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Spark and HPC for High Energy Physics Data Analyses

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Introduction

- High energy physics (HEP) data analyses are data-intensive; 3×10^{14} particle collisions at the Large Hadron Collider (LHC) were analyzed in Higgs boson discovery.
- Most analyses involve compute-intensive statistical calculations.
- Future experiments will generate significantly larger data sets.

Our question

Can “Big Data” tools (e.g. Spark) and HPC resources benefit HEP’s data- and compute-intensive statistical analysis to improve time-to-physics?

A physics use case: search for Dark Matter

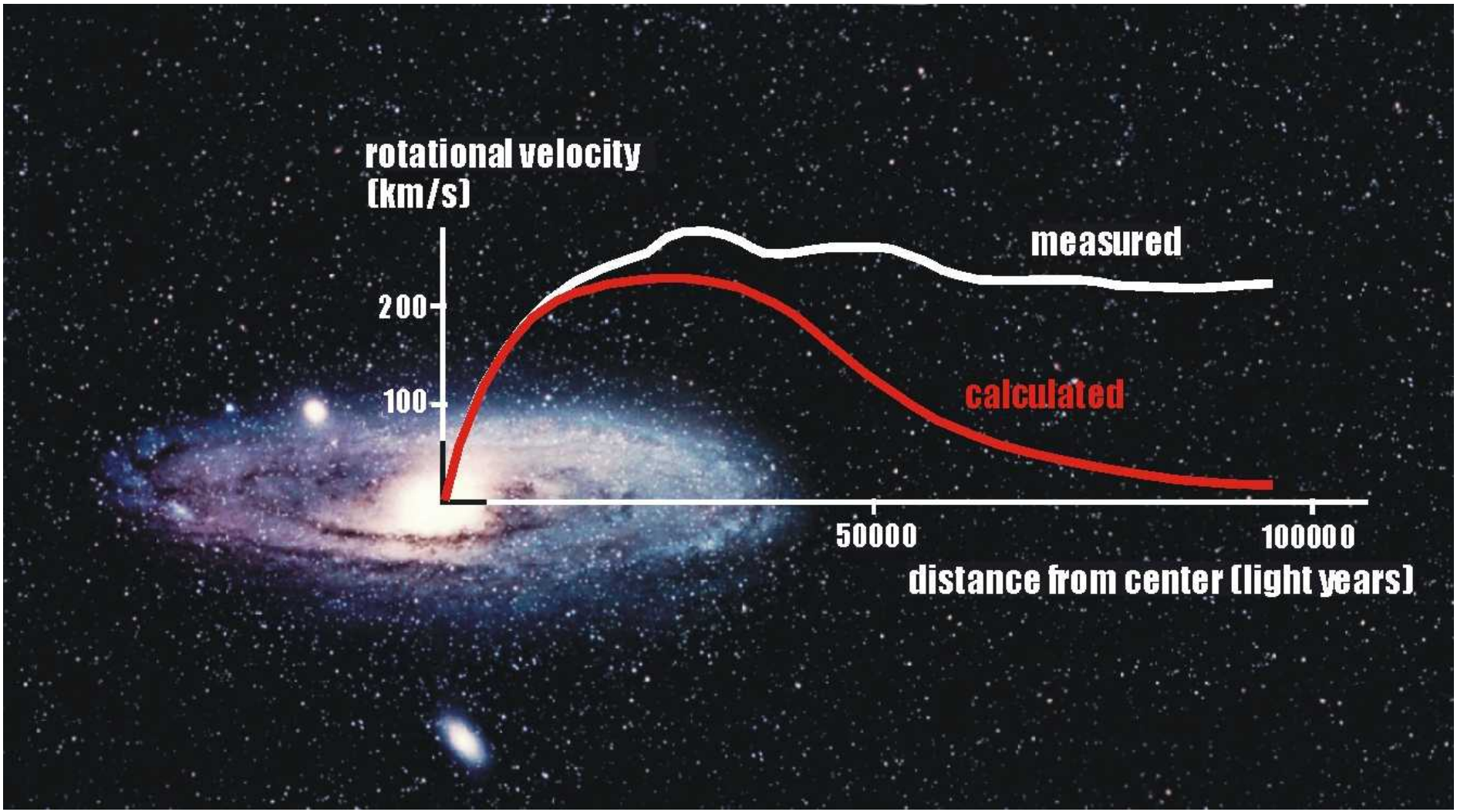
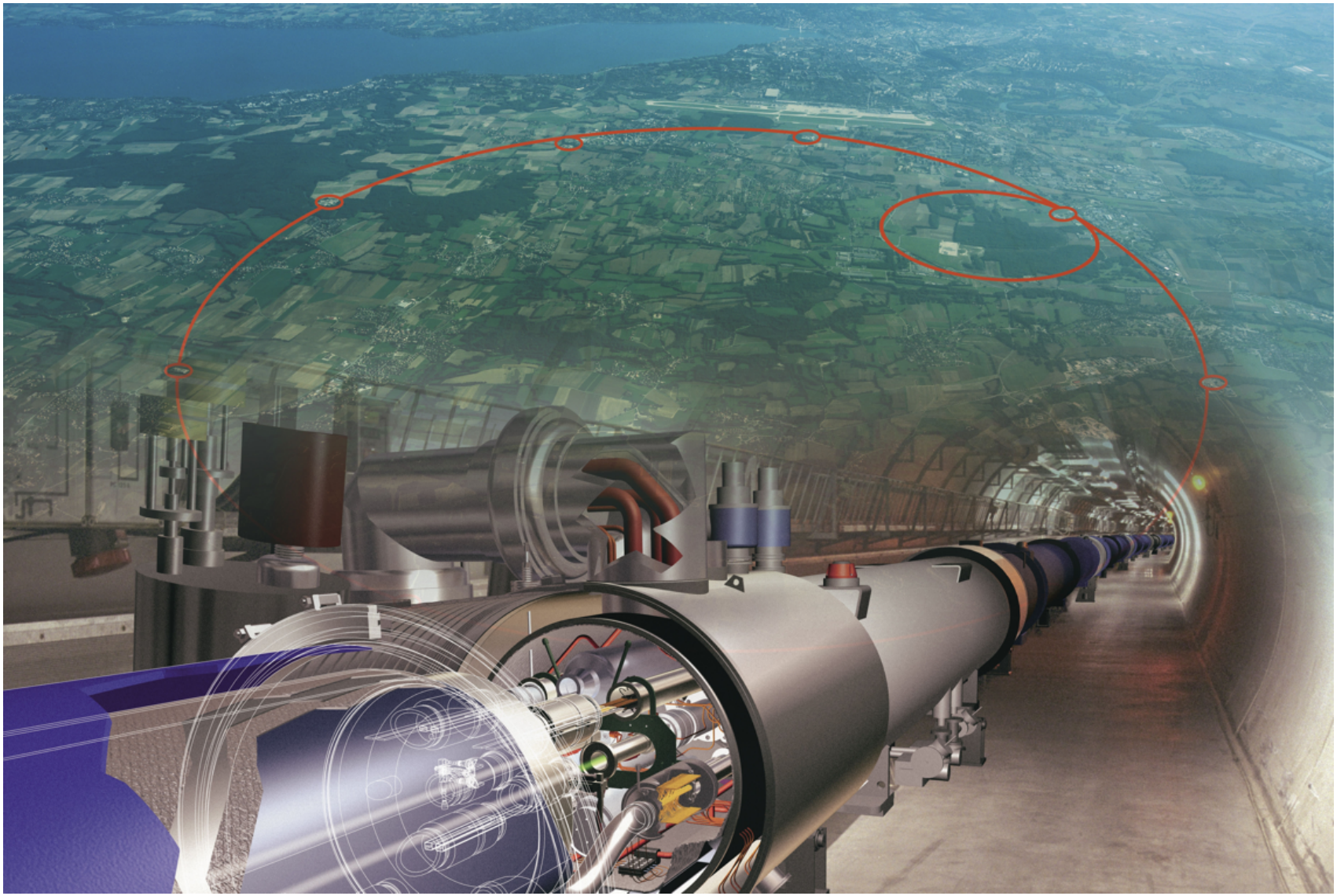
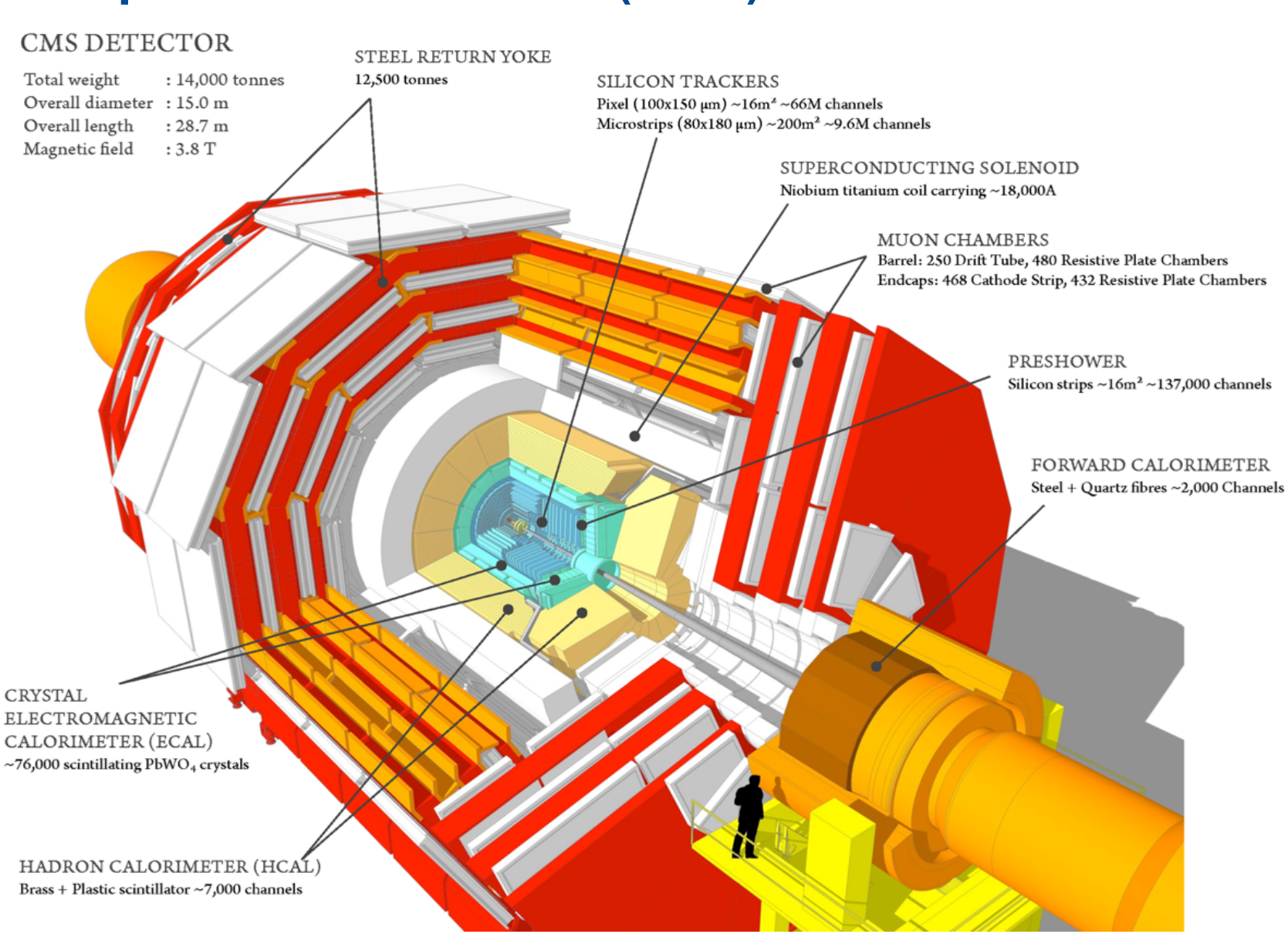


