Scientific software in-the-large

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September 7, 2018

Outline

Introduction

Bioconductor as a software distillery

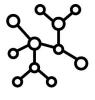
The plyranges package as a catalyst of Bioconductor

Scalability through deferred evaluation and the hailr package

Challenges in genomics software development



BreadthMany data types
Many questions



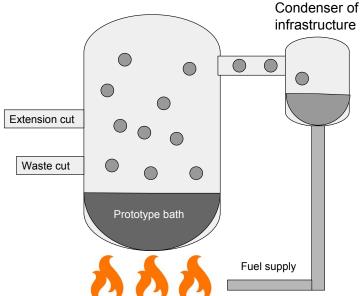
Complexity
Algorithms
Scalability



EvolutionNew questions
New technologies

Distilling scientific software

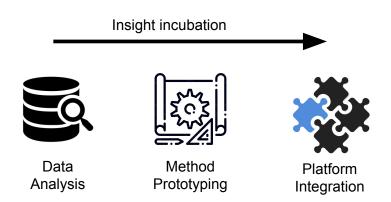
Bottom-up innovation, top-down consolidation



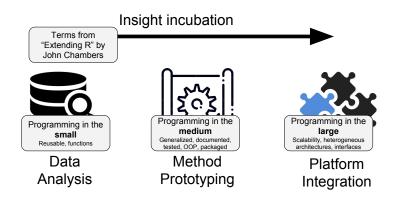
Roles are fluid and context-dependent



Enabling insight incubation



Programming at different scales



Challenges to *scientific* programming in-the-large

Integration of independently developed modules into a platform on top of shared infrastructure

Translation of analyses and prototypes to software, based on transitable interfaces

Scalability through object-oriented abstractions

Outline

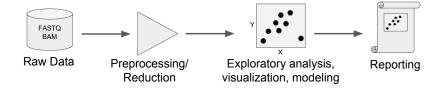
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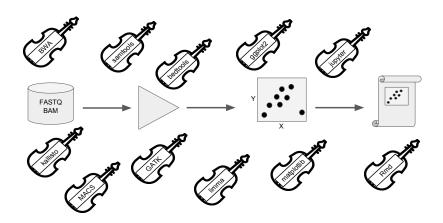
The plyranges package as a catalyst of Bioconductor

Scalability through deferred evaluation and the hailr package

Genomics workflows rely on a multitude of tools



Genomics workflows rely on a multitude of tools





brent pedersen @brent_p · 10 Jan 2014

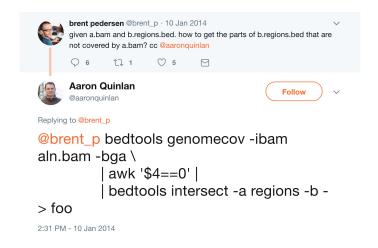
given a.bam and b.regions.bed. how to get the parts of b.regions.bed that are not covered by a.bam? cc @aaronquinlan

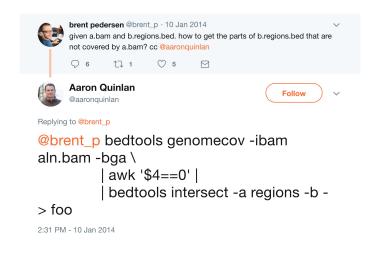














Compute coverage

bedtools genomecov -i a.bam -bga



Select zero runs

awk '\$4 == 0'

Find intersection with regions

bedtools intersect -a b.bed -a -

Typical real-world example from bedtools tutorial

Compute the pairwise similarity between samples of DNAse hypersensitivity regions, according to the bedtools Jaccard statistic.

