

Status and Plans of the CMS Big Data Project

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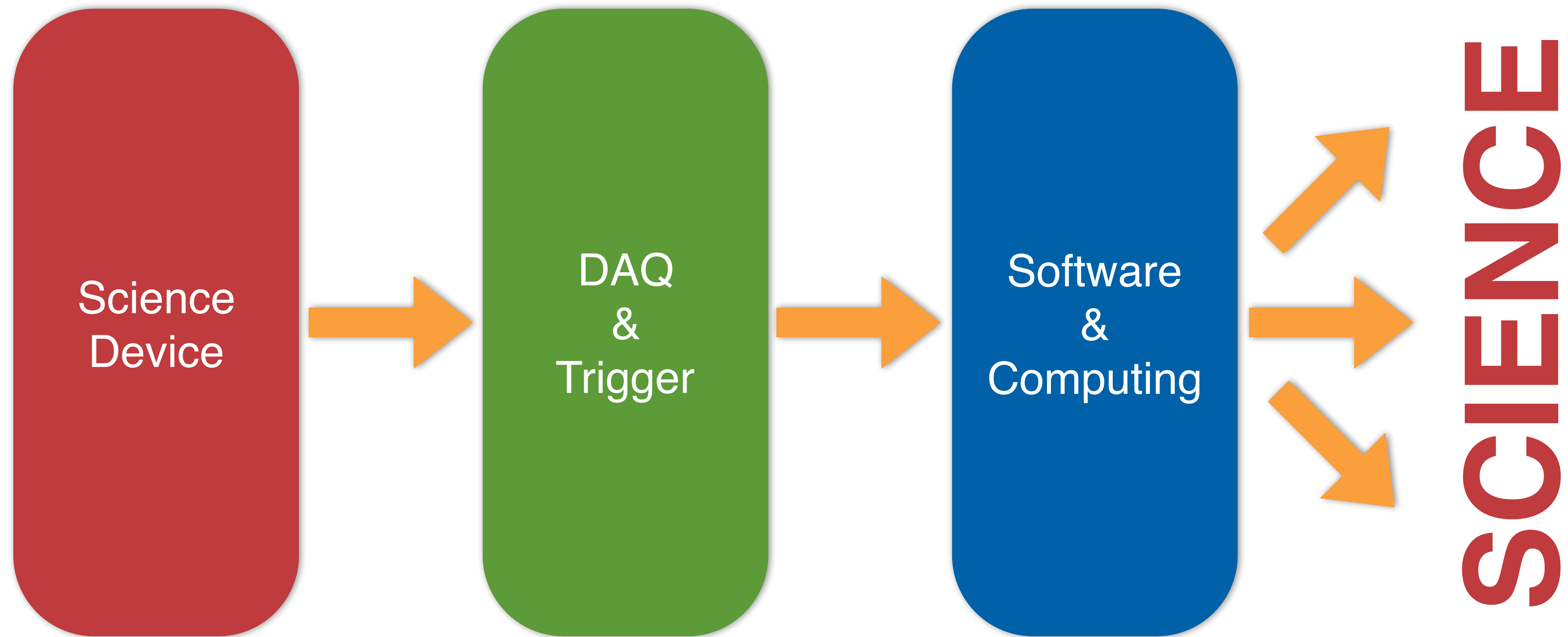
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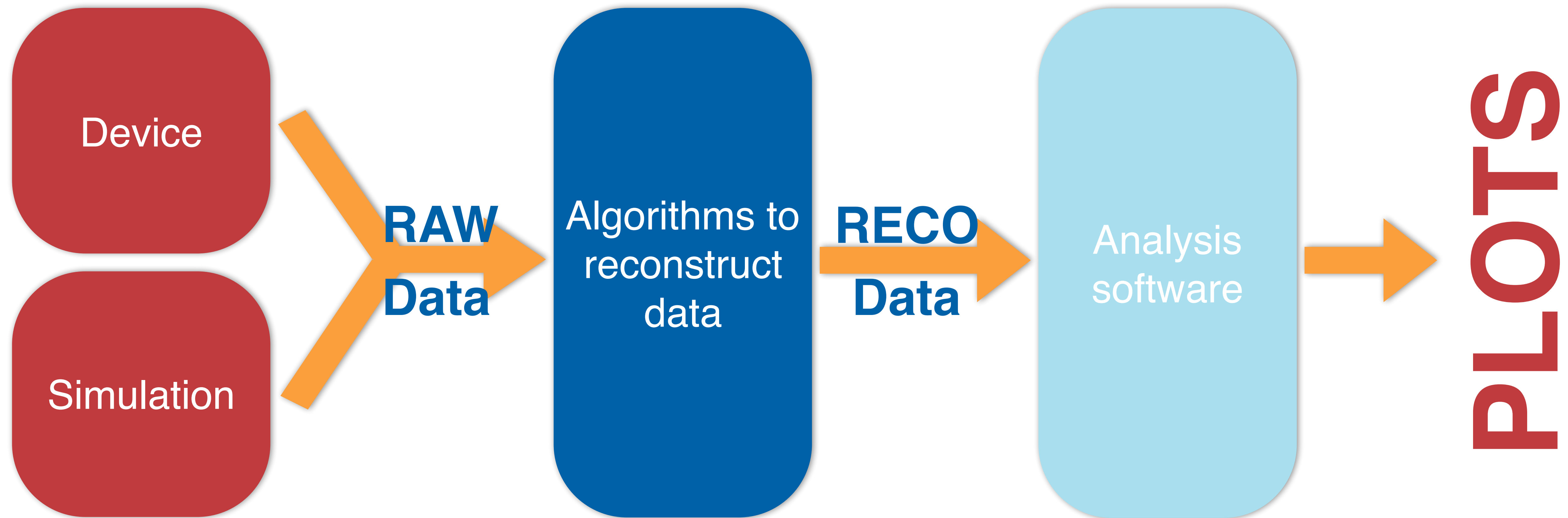
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The Scientific Process