Image from http://cdms.phy.queensu.ca/PublicDocs/DM_Intro.html.

The Large Hadron Collider (LHC) at CERN



The Compact Muon Solenoid (CMS) detector at the LHC



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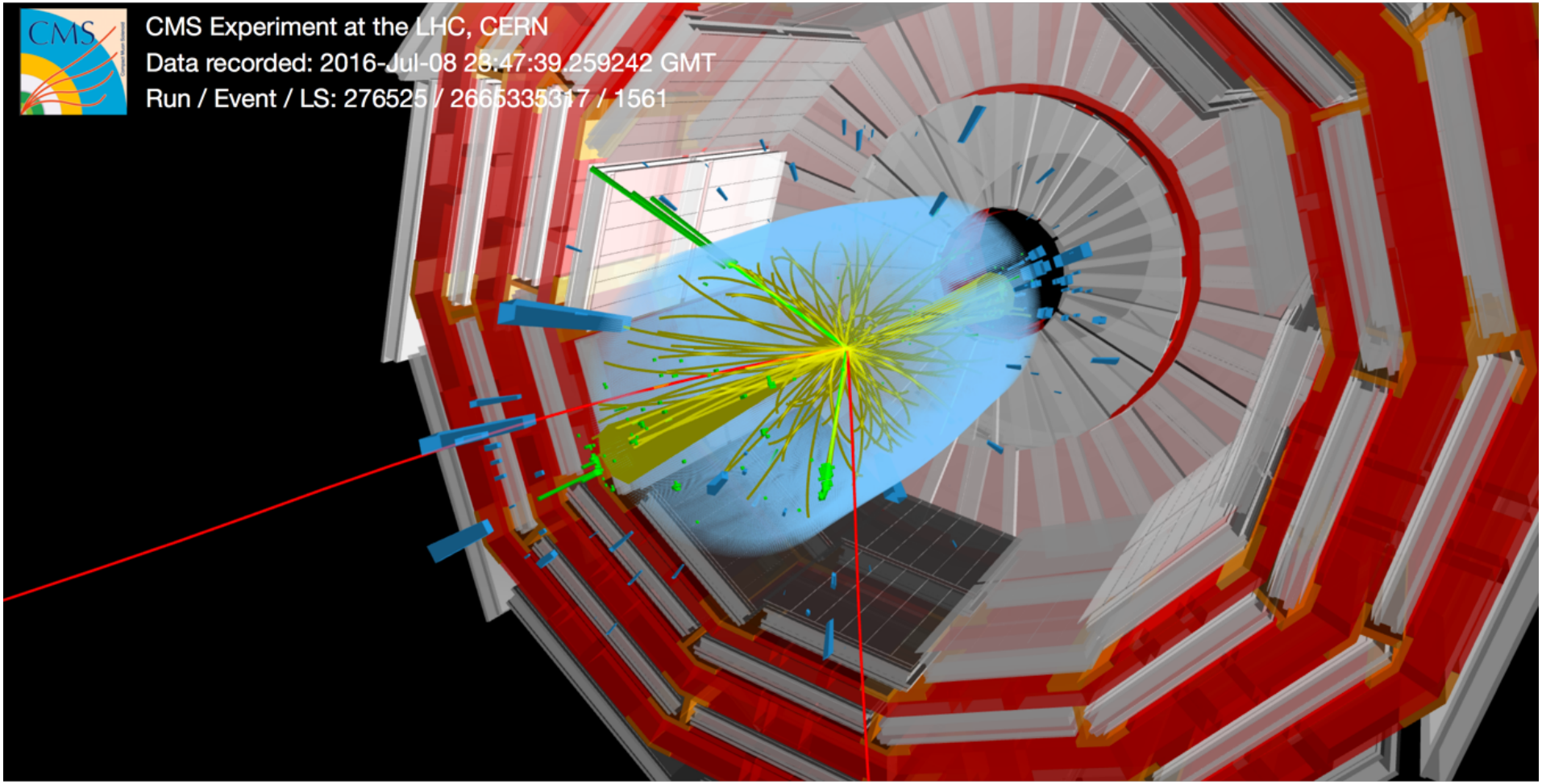
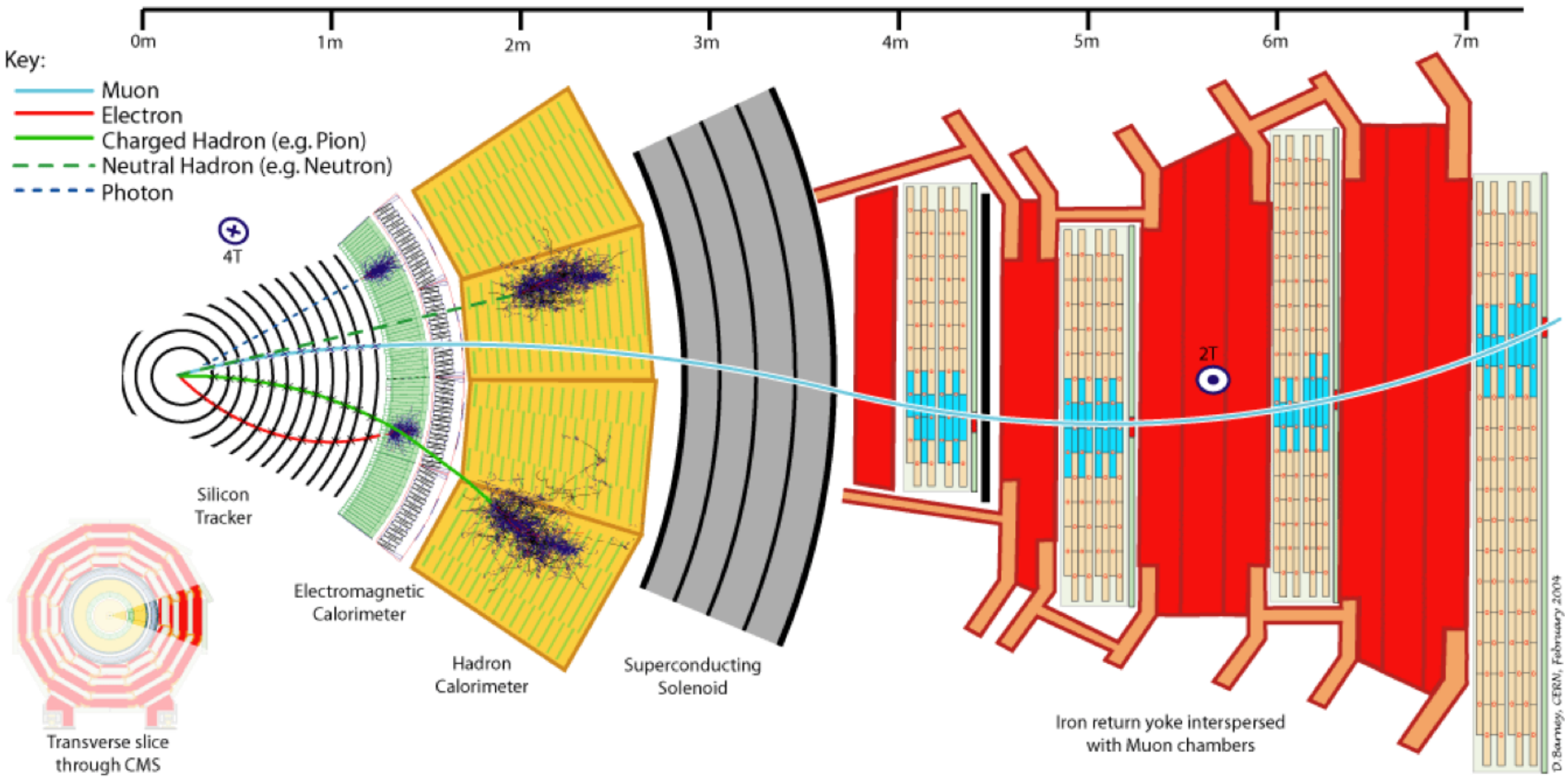
A particle collision in the CMS detector



