iotools and ROctopus

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Overview

- Big Data analytics in R
- High-throughput chunk-wise processing
  iotools + hmr
- In-memory computing
  ROctopus
- Lessons learned
- Conclusions

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Big Data Analytics

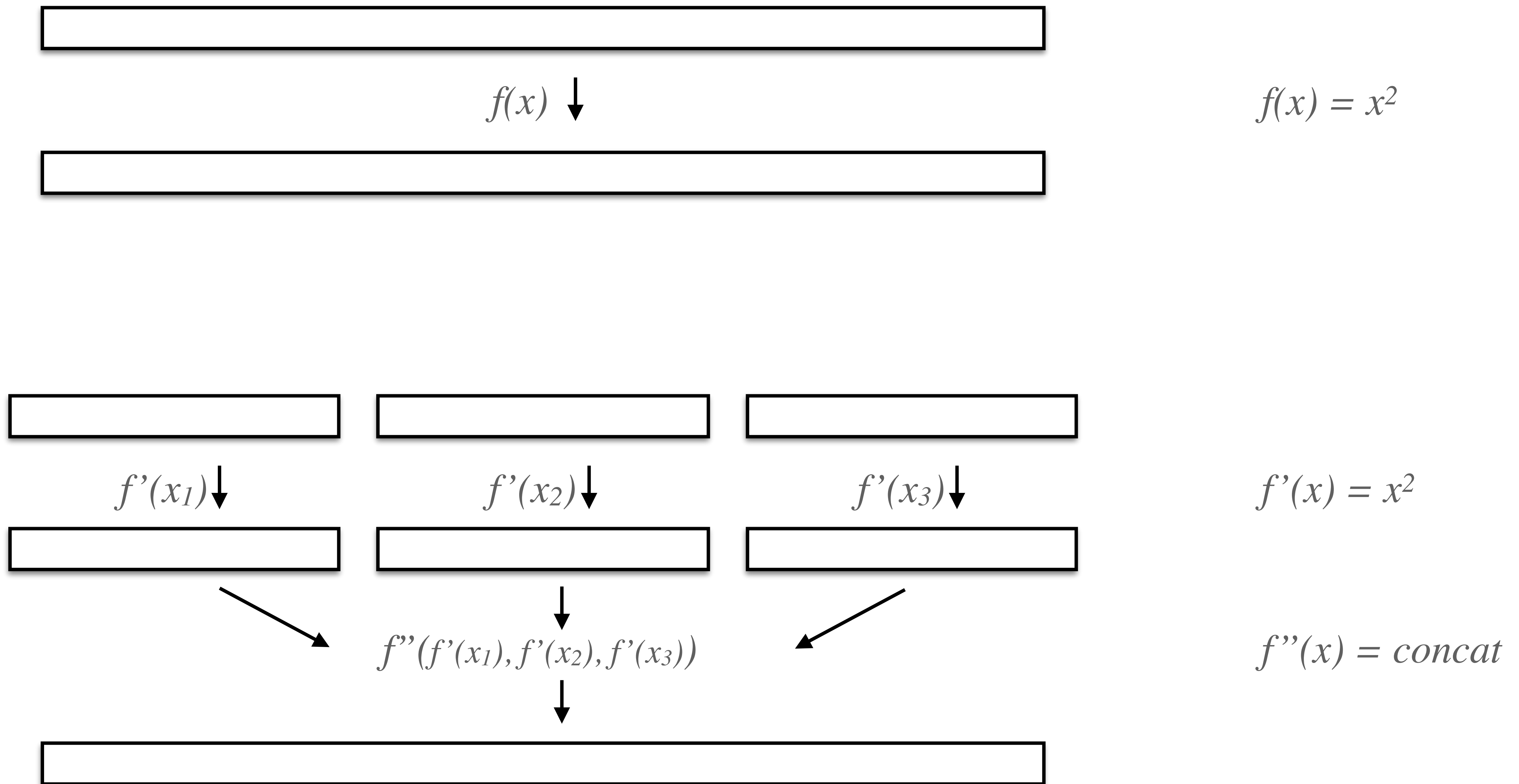
- Data input/output
  - we typically do not have control over data formats
  - need efficient ways to convert on-disk data to native R objects
- R is great for sending computing to data
- Vectorized nature of R works well

- Two different approaches:
  - high throughput computing (typically one-time scan)
  - distributed in-memory computing (complex algorithms)

iotools: high-performance I/O

- originally created to optimize data loading: all raw input data lives in ASCII files
- chunk reader: content-aware reader of binary connections into raw vector buffers
- parses ASCII representation of data into R objects efficiently (uses raw vectors I/O, all parsing in-memory)
- uses matrix representation where possible (numeric or string), data frames otherwise