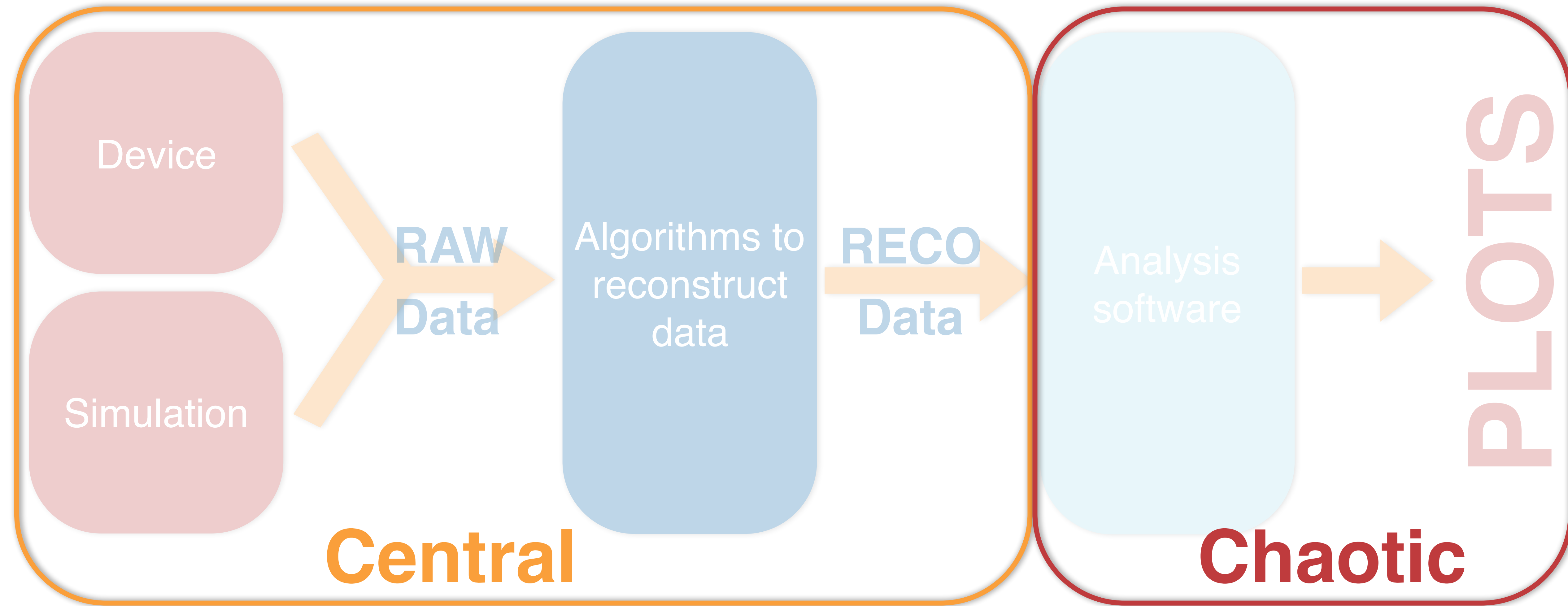


- Software & Computing is an integral part of the scientific process



- **Software** is important for every step on the way to scientific results

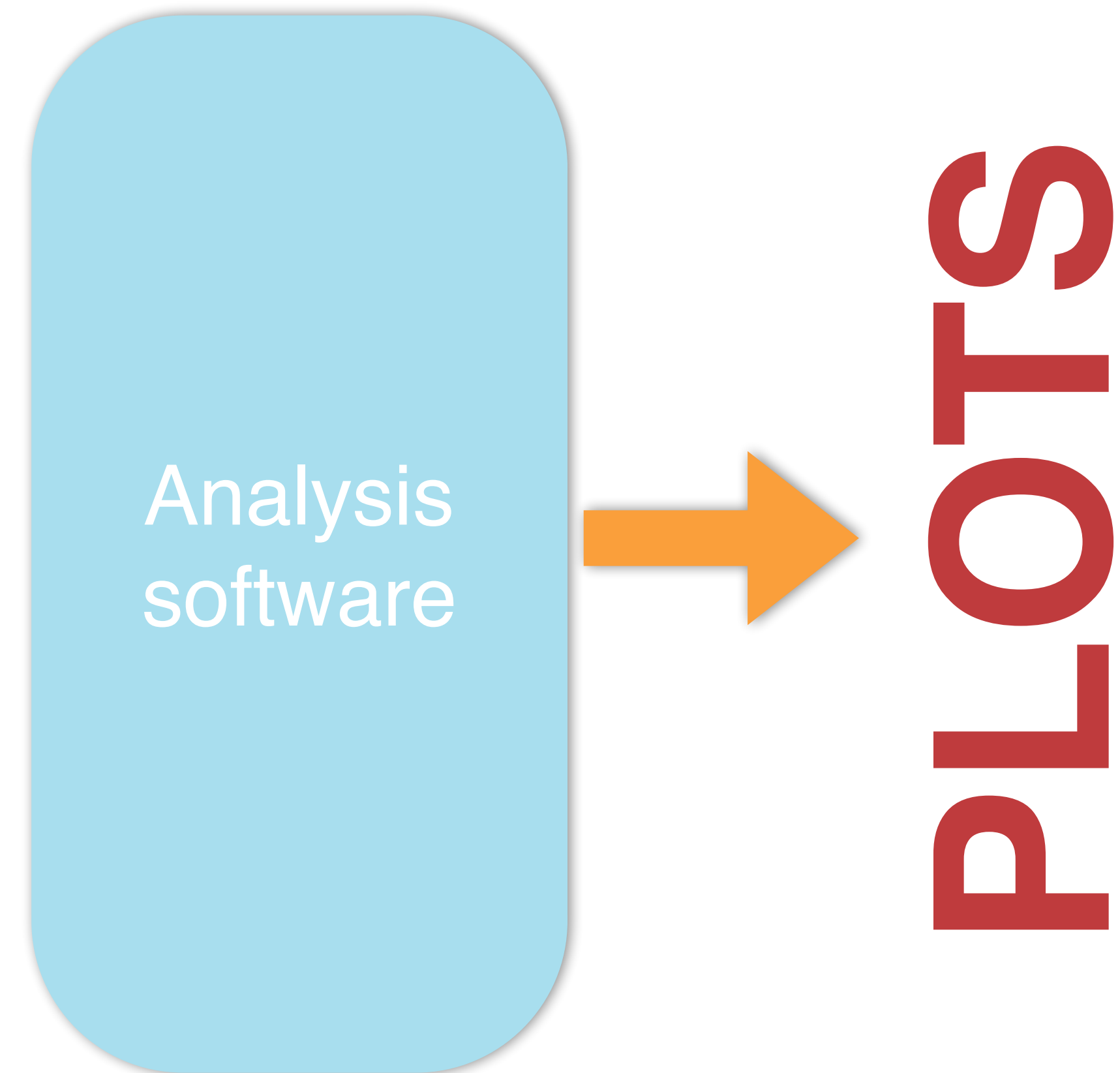
Software & Computing



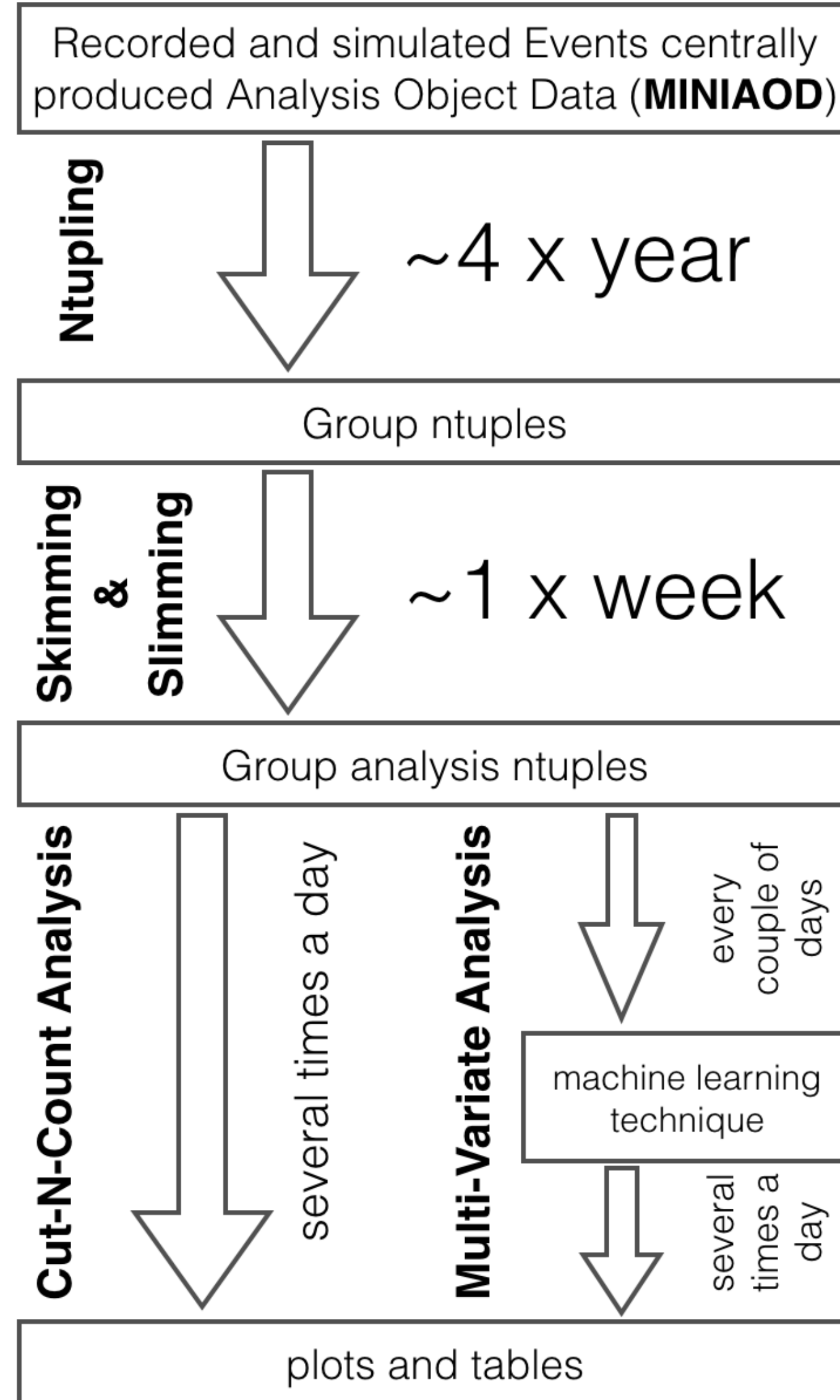
- **Central:** organized processing/production, one software stack/framework per experiment (C++), one or few output sets, shared by large parts of the experiments for analysis
- **Chaotic:** smaller groups down to individuals explore the data for analysis, individually implemented analysis code, because of data volumes