How particles are detected



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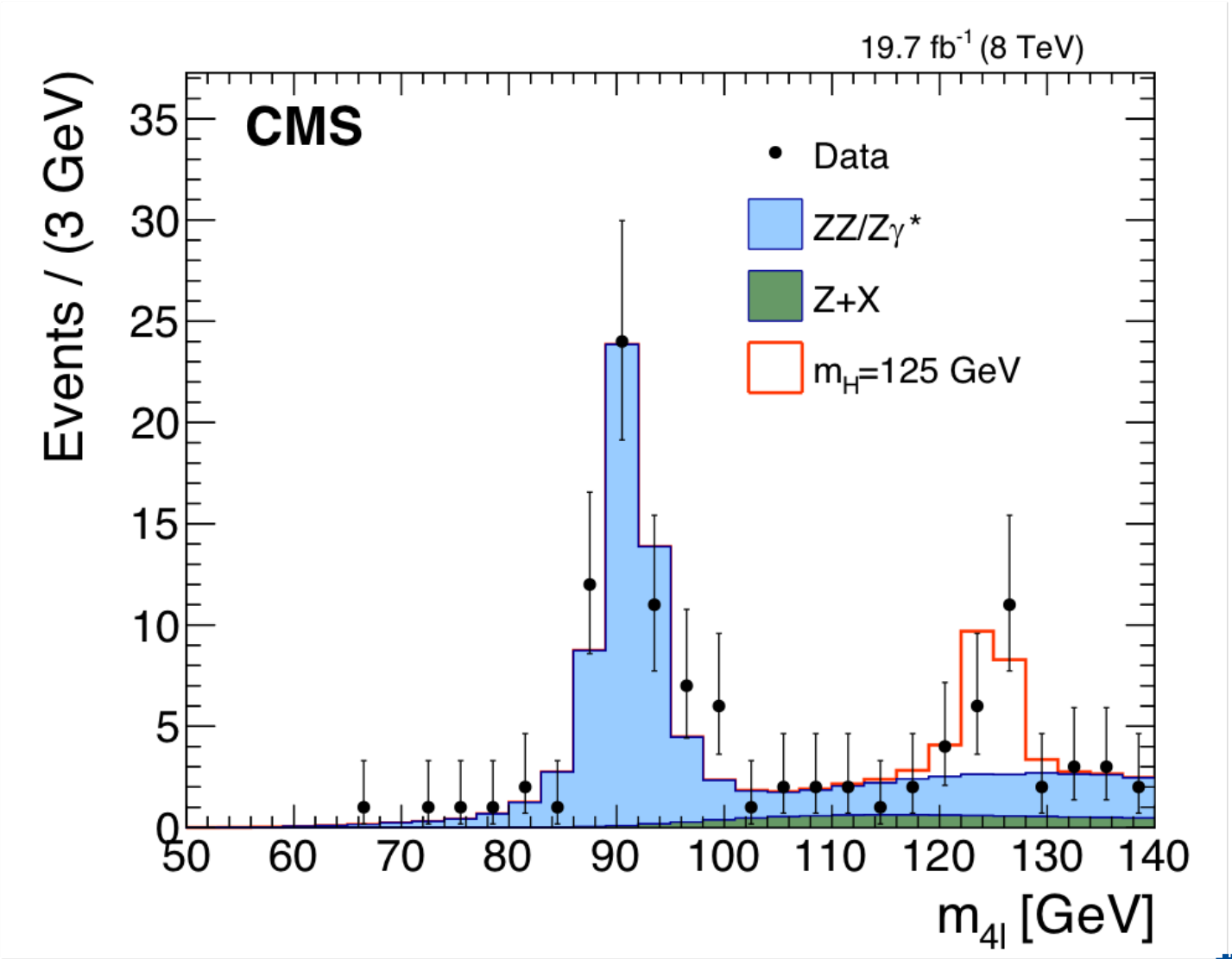
Statistical analysis: a search for new particles



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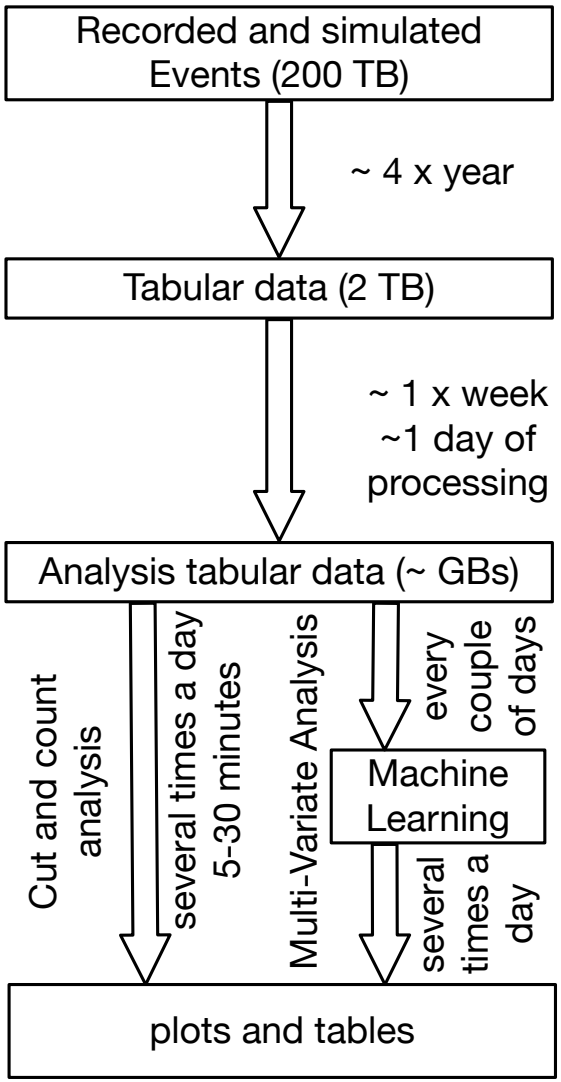
The current computing solution

- Whole-event based processing, sequential file-based solution
- Batch processing on distributed computing farms
- 28,000 CPU hours to generate 2 TB tabular data, $\sim$ 1 day of processing to generate GBs of analysis tabular data, 5–30 minutes to run end-user analysis
- Filters used on analysis data to:
  - Select interesting events
  - Reduce the event to a few relevant quantities
  - Plot the relevant quantities



Why Spark might be an attractive option

- In-memory large-scale distributed processing: *Resilient distributed datasets* (RDDs): collections of data partitioned across nodes, operated on in parallel
- Able to use parallel and distributed file system
- Write code in a high level language, with implicit parallelism
  - Spark SQL: a Spark module for structured data processing.
  - DataFrame: a distributed collection of rows organized into named columns, an abstraction for optimized operations for selecting, filtering, aggregating and plotting structured data.
- Good for repeated analysis performed on the same large data
- Lazy evaluation used for transformations, allowing Spark's Catalyst optimizer to optimize the whole graph of transformations before any calculation
  - *Transformations* map input RDDs into output RDDs; *actions* return the final result of an RDD calculation
- Tuned installation available on (some) HPC platforms

HDF5: essential features

- Tabular data representable as columns (datasets) in tables (groups).
- HDF5 is a widely-used format for the HPC systems; this allows us to use traditional HPC technologies to process these files.
- Parallel reading supported

Overview: computing solution using Spark and HDF5

- Read HDF5 files into multiple DataFrames, one per particle type.
  - First, we had to translate from the standard HEP format to HDF5.
- Define filtering operations on a DataFrame as a whole (as opposed to writing loops over events).
- Data are loaded once in memory and processed several times.
- Make plots, repeat as needed.

Simplified example of data

Standard HEP event-oriented data organization.

Event ID	Event Info		Electrons		Taus	
1	met	weight	pt	eta	pt	eta
	150	0.5	130	0.4	17	0.1
			50	1.3	55	0.3
					44	1.9
2	met	weight	pt	eta	pt	eta
	210	0.65	67	-0.5	34	1.5
			87	1.9	44	0.3