Parallelization via Map and Fold



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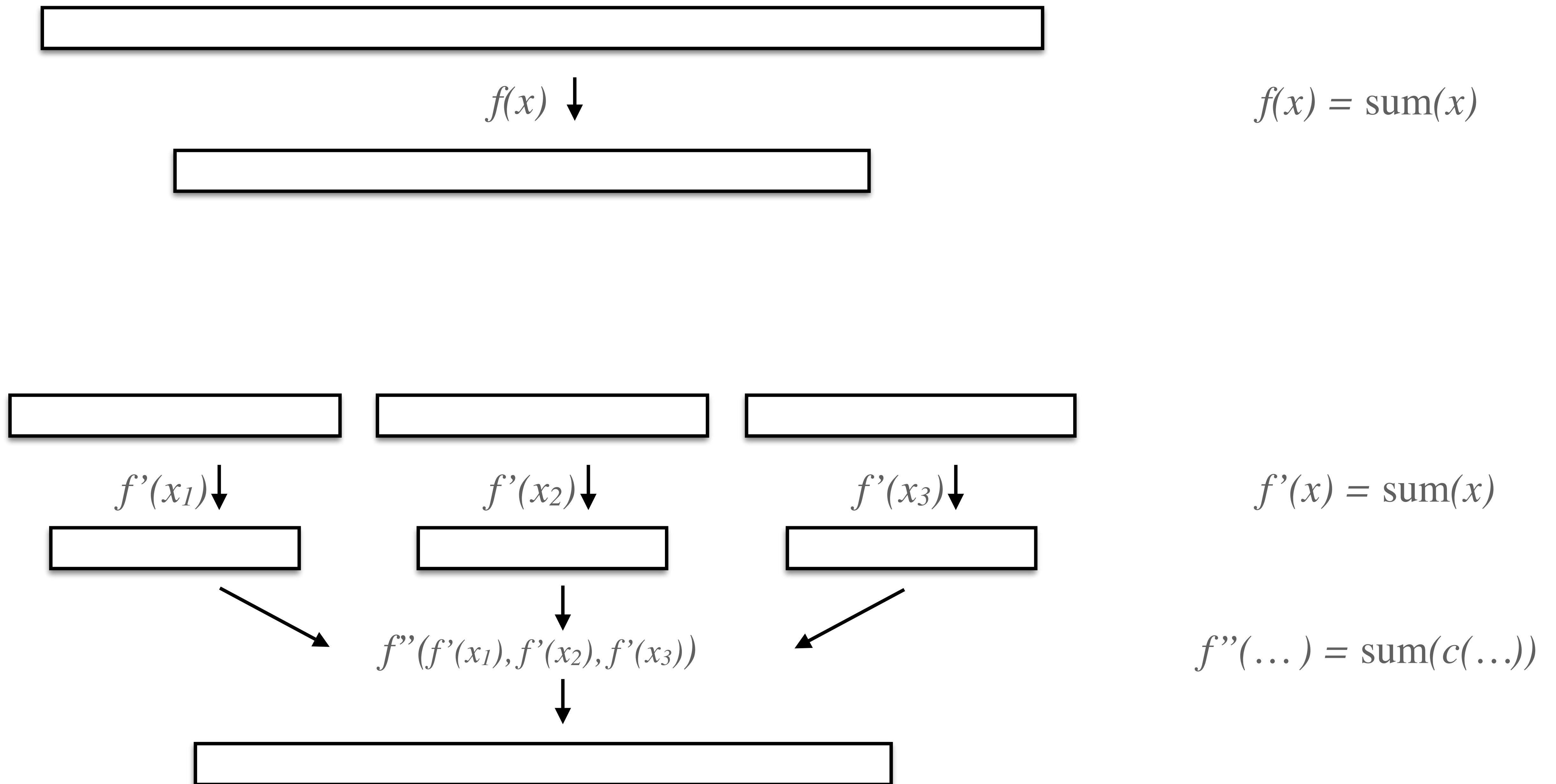
Parallelization via Compute + Combine



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Compute/combine processing

- At least three stages:
  - split (often implicit)
  - compute
  - combine
- Define functions using this paradigm simple examples:

```
cc.sum   <- function(x) cc(x, sum, sum)

cc.table <- function(x) cc(x, table, function(x) tapply(x, names(x), sum))

cc.mean  <- function(x) cc(x, function(x) c(sum(x), length(x)),
                              function(x) sum(x[1,]) / sum(x[2,]))
```


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iotools: hmr() - Hadoop Map Reduce

