Survey of data formats and conversion tools

Jim Pivarski

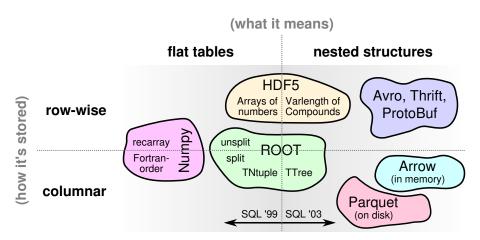
Princeton University - DIANA

May 23, 2017



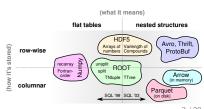


By "generic," I mean file formats that define general structures that we can specialize for particular kinds of data, like XML and JSON, but we're interested in binary formats with schemas for efficient numerical storage.





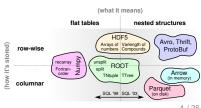
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HDF5: stores block-arrays well, good for flat ntuples; can use variable-length arrays of compounds to store e.g. lists of particles, but not in an efficient, columnar way (?)

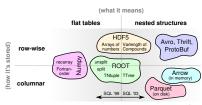




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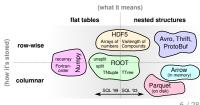


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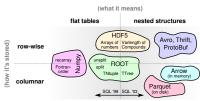
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Arrow: in-memory extension of Parquet intended for zero-copy communication among databases, query servers, analysis frameworks, etc.

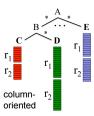
Is there a performance penalty?



Formats differ most in how nested structure is represented:

Avro: whole records are contiguous ROOT: each leaf is contiguous with list sizes in a separate array Parquet: each leaf is contiguous with depth in "repetition levels"





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Nevertheless, differences (with gzip/deflate) are only ~15%.
Use-cases may have more variation than choice of format.

 $47\,407$ $t\bar{t}$ Monte Carlo events in TClonesArrays or variable-length lists of custom classes.

ROOT 6.06, Avro 1.8.1, Parquet 1.8.1.

format	MB	rel.
ROOT none	399	1.96
ROOT gzip 1	204	1.00
ROOT gzip 2	208	1.02
ROOT gzip 9	202	0.99
Avro none	237	1.16
Avro snappy	198	0.97
Avro deflate	180	0.88
Avro LZMA	169	0.83
Parquet none	210	1.03
Parquet snappy	200	0.98
Parquet gzip	176	0.86

I don't have a grand study of all formats.

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- Nevertheless, differences (with gzip/deflate) are only ~15%.
 Use-cases may have more variation than choice of format.
- Speed depends more on runtime representation than file format. E.g. Avro's C library loads into its custom C objects in 113 sec; Avro's Java library in 8.3 sec! But if Avro's C library reads through the same row-wise data and fills minimalist objects, it's 5.4 sec.

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What matters is what you'll use it with

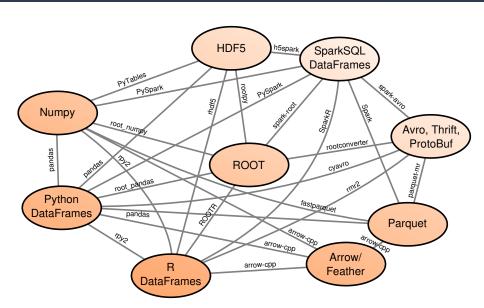


ROOT	is the best way to access petabytes of HEP data and use tools developed in HEP	
HDF5	is the best way to use tools developed in other sciences, particuarly R, MATLAB, HPC	
Numpy	is the best way to use the scientific Python ecosystem, particularly recent machine learning software	
Avro et al	is the best way to use the Hadoop ecosystem, particularly streaming frameworks like Storm	
Parquet	is the best way to use database-like tools in the Hadoop ecosystem, such as SparkSQL	
Arrow	is in its infancy, but is already a good way to share data between Python (Pandas) DataFrames and R DataFrames	

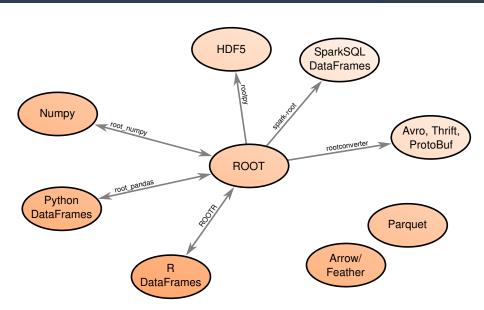


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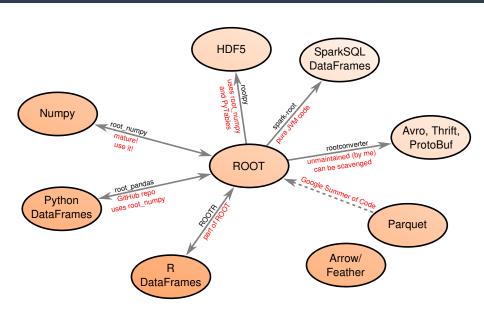




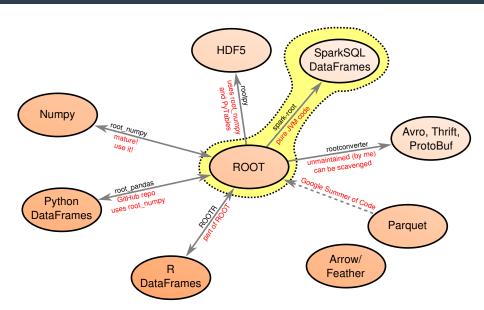












ROOT is now a Spark DataFrame format



Launch Spark with JARs from Maven Central (zero install).

```
pyspark --packages org.diana-hep:spark-root_2.11:0.1.11
```

Access the ROOT files as you would any other DataFrame.

```
df = sqlContext.read \
       .format("org.dianahep.sparkroot") \
       .load("hdfs://path/to/files/*.root")
df.printSchema()
root.
 |-- met: float (nullable = false)
 |-- muons: array (nullable = false)
      |-- element: struct (containsNull = false)
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FreeHEP ROOTIO



Last Published: 2013-03-01 | Version: 2.2.1

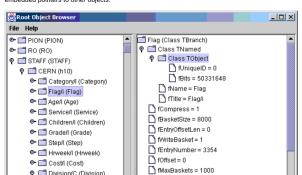


Root Object Browser

As an illustration of the use of the Java interface, we have built a sample application which is a simple Root Object Browser. It can be used to open any Root file and look at all the objects inside the file. If you already have Java 2 installed (JDK 1.3), you can download the root jar file containing the application, and run it using the command:

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java -jar root.jar
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(on Windows you can just double-click on the root, ar file). A screen shot of the application is show below. The pane on the left shows the directory structure of the file. The object browser knows how to navigate directories (TDirectories), trees (TTrees and TBranches) and these will all be shown in the left pane. Clicking on any object in the left pane will cause the details of the object to be shown in the right pane. The right pane knows how to follow embedded pointers to other objects.



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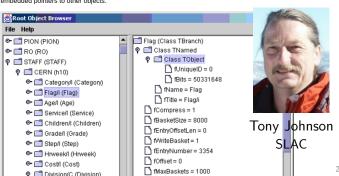


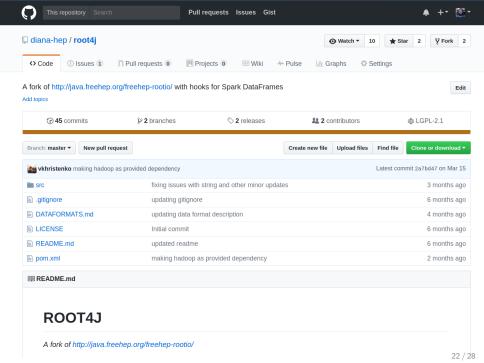
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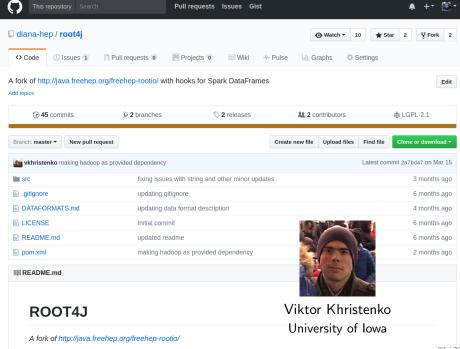
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ROOT I/O implementations



As far as I'm aware, root4j is one of only five ROOT-readers:

standard ROOT	C++	
	JavaScript	for web browsers
root4j RIO in GEANT	Java	can't link Java and ROOT
RIO in GEANT	C++	to minimize dependencies
go-hep	Go	to use Go's concurrency

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As far as I'm aware, root4j is one of only five ROOT-readers:

Most file formats are fully specified in the abstract and then re-implemented in dozens of languages.

But ROOT is much more complex than most file formats.

Dreaming...



Serialization mini-languages:

DSLs that transform byte sequence \rightarrow abstract data types

- ► Construct: http://construct.readthedocs.io
- ► PADS: http://pads.cs.tufts.edu
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That is, a disciplined use of minimal language features, allowing for automated translation to C, Javascript, Java, Go...?