Tabular organization

Event Info

Event ID	met	weight
1	150	0.5
2	210	0.65

Electrons

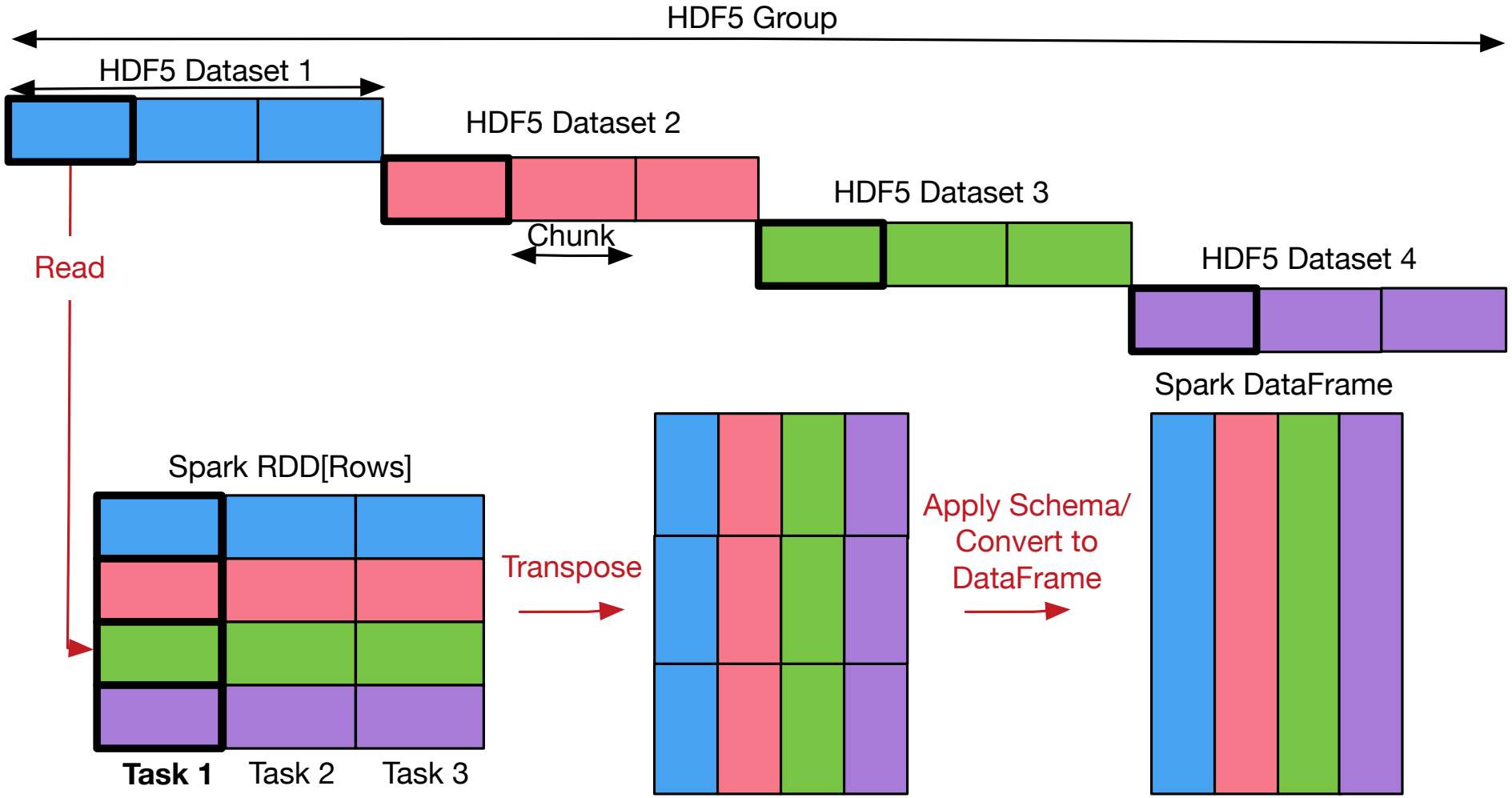
Event	pt	eta
1	130	0.4
1	50	1.3
2	67	-0.5
2	87	1.9

Taus

Event	pt	eta
1	17	0.1
1	55	0.3
1	44	1.9
2	34	1.5
2	44	0.3

Reading HDF5 files into Spark

The columns of data are organized as we want them in the HDF5 file, but Spark provides no API to read them directly into DataFrames.



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An example analysis

- Find all the events that have:
  - missing E_T (an event-level feature) greater than 200 GeV
  - one or more electrons candidates with
    - $p_T > 200$ GeV
    - eta in the range of -2.5 to 2.5
    - good "electron quality": qual > 5
- For each selected event record:
  - missing E_T
  - the leading electron p_T

Some observations

- Range queries across multiple variables are very frequent
- Hard to describe by just using SQL declarative statements
- Relational databases that we are familiar with are unable to efficiently deal with these types of queries

Coding a physics analysis with the DataFrame API

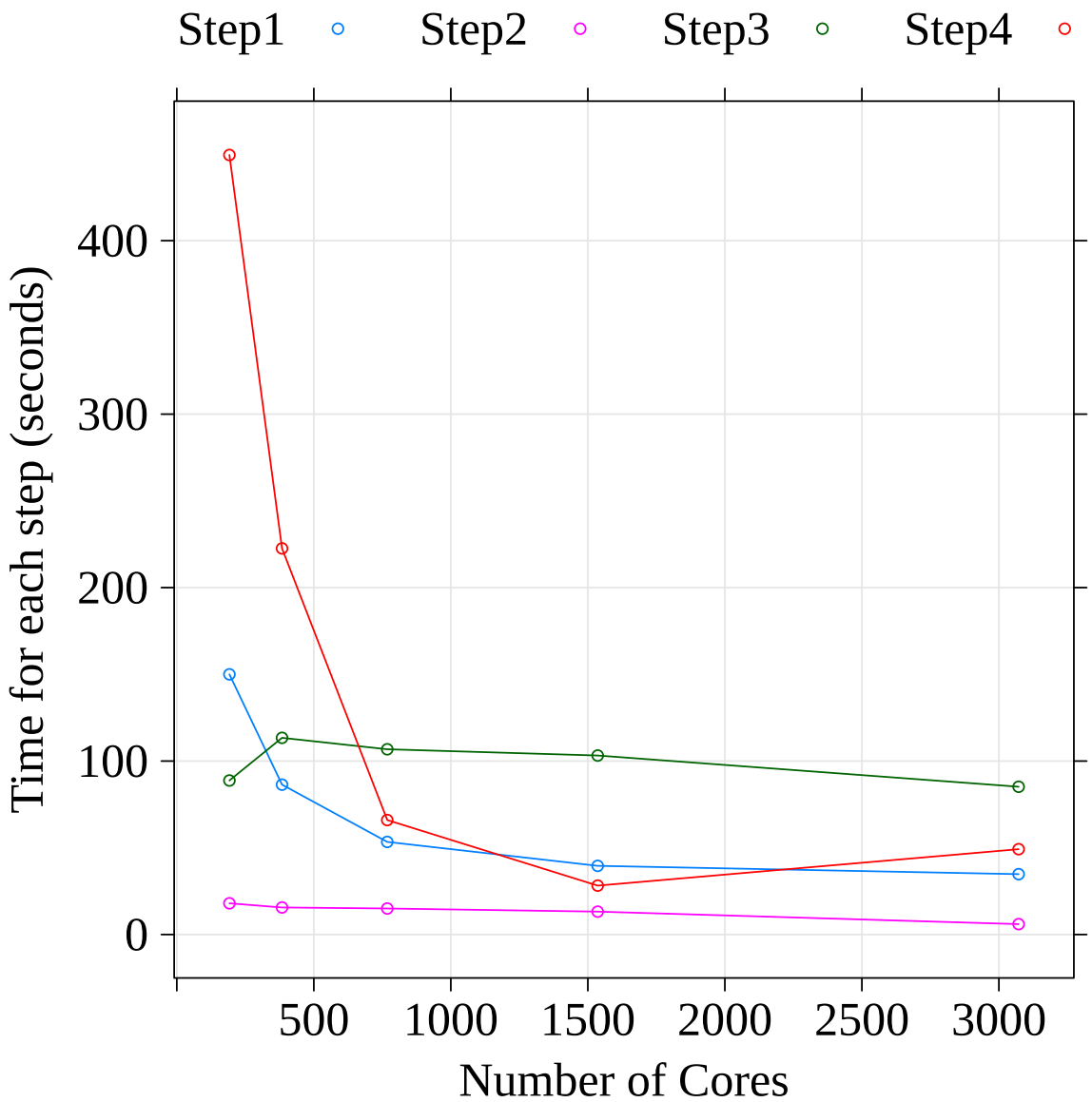
```
val good_electrons =
  electrons.filter("pt">200)
           .filter(abs("eta")<2.5)
           .filter("qual">5)
           .groupBy("event")
           .agg(max("pt"),"eid")

val good_events =
  events.filter("met">200)

val result_df =
  good_events.join(good_electrons)
```

Using `result`, make a histogram of the p_T of the "leading electron" for each good event.

Measuring the performance

- The real analysis we implemented involves much more complicated selection criteria, and many of them. It required the use of *user defined functions* (UDFs).
- In order to understand where time is spent by Spark, we determined
  - the time to read from HDF5 file into RDDs (*step 1*)
  - the time to transpose RDDs (*step 2*)
  - the time to create DataFrames from RDDs (*step 3*)
  - the time to run analysis code (*step 4*)
- Tests run on Edison at NERSC, using Spark v2.0.
- Tested using 8, 16, 32, 64, 128 and 256 nodes.
- Input data consists of
  - 360 million events
  - 200 million electrons
  - 0.5 TB in memory

Scaling results



- *Steps 1–3* read the files and prepare the data in memory. Different steps exhibit different (or no) scaling.
- *Step 4* is performing the analysis on in-memory data.

Lessons learned

The goal of our explorations is to shorten the time-to-physics for analysis.

- We have observed good scalability and task distribution.
- However, absolute performance does not yet meet our needs.
- It is hard to tune a Spark system:
  - Optimal number of executor cores, executor memory, *etc*.
  - Optimal data partitioning to use with the parallel file system, *e.g.*, Lustre File System stripe size, OST count.
  - Difficult to isolate slow performing stages due to lazy evaluation.
- *pySpark* and *SparkR* high-level APIs may be appealing to the HEP community.
- Our understanding of Scala and Spark best practices is still evolving.
- Documentation and error reporting could be improved.

Future work

- Scale up to multi-TB data sets.
- Compare performance with a Python+MPI approach.
- Improve our HDF5/Spark middleware.
- Evaluate the I/O performance of different file organizations, *e.g.* all backgrounds in one HDF5 file.
- Optimize the workflow to filter the data: try to remove UDFs, which prevents Catalyst from performing optimizations.

References

1. Kowalkowski, Jim, Marc Paterno, Saba Sehrish:*Exploring the Performance of Spark for a Scientific Use Case*. In IEEE International Workshop on High-Performance Big Data Computing.In conjunction withThe 30th IEEE International Parallel and Distributed Processing Symposium (IPDPS 2016).
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3. CMS http://cms.web.cern.ch
4. HDF5 https://www.hdfgroup.org
5. Spark at NERSC
   http://www.nersc.gov/users/data-analytics/data-analytics/spark-distributed-analytic-framework
6. Traditional analysis code:
   https://github.com/mcremone/BaconAnalyzer
7. Our approach:
   https://github.com/sabasehrish/spark-hdf5-cms

Acknowledgments

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