at the full data grouped into 5-minute subsets suggested several summaries that captured a lot more information
  - First-order autocorrelation
  - Distribution of repeating sequence length for each discrete frequency value
  - etc.

This led to the discovery and statistical characterization of a significant amount of bad sensor data previously unnoticed (~20% of the data!).



“We can rely on other systems to apply algorithms to big data and simply analyze the small results in R”

NOT FLEXIBLE

- Most big data systems I've seen only give you a handful of algorithms
- We need to be able to apply ad-hoc code
  - R has thousands of packages…
  - In the power grid example, we needed to specify ad-hoc algorithms such as repeated sequence, ACF, etc.
- Also, what about diagnostics?

“We can analyze it in RAM”

NOT FLEXIBLE

- It’s great when we can do it but it’s not always possible
- R makes copies, which is not RAM friendly
- It’s natural in data analysis in general to make copies - the structure of our data for a given analysis task is a first class concern (different copies / structures for different things)
- Trying to manage a single set of data in some RAM-optimal way and avoid copies can result in unnatural / uncomfortable coding for analysis
- It's not just RAM, it’s also needing more cores than you can get on one machine - once things get distributed, everything gets more complicated

“We can analyze a subset of the data”

This is a good idea

- Analyze a subset in a local session to get a feel for what is going on
- We should be in local R as often as possible
- However, if you cannot take an interesting calculation or result from studying a subset and apply it to all or a larger portion of the data in a distributed fashion (using R), it is…

NOT FLEXIBLE

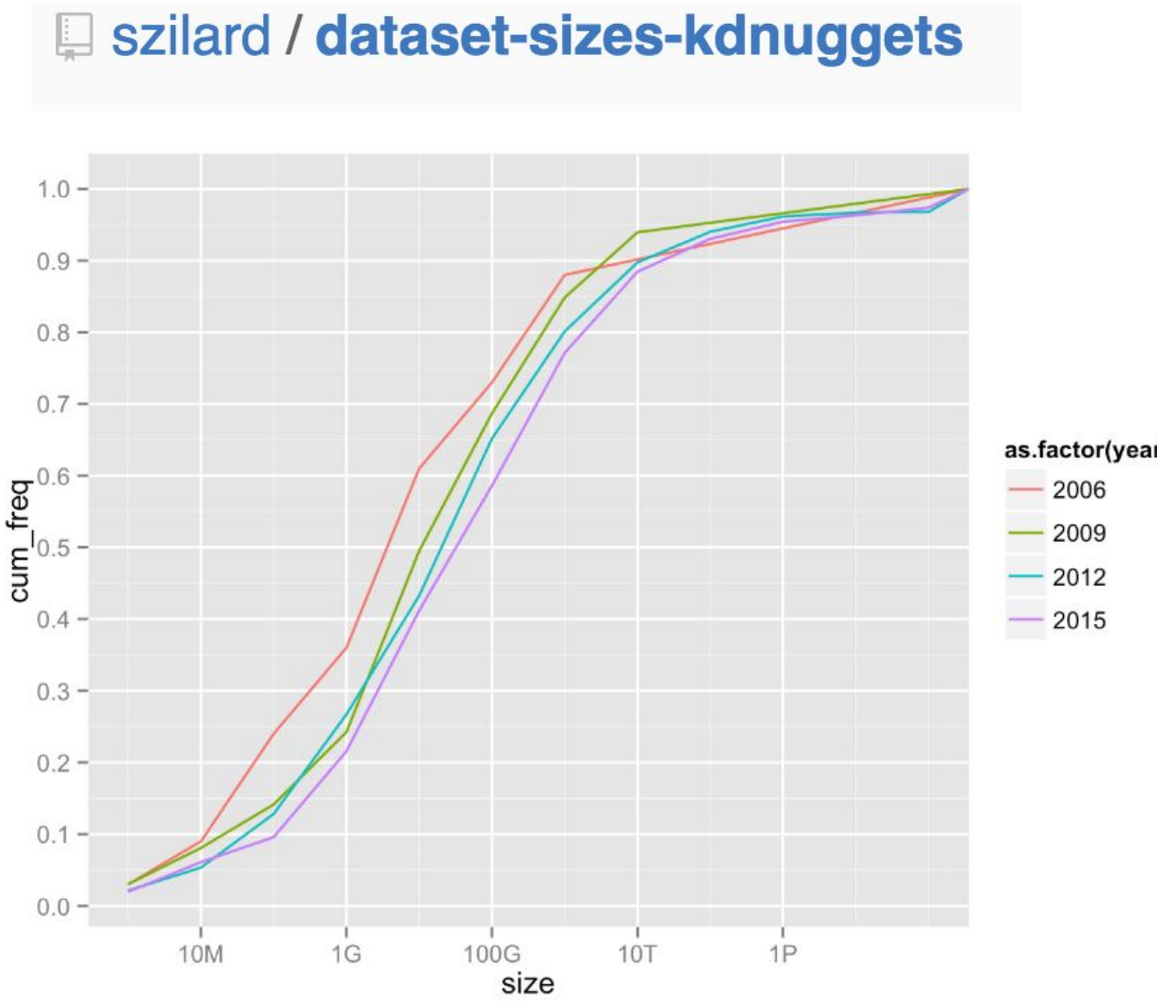
With data analysis, large or small, the 80/20 rule seems to apply in many cases:

- **80%** of tasks / use cases fit a relatively nice, clean, simple abstraction (e.g. data frames, in-memory, simple aggregations, etc.)
- **20%** do not (ad-hoc data structures, models, large data, etc.)
- But to do effective analysis, in my experience, **tasks almost always span the full 100%**

For small data, R does a great job spanning the full 100%
For big data, most R tools just cover the 80%

80/20 Data Size

- **80%**: fits in memory
- **20%**: larger than memory - must be distributed



What can we do to address the 20%?

- Connect R to distributed systems
- Provide R-like interfaces to these systems

Tessera

Interface

datadr / trelliscope

Computation	Computation	Computation	Computation
R	Multicore R	RHIPE / Hadoop	SparkR / Spark (under development)
Storage	**Storage**	**Storage**	**Storage**
Memory	Local Disk	HDFS	HDFS

80/20 Data Structures

- **80%**: data frames of standard types
- **20%**: more complex structures
  - ~15%: fits into Hadley's data frames with “list columns” paradigm
  - ~5%: unstructured / arbitrary

What can we do to address the 20%?

- Storage abstractions that allow for ad-hoc data structures (key-value stores are good for this)
- Data frames as a special case of these
- In datadr, we have ddo (ad-hoc) and ddf (data frame) objects
- In ddR, there are lists, arrays, data frames, which covers it

Data partitioning

- **80%**: data is partitioned in whatever way it was collected
- **20%**: re-group / shuffle the data in a way meaningful to the analysis (the **split** in split-apply-combine)

- This is the way of Divide and Recombine (D&R)
- Meaningful grouping of data enables meaningful application of ad-hoc R code (e.g. apply a method to each host)
- But requires the ability to shuffle data, which is not trivial
- Systems that support MapReduce can do this

80/20 Flexibility of Methods

- **80%**: aggregation / queries / handful of statistical / ML methods
- **20%**: any ad-hoc R code / scalable vis

What can we do to address the 20%?

- We need to be able to run R processes on the nodes of a cluster against each chunk of the data
- Usually this makes most sense when the chunking is intentional (hence the importance of being able to repartition the data)

A note on scalable visualization

- The ability to intentionally group distributed data is critical for scalable statistical visualization
- Trelliscope is a scalable framework for detailed visualization that provides a way to meaningfully navigate faceted plots applied to each subset of the data
- Demo of prototype pure JS, client-side Trelliscope viewer: http://hafen.github.io/trelliscopejs-demo/

We need tools that support the 20%

- 80/20 is not a dichotomy (except maybe for separating big data vs. small data problems)
- Inside either the big / small setting, our tasks almost always span the full 100%
- Just because 80 is the majority doesn't mean the 20 isn't important

Summary of needs

Things (I think) we need to make sure we accommodate to achieve flexibility with big data:

- Support for arbitrary data structures
- Ability to shuffle / regroup data in a scalable fashion
- R executing at the data on a cluster
- Others?

Some thoughts...

- Data abstraction and primitives for computing on them: ddR
  - Is it flexible enough?
  - Can it provide the ability to group data?
- Interfaces:
  - **datadr**: goal is to address full 100% - too esoteric?
  - **dplyr**: with sparklyr, list columns, group_by(), and do() (plus everything else), we are in good shape for a vast majority of cases
  - **purrr**: would be a nice interface for non-data-frame case
- Distributed R execution engines
  - Hadoop (RHIPE, hmr, rhadoop), sparkapi, SparkR, ROctopus, etc.
  - Are there “best practices” these should accommodate for being useful to many projects?

Discussion

- What can we standardize?
- Can we modify existing 80% solutions to provide capabilities that help address the 20% cases?
- Can we build a consensus on basic functionality that will support flexibility for multiple projects?