Physics Data Reduction

- Data analysis needs fast turn-around
 - “Interactivity” is a big need for efficient data exploration
- Each analysis is different
 - looks for different physics
- Data volumes will reach multi-PB sizes in the future
 - input data composition different for every analysis
- Analysts need to reduce data to be able to analyze it (or do they?)
- Requirements:
 - Reduce data by skimming (filter specific collisions) and slimming (reduce content per collision)
 - Calculate new properties before skimming and slimming
 - Re-calculate properties previously calculated centrally
 - All this by multiple users in parallel



Analysis - A multi-step process



Current Analysis Workflow

- Touches only a subset of the total data volume, but subset varies from analysis to analysis
- Complicated multi-step workflow because dataset is too large for interactive analysis
 - Slimming & Skimming, analysis dependent
 - Calculation of new quantities
 - Rerun framework code (b-tagging with non-default parameters, etc.)
 - Recipes on top of centrally produced samples to correct problems/mistakes
- Can take weeks using GRID resources and local batch systems
 - Experiments started to centralize first step
- Not all time spent is actual CPU, a lot of time is bookkeeping, resubmission of failed jobs, etc.

Currently based on ROOT

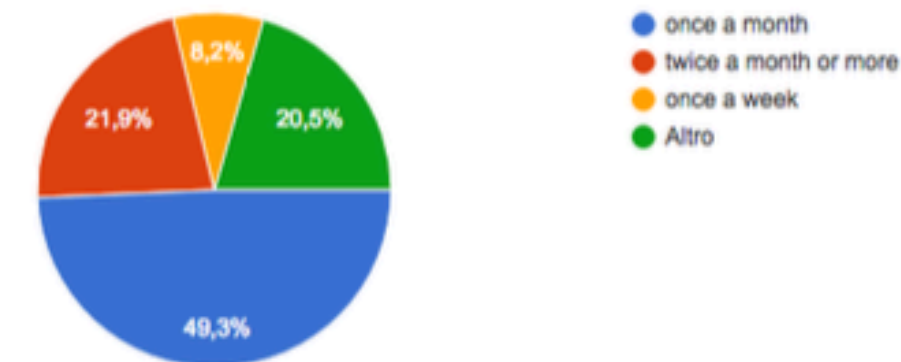
- ROOT is the community's statistics, plotting and I/O toolkit
- Developed by the community and optimized for this purpose

CMS User Analysis Survey

■ Main outcomes

- ◉ 85% of the users use an independent Framework...
- ◉ Almost all users mention 1 or 2 intermediate steps to produce User/Group specific root trees
 - At least 40% of the answers mention the word flat trees
 - Counted around 40 different FW used within the CMS community
- ◉ More than 35% of the answers mention the words skim/reducing

Could you tell us how many times on average you or your group run the framework on the full dataset you use for your analysis (data and MC)? As a reference we suggest to consider the analysis presented at Moriond 2016 and/or ICHEP 2016
(73 risposte)

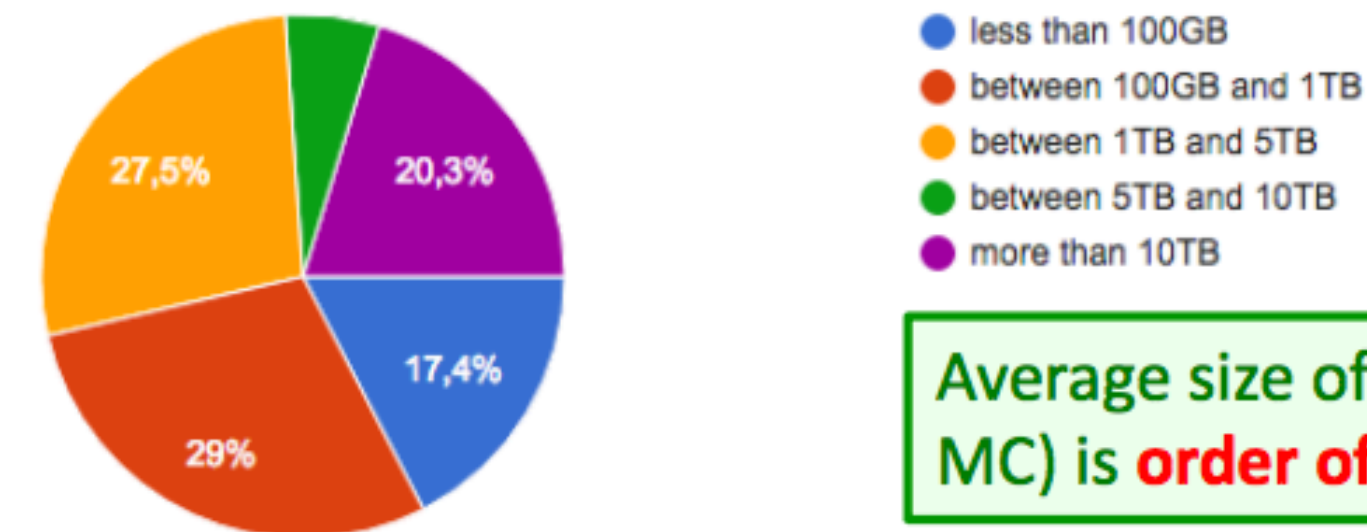


Hard to quantify (I cannot check how many users refers to the same FW) but...

It seems that **each year** the CMS computing infrastructure is used **order of 1000 times** to run on a full dataset (data and MC)

Main reasons to rerun are **POG updates** and adding **new variables**

What is the size of your full processed sample (data and MC)? (69 risposte)

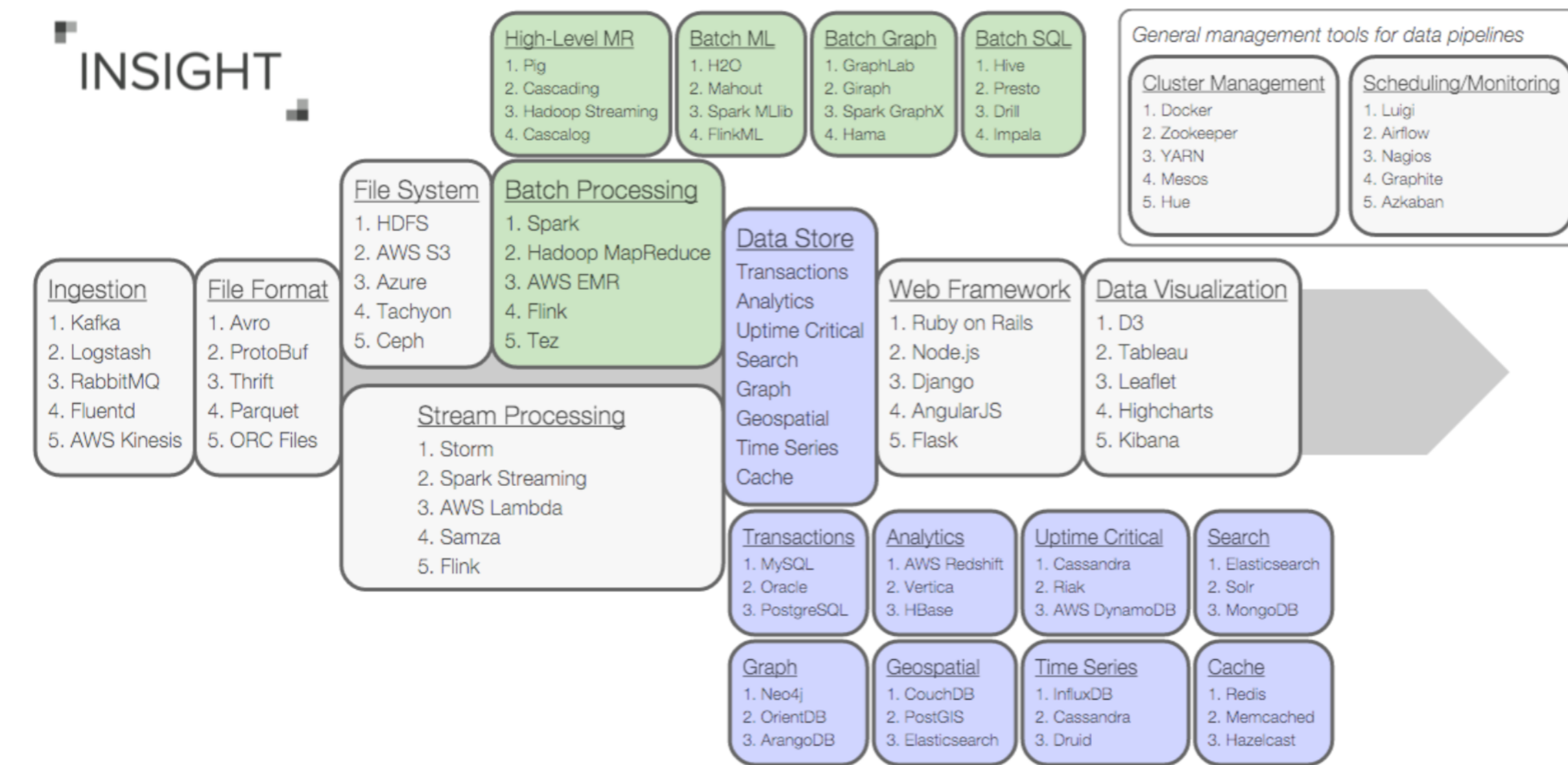


Average size of a processed dataset (data and MC) is **order of 5TB** but it could much bigger

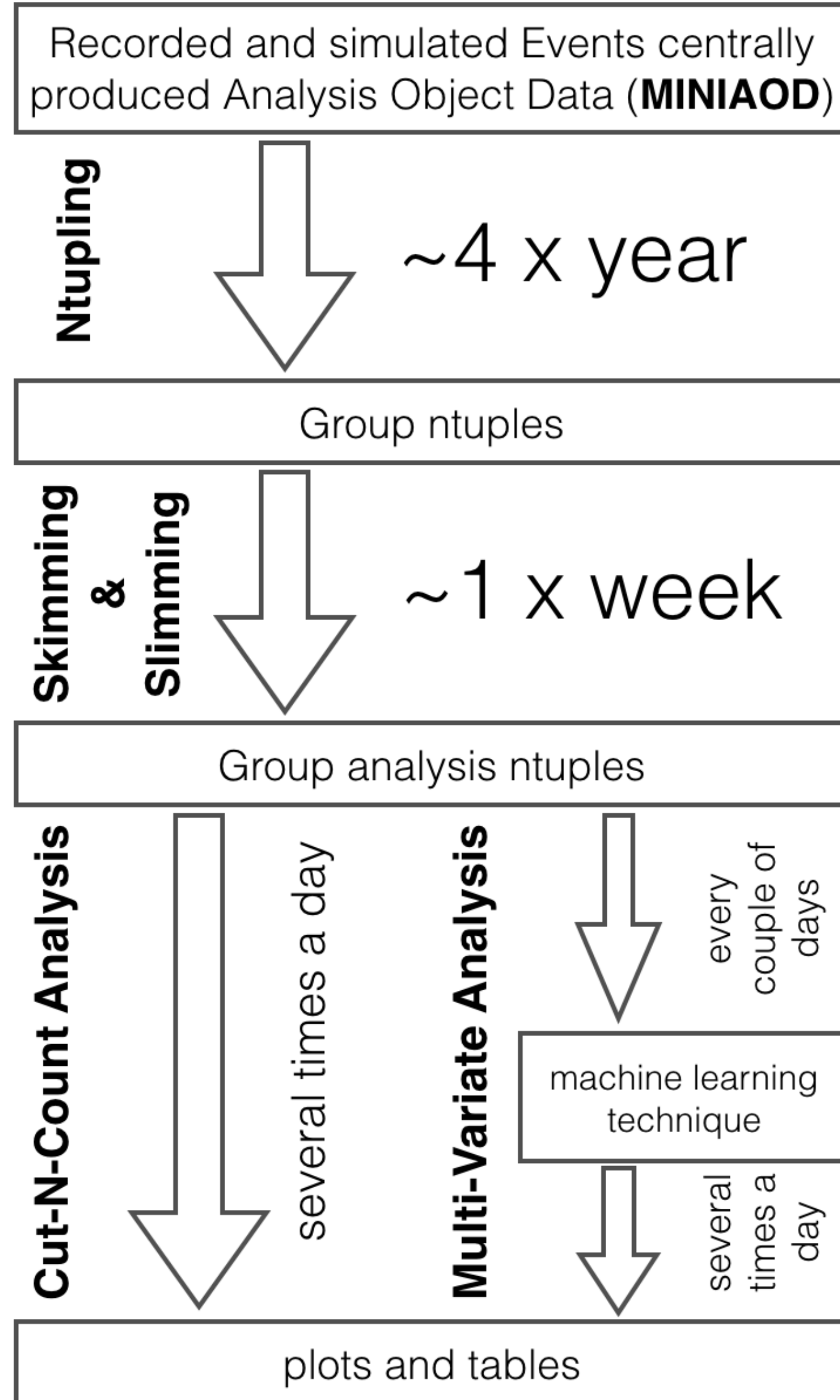
Big Data

- New toolkits and systems collectively called “Big Data” technologies have emerged to support the analysis of PB and EB datasets in industry.

- Our goals in applying these technologies to the HEP analysis challenge:
 - ◉ Reduce time-to-physics
 - ◉ Educate our graduate students and post docs to use industry-based technologies
 - Improves chances on the job market outside academia
 - Increases the attractiveness of our field
 - ◉ Be part of an even larger community



Feasibility Studies: Two Thrusts



■ Input: MINIAOD

- Caveat: Applying recipes or re-running framework code currently not being considered

■ Thrust 1:

- Use analysis-specific data formats that have all recipes applied and framework code re-run
- Explore using Apache spark producing plots and tables

■ Thrust 2:

- Use official input
- Demonstrate reduction capabilities producing group analysis ntuples
 - Goal: reduce 1 PB input to 1 TB output in 5 hours
- Intel CERN Openlab project

New Tools

DIANA: Histogrammar

- <http://histogrammar.org>
- The ROOT histogram API is intended to be used in a **user-controlled event loop**, which **isn't available in Spark** because Spark manages concurrency for you.
- Histogrammar was designed to be a better fit to this sort of environment because it additionally provides a functional interface:
 - You fill histograms by passing lambda functions, in the same way that you perform transformations in Spark.
 - Filled Histogrammar histograms can be immediately converted to ROOT for further processing.
 - Analysis code is now independent of where the data are analyzed.
- Side effect: moving the logic of data analysis out of the for loop allows the analyst to describe an entire analysis declaratively.

histo·grammar
/histō,'græm.ər/

MAKING HISTOGRAMS FUNCTIONAL

ROOT:

```
histogram = ROOT.TH1F("name", "title", 100, 0, 10)
for muon in muons:
    if muon.pt > 10:
        histogram.fill(muon.mass)
```

Histogrammar:

```
histogram = Select(lambda mu: mu.pt > 10,
                   Bin(100, 0, 10, lambda mu: mu.mass,
                      Count()))
for muon in muons:
    histogram.fill(muon)
```

DIANA: spark-root

- Read ROOT files directly from Apache Spark
 - ◉ Connect ROOT to ApacheSpark to be able to read ROOT TTrees, infer the schema and manipulate the data via Spark's DataFrames/Datasets/RDDs.
- <https://github.com/dianahep/spark-root>

```
df = sqlContext.read.format("org.dianahep.sparkroot").option("tree", "Events").load("hdfs:/cms/bigdatasci/vkhriste/data/publiccms_muionia_aod")
#df1 = sqlContext.read.format("org.dianahep.sparkroot").option("tree", "Events").load("hdfs:/cms/bigdatasci/vkhriste/data/publiccms_muionia_aod/0000/FEEFB039-0978-E011-BB60-E41F131815BC.root")
df.printSchema()
```

```
root
|-- EventAuxiliary: struct (nullable = true)
|   |-- processHistoryID_: struct (nullable = true)
|   |   |-- hash_: string (nullable = true)
|   |   |-- id_: struct (nullable = true)
|   |   |   |-- run_: integer (nullable = true)
|   |   |   |-- luminosityBlock_: integer (nullable = true)
|   |   |   |-- event_: integer (nullable = true)
|   |   |-- processGUID_: string (nullable = true)
|   |   |-- time_: struct (nullable = true)
|   |   |   |-- timeLow_: integer (nullable = true)
|   |   |   |-- timeHigh_: integer (nullable = true)
|   |   |-- luminosityBlock_: integer (nullable = true)
|   |   |-- isRealData_: boolean (nullable = true)
|   |   |-- experimentType_: integer (nullable = true)
|   |   |-- bunchCrossing_: integer (nullable = true)
|   |   |-- orbitNumber_: integer (nullable = true)
|   |   |-- storeNumber_: integer (nullable = true)
|   |-- EventBranchEntryInfo: array (nullable = true)
|   |   |-- element: struct (containsNull = true)
|   |   |   |-- branchID_: struct (nullable = true)
|   |   |   |   |-- id_: integer (nullable = true)
|   |   |   |   |-- productStatus_: byte (nullable = true)
|   |   |   |   |-- parentageID_: struct (nullable = true)
|   |   |   |   |   |-- hash_: string (nullable = true)
|   |   |   |   |-- transients_: struct (nullable = true)
|   |   |-- EventSelections: array (nullable = true)
|   |   |   |-- element: struct (containsNull = true)
|   |   |   |   |-- hash_: string (nullable = true)
|   |   |-- BranchListIndexes: array (nullable = true)
|   |   |   |-- element: short (containsNull = true)
|   |-- L1GlobalTriggerObjectMapRecord_hltL1GtObjectMap_HLT_: struct (nullable = true)
|   |   |-- edm::EDProduct: struct (nullable = true)
```

```
In [6]: df.count()
```

```
Out[6]: 12058887
```

```
In [7]: slimmedEvents = df.select("recoMuons_muons__RECO_.recoMuons_muons__RECO_obj.reco::RecoCandidate.reco::LeafCandidate")
```

```
slimmedEvents.show()
```

```
+-----+
| reco::LeafCandidate |
+-----+
| [[[],-3,3.085807,...] |
| [[[] ,3,4.1558356,...] |
```


Thrust 1: Usability Study

Thrust 1: Usability Study - Status

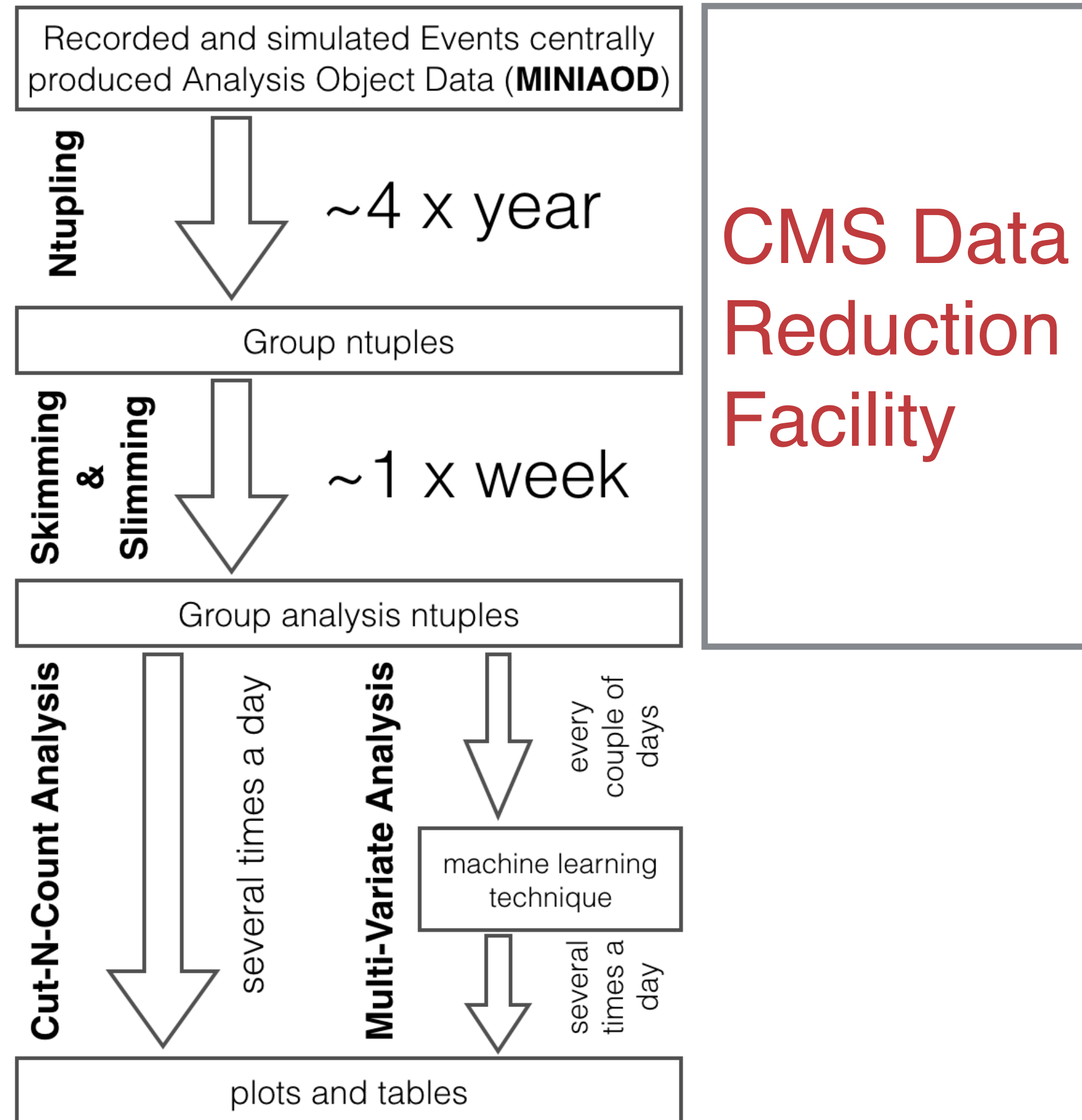
- CHEP 2016 paper accepted for publication
 - <https://arxiv.org/abs/1703.04171>

- Study based on monoTop Dark Matter analysis
 - Conversion to AVRO format and upload to HDFS
 - Analysis implemented in Scala
 - Processing in Apache Spark
 - Result:
 - Spark analysis simpler to structure (functional programming) and easier to port
 - Performance comparison challenging (apples-to-apples comparison)

- Next steps
 - New analysis framework for monoTop
 - Use ROOT files directly in Spark
 - Use analysis code in Scala and use Histogrammar
 - Achieve apples-to-apples comparison to ROOT analysis

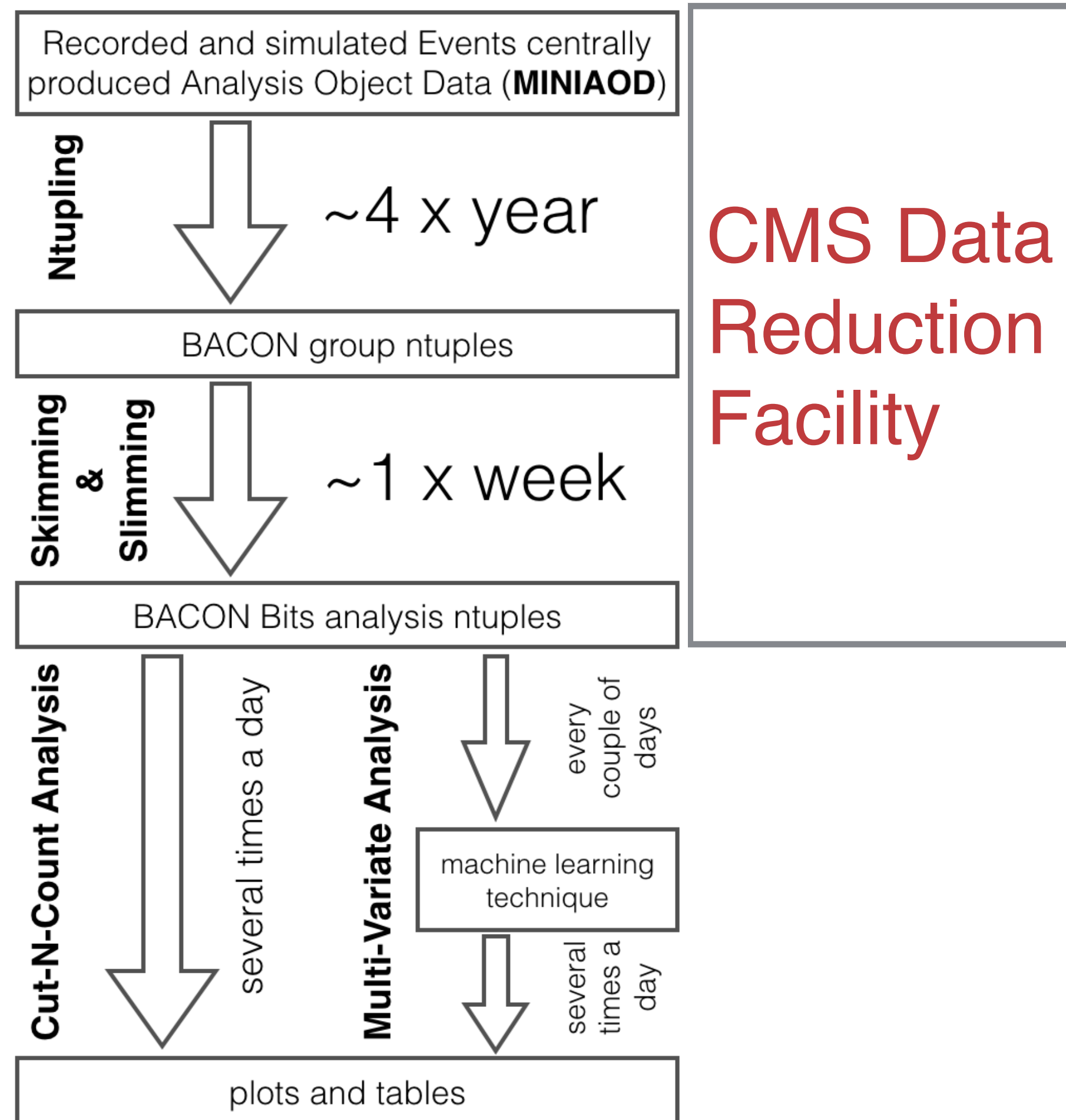
CERN Openlab/Intel CMS Data Reduction Facility Project

CMS Data Reduction Facility



- CERN Openlab project with Intel (2 years)
- Demonstration facility optimized to read through petabyte sized storage volumes
 - Produce sample of reduced data based on potentially complicated user queries
 - Time scale of hours and not weeks as it currently requires.
- If successful, this type of facility could be a big shift in how effort and time is used in physics analysis
 - Same infrastructure and techniques should be applicable to many sciences

Project Objectives



- We would like to demonstrate the ability to reach **at least a 1000 fold reduction** in selected data
- We would like to show that with an optimized prototype center that we can perform this task **roughly 100 times faster** than it can currently be done
- Goal:
 - ◉ Process an input sample of 1PB within 5 hours
 - ◉ Export a selected sample that is at least 1000 times smaller

Thrust 2: CMS Data Reduction Facility

Thrust 2: CMS Data Reduction Facility - Status

- Intel/CERN fellow started at CERN in March 2017
 - Welcome Vaggelis!
- Work on CERN Hadoop using Spark
 - Enable Spark to read ROOT files through spark-root directly from EOS (Vaggelis)
- Started with using CMS open data
 - Copied small amounts to HDFS (currently using 1.2 TB)
- Next steps
 - Start with CMS Open Data and execute a suitable ntuple production step with significant reduction
 - Download reduction result and make physics-style plots
 - Scale up and study performance

Conclusions & Outlook

Conclusions & Outlook

- Investigating Big Data technologies to solve the HL-LHC data analysis challenge → Apache Spark as a starting point
 - ◉ Fulfills immediately 2 out of 3 goals:
 - Educates our community to use industry-based technologies
 - Uses tools developed in larger communities reaching outside of our field
 - ◉ First study accepted for publication in CHEP 2016 proceedings

- Thrust 1: Usability Study
 - ◉ Adapt to new framework, read ROOT files directly, use Histogrammar

- Thrust 2: Intel/CERN openlab CMS Data Reduction Facility
 - ◉ Use CMS open data as a starting point, read ROOT files directly from EOS, scale up and study performance