- iotools: highly efficient chunk-wise I/O on streams: let's use it with Hadoop streaming!
- "formatters" define how to parse raw bytes into R objects - iotools provide ASCII-based formatters
- "as.output" method for arbitrary serialization, iotools provide by default to ASCII conversion
- handles matrices, vectors, tables, ... intuitively (row) names are treated as keys
- very efficient and R-native syntax

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Example

- Aggregate point locations by ZIP code (match points against ZCTA US/Census 2010 shapefiles)

```
r <- read.table(open(hmr(
  hinput("/data/2014/08"),
  function(x)
    table(zcta2010.db()[
       inside(zcta2010.shp(), x[,4], x[,5]), 1]),
  function(x) ctapply(as.numeric(x), names(x), sum))))
```

- Fairly native R programming
- Implicit defaults (read.table parser, conversion of named vectors to key/value entries)

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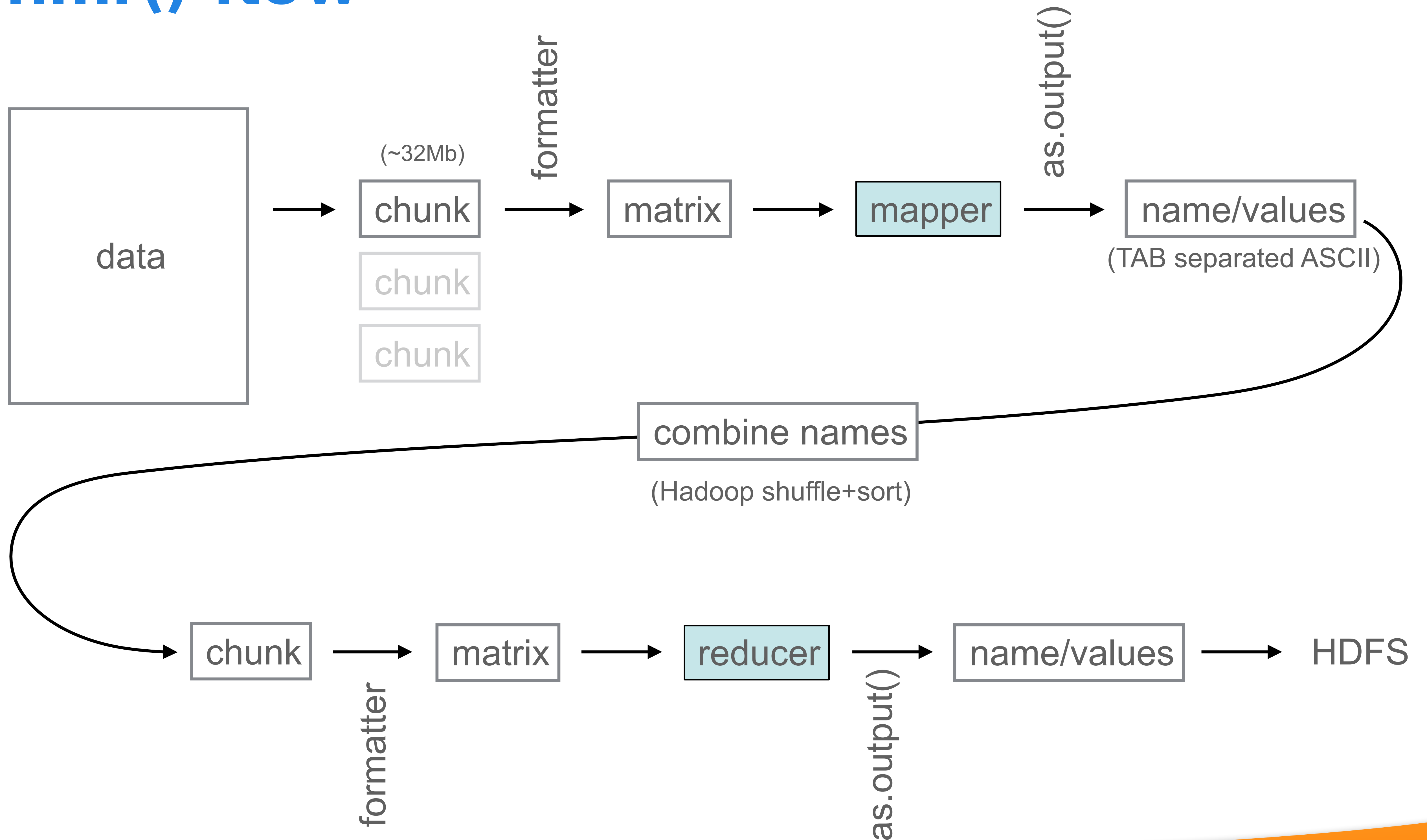
hmr() flow



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hmr behind the scenes

- loads the same packages as the calling session
- auxiliary data can be passed using **aux** parameter - it will be serialized and sent to the cluster (we deliberately make this explicit)
- indices, hash tables, etc. can be re-used across chunks (R is extremely efficient with hash lookup and joins - see also *fastmatch*, *mindex*, ...)
- reducers use key-aware chunking such that chunks will grow to contain all rows for a key

iotools vs classic map/reduce

```
library(iotools)
hmr(hinput("twitter", formatter = function(x) mstrsplit(x, "\n", quiet=TRUE)),
    map = function(m)  table(unlist(strsplit(m, "[^a-zA-Z]+"))),
    reduce = function(m)  ctapply(as.numeric(m), names(m), sum))


library(rmr2)
mapreduce(
    input = “twitter", input.format = "text",
    map = function(., lines)
            keyval(unlist(strsplit(x = lines, split = "[^a-zA-Z]+")), 1),
    reduce = function(word, counts) keyval(word, sum(counts)),
    combine = TRUE)
```


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Main differences

- chunk-wise processing
  - iotools read a chunk (typically dozens of megabytes) at a time - can contain many keys at once
  - one function evaluation per chunk, not key/value pair!
  - reducer chunking “smart” to not break keys apart
- highly efficient parsing
  - low-level optimization when creating R objects
- “native” R objects
  - more natural R programming: matrices, data.frames

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Report from the (AT&T) trenches

- popular claim: M/R is not sufficient, not all algorithms fit
- true, BUT in real life raw data is big and needs heavy processing before one can even think about modeling (typical example: ca. 200Tb input)
- most models typically fit on today's machines (mid-size machines have ca. 0.5Tb RAM, 40HTs)
- in the vast majority of applications M/R works just fine pre-processing and even model search
- for those few that don't …

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ROctopus

- Using R containers as “hot” in-memory compute elements
- Native support for passing closures across R instances - send code to data
- Easy to send data/code from any container to another container
- Example configuration:
  use iotools/hmr to load data into ROctopus

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ROctopus benefits

- no data transfer needed
  - transfer only update information where needed
- no data conversion after loading - the session is “hot” with R objects ready to compute on
- arbitrary additional state can be kept in the workspace for fast updates (abstraction for data + abstraction of mutable state)
- simple R function calls (very similar to snow!)
- each container has an address (URL) by which it can be addressed (any-to-any)

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ROctopus example: GLM

```
dev = wqapply(d, sum(fam$dev.resids(y, mu, WEIGHTS)), fold=`+`)

for (iter in 1L:maxit) {
  XtX = wqapply(d,
    crossprod( mm[, , drop = FALSE] * w ), fold=`+`)

  Xty = wqapply(d, t(mm[, , drop = FALSE] * w) %*% (z * w),
                fold=`+`)

  beta = solve(XtX, Xty)

  wrun(d, bquote(update_vals(.(beta))))

  devold = dev
  dev = wqapply(d, sum(fam$dev.resids(y, mu, WEIGHTS)), fold=`+`)

  cat("Deviance = ", dev, " Iterations - ", iter, "\n", sep = "")
  if (abs(dev - devold)/(0.1 + abs(dev)) < epsilon) break;
}
```


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Models

- Generalized Linear Models
  - Logistic regression
  - Multinomial, mixed, ordered logit
  - Probit, multinomial and ordered probit
  - Poisson
  - Survival analysis
- Regularized LSQ (Ridge regression)
- Planned: LASSO

implemented by Mike Kane using foreach, moving to ROctopus

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Lessons from ROctopus

- Low-level API
  - evaluate code in target instance (any-to-any)
- Mid-level API
  - common paradigms: e.g., distribute, evaluate, collect
- High-level API: include data abstraction
  - data represented as an opaque object

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Lessons from iotools

- Work on native R objects simplifies debugging and development
- Leverage R's strengths (vectorization, functional nature)
- "natural" R programming is very important for adoption
- R works well on Big Data when scaled

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Desired Action Items

- Core frameworks (API)
  - for chunkwise processing (streaming)
  - for compute/combine (distributed HTP)

  such that packages can provide streaming and distributed algorithms
- Unification of distributed computing
  - merge concepts from snow and other packages in an implementation-independent manner
  - also define higher-level APIs

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Conclusions

- Need for distributed API such that packages can provide algorithms *independently* of the back-end
- Chunk/blockwise processing is a must for large scale analytics
- Path via compute/combine was very successful for practical use (iotools/hmr)
- In-memory computing is converging but its place is not quite settled. But we should have an R solution

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Contact

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- iotools/hmr
  http://github.com/s-u/iotools
  http://github.com/s-u/hmr

- ROctopus
  (in progress, also on GitHub but don't use yet ;))

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