

Data **A**nalysis **W**orking **G**roup

Analysis today

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BROOKHAVEN
NATIONAL LABORATORY



Introduction to the Data Analysis Working Group

- **Aim** - make publication of physics results more efficient, eliminate monotonous and laborious tasks from physics analysis
- **1st priority** - capture the requirements of analysis by direct consultation:
 - <https://indico.cern.ch/event/782504/>
- **Second 1st priority** - survey work of technology pioneers:
 - <https://indico.cern.ch/event/789007/>
- **18 excellent talks** which the three **DAWG** convenors will try to summarise
 - **What have we learned? What can we improve? How bad is it?**
- Many thanks to the speakers, most of the material in this talk originated there
 - Credit goes to the original presentations (not always credited here, sorry!)