Compute pairwise Jaccard statistic

File 1

File 2

File 2

File 3

Munge

20 x 20

distance matrix

Languages used

Side-effects

Languages used

- shell
- GNU parallel
- awk

Compute pairwise distances in parallel

Side-effects

▶ 400 .jaccard

Languages used

- shell
- GNU parallel
- awk
- ▶ sed
- perl

Side-effects

- ▶ 400 .jaccard
- ▶ pairwise.txt

Combine jaccard files

```
find . \
   | grep jaccard \
   | xargs grep "" \
   | sed -e s"/\.\//" \
   | perl -pi -e "s/.bed./.bed\t/" \
   | perl -pi -e "s/.jaccard:/\t/" \
   > pairwise.txt
```

Languages used

- shell
- GNU parallel
- awk
- ▶ sed
- perl
- python

Side-effects

- ▶ 400 .jaccard
- ▶ pairwise.txt
- ▶ pairwise.mat

Reshape into matrix

```
awk 'NF==3' pairwise.txt \
| awk '$1 ~ /^f/ && $2 ~ /^f/' \
| python make-matrix.py \
> pairwise.mat
```

Languages used

- shell
- GNU parallel
- awk
- sed
- perl
- python
- R

Side-effects

- ▶ 400 .jaccard
- pairwise.txt
- pairwise.mat

Plot the matrix

```
R
library(gplots)
library(RColorBrewer)
jaccard_df <-
    read.table('pairwise.dnase.mat')
jaccard_matrix <-</pre>
    as.matrix(jaccard_df[,-1])
heatmap.2(jaccard_matrix,
          col = brewer.pal(9, "Blues"),
          margins = c(14, 14),
          density.info = "none",
          lhei = c(2, 8),
          trace = "none")
```

Typical obstacles in implementing genomic data analyses

- ► Tools are difficult to build, install and run
- ► Limitations require mixing languages and semi-compatible, inconsistently documented toolsets
- ▶ Interoperability depends on inefficient, complex file formats
- Analyst has to directly manipulate and manage files, instead of focusing on the analysis
- Reproducibility is hard



Bioconductor

A unified platform for the analysis and comprehension of high-throughput genomic data.

- ▶ Started 2002
- Led by Martin Morgan
- Core infrastructure maintained by about 8 people, based in Roswell Park CRC in Buffalo, NY
- ► >1500 software packages that form a unified platform
- Well-used and respected.
 - 53k unique IP downloads / month.
 - ▶ 21,700 PubMedCentral citations.
- Embraces the R principles of object, function, interface and package





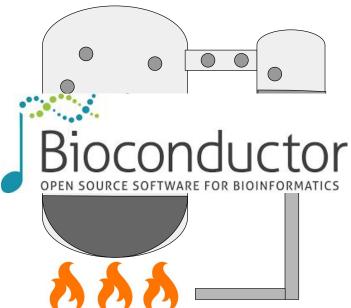








Bioconductor distills the cacophony to a symphony



- Discoverable
- ► Installable
- Reliable
- Documented
- Supported
- Integrated
- Scalable
- State of the art
- Communitydriven



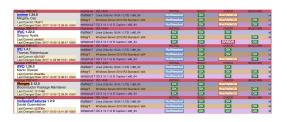
SingleCellExperiment



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```
source("https://bioconductor.org/biocLite.R")
biocLite()
biocLite("Gviz")
```

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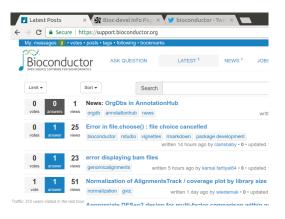
Documentation

To view documentation for the version of this package installed in your system, start R and enter:

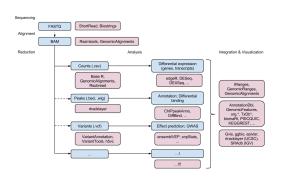
browseVignettes("GenomicRanges")

PDF	R Script	1. An Introduction to the GenomicRanges Package
PDF	R Script	2. GenomicRanges HOWTOs
PDF	R Script	3. A quick introduction to GRanges and GRangesList objects (slides)
PDF	R Script	4. Ten Things You Didn't Know (slides from BioC 2016)
PDF	R Script	5. Extending GenomicRanges
PDF		Reference Manual
Text		NEWS

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```
se <- TENxBrainData()
se

## class: SingleCellExperiment
## dim: 27998 1306127
## metadata(0):
## assays(1): counts
## rownames: NULL
## rowData names(2): Ensembl Symbol</pre>
```

```
## rowbata names(2): Ensembl Symbol
## collames(1306127): AAACCTGAGATAGGAG-1 AAACCTGAGCGGCTTC-1 ...
## TITGTCAGTTAAAGT-133 TITGTCATCTGAAAGA-133
## collata names(4): Barcode Sequence Library Mouse
```

```
## colData names(4): Barcode Sequence Library Mouse
## reducedDimNames(0):
## spikeNames(0):
```

```
libSize <- colSums(assay(se)[, 1:1000])
range(libSize)</pre>
```

[1] 1453 34233

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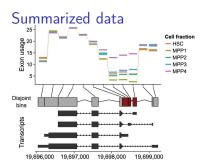
- 1064 unique package maintainers
- ▶ Web users by country:

1.	i de	United States	58,384	(32.78%)
2.	*2	China	20,910	(11.74%)
3.		United Kingdom	12,265	(6.89%)
4.		Germany	10,024	(5.63%)
5.		France	5,536	(3.11%)
6.		Canada	4,999	(2.81%)
7.	8	Spain	4,864	(2.73%)
8.	•	Japan	4,539	(2.55%)
9.	0	India	4,397	(2.47%)
10.	***	Australia	4,043	(2.27%)

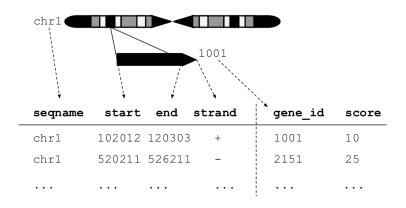
Central data structures of Bioconductor

Data on genomic ranges

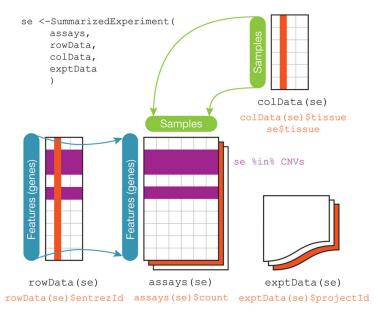




GRanges: data on genomic ranges



SummarizedExperiment: the central data model



Bioconducting the tweeted workflow



Bioconducting the tweeted workflow



Bioconducting the pairwise Jaccard workflow

Define a function for the Jaccard statistic

```
jaccard <- function(x, y) {
    gr_x <- import(x)
    gr_y <- import(y)
    intersects <- intersect(gr_x, gr_y, ignore.strand=TRUE)
    unions <- union(gr_x, gr_y, ignore.strand=TRUE)
    sum(width(intersects)) / sum(width(unions))
}</pre>
```

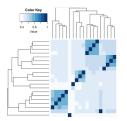
Bioconducting the pairwise Jaccard workflow

Compute the statistics in parallel

Bioconducting the pairwise Jaccard workflow

Make the plot

```
library(gplots)
library(RColorBrewer)
heatmap.2(jaccard_matrix, col = brewer.pal(9, "Blues"))
```



Outline

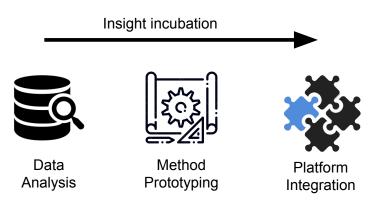
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The Ranges infrastructure is an incubator



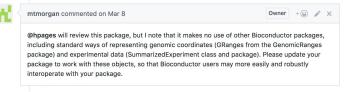
► Should be accessible to the average Bioconductor user

Is the transition happening?

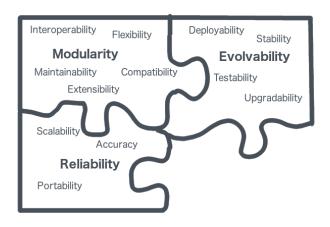
From a typical package submission:

Imports: checkmate, dplyr, ggplot2, tidyr

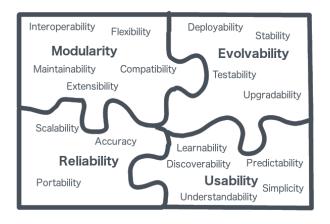
A typical initial response:



Aspects of software quality: the ilities



Aspects of software quality: the ilities



Bioconductor is complex

28

```
pkgs_to_get_started <-</pre>
  c("S4Vectors", "IRanges", "GenomicRanges")
pkg_classes <- function(.)</pre>
  methods::getClasses(asNamespace(.))
n_classes <- sum(lengths(lapply(pkgs_to_get_started,</pre>
                                    pkg_classes)))
n_classes
143
n_methods <- length(methods(class = "Ranges"))</pre>
n_methods
```

Taking cues from the dplyr package

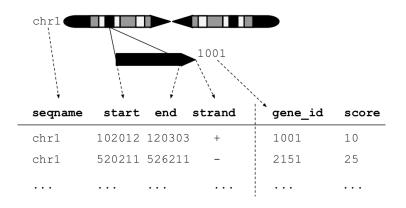
- dplyr is a API for tabular data manipulation
- Inspired by relational algebra, SQL
- Unified about a single, data model: the tibble
- Operations are:
 - Cohesive (do a single thing)
 - Endomorphic (return the same type as their input)
 - Verb-oriented in syntax
- Fluency emerges from chaining of verbs

```
genes %>%
   group_by(seqnames) %>%
   summarize(count_per_chr=n())
```

Goal

Extend dplyr to genomics, a more complex problem domain, to achieve the accessibility of bedtools

GRanges are tidy!

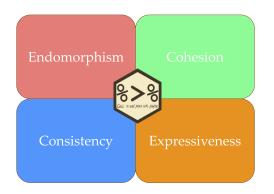


- A dplyr-based API for computing on genomic ranges
- Extending the relational algebra with genomic notions
- Large set of visible verbs acting only on the core data structures:

GRanges represents annotated genomic ranges
SummarizedExperiment coordinates experimental assay data
with sample and feature annotations

► Collaboration with Stuart Lee and Di Cook @ Monash

Designing a grammar



Genomic semantics on common operations

Arithmetic mutating/shifting/re-sizing/flanking/coverage
Restriction filtering by metadata or ranges
Aggregation summarizing over groups/overlaps/unions
Merging combining ranges based on overlaps/nearest neighbors

Verbs are explicit about genomic features and their intentions

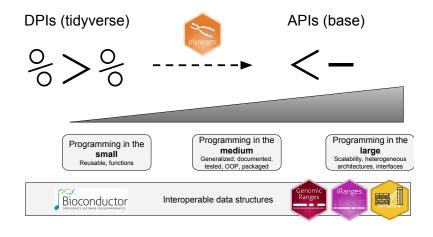
```
exons %>%
  flank_downstream(2L)
exons %>%
  anchor_3p() %>%
  mutate(width = 2*width)
exons %>%
  shift_upstream(10L)
```

Merging ranges through overlap joins

- ► Reimagine overlap/nearest neighbour operations as table joins
- Carry over metadata
- Flatten API via function calls

```
join_overlap_inner(a, b)
join_overlap_inner_within(a, b)
join_overlap_inner_directed(a, b)
join_overlap_intersect(a, b)
join_overlap_left(a, b)
```

Formal data structures enable interface fluidity



Outline

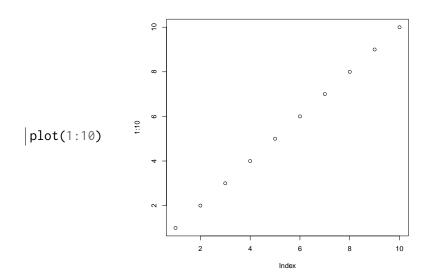
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Scalability through deferred evaluation and the hailr package

R's magical axis labels



Dispelling the magic

```
fun <- function(arg) substitute(arg)
fun(1:10)
1:10</pre>
```

Lazy evaluation

 Delay the evaluation of an expression until its value becomes necessary

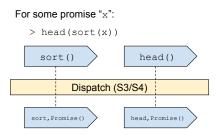
```
fun <- function(arg) {
    z <- arg
    substitute(z)
}
fun(1:10)</pre>
11 1 2 3 4 5 6 7 8 9 10
```

Strategic laziness, eager evaluation

For some promise "x":

> head(sort(x))

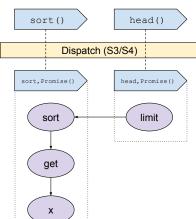
Strategic laziness, eager evaluation



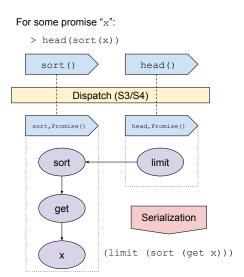
Strategic laziness, eager evaluation

For some promise "x":

> head(sort(x))



Strategic laziness, eager evaluation





- ► A platform for distributed genomics on Apache Spark
- Initially aimed at genetics but becoming more general
- ▶ Defines MatrixTable, an analog of SummarizedExperiment
 - Stored with efficient parquet-based storage format (VDS)
 - Represented outside of Java heap (Java Unsafe) for performance and interoperability
- ▶ Defines its own byte code targeted by Python and now R
 - Filtering, transformation, aggregation, joins of matrix data and tabular metadata
 - ▶ Implemented in C++ where beneficial via Java Unsafe

The hailr package

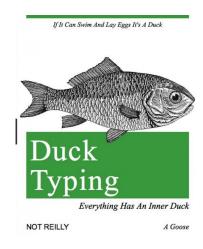




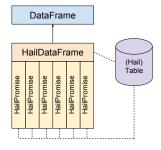
haiR							
HailDataFrame, HailExperiment, HailPromise							
SparkObject							
SparkDriver							
sparklyr	SparkR? Other?						
hašl							
Spark							

Bioconductor containers are generic

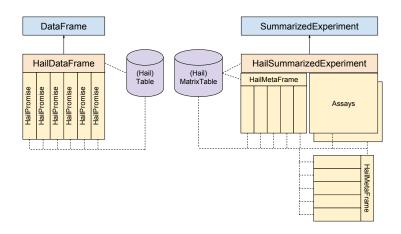
- Bioconductor containers assume elements implement key functions from the base API
 - DataFrame allows anything "vector-like" to be a column
 - SummarizedExperiment allows anything "matrix-like" to hold assay values
- Since our promises implement the base API, they just work
- But we still want to map DataFrame operations to Hail Table operations



Hierarchical extension of Bioconductor



Hierarchical extension of Bioconductor



Load data into Hail

Directly from a text file:

```
library(hailr)
data_dir <- system.file("extdata", package="hailr")
tsv1 <- file.path(data_dir, "kt_example1.tsv")
df <- readHailDataFrameFromText(tsv1, header=TRUE)
Copying from an R data.frame:
df <- copy(read.table(tsv1, header=TRUE), hail())</pre>
```

Get it back out

df

df\$ID

[1] 1 2 3 4

A glimpse into the compiler

```
as.character(df$ID@expr)
[1] "(GetField ID (Ref row))"
```

Abstractions enable mixed evaluation

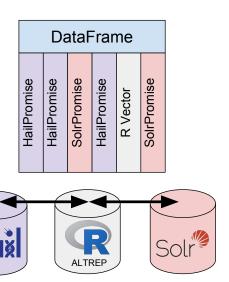
DataFrame						
HailPromise	HailPromise	SolrPromise	HailPromise	R Vector	SolrPromise	

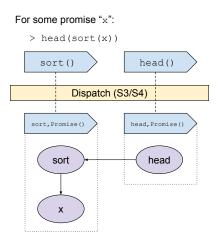


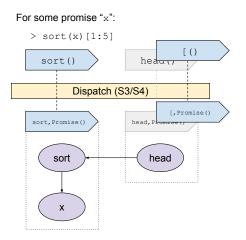


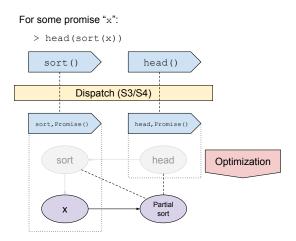


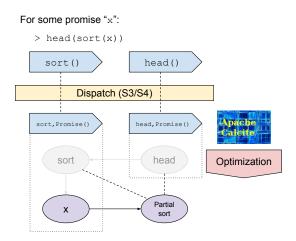
Abstractions enable mixed evaluation

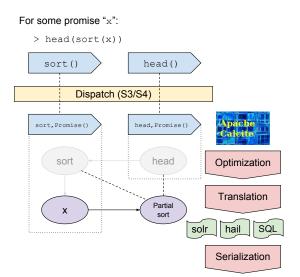












Related developments

DelayedArray Bioconductor framework for operating on large, out-of-core arrays

- Pluggable backends for different storage modes
- Defers operations
- Processes chunkwise

ALTREP Generalization of internal R vector implementation

- Compact representations
- Out-of-core storage
- Extensible by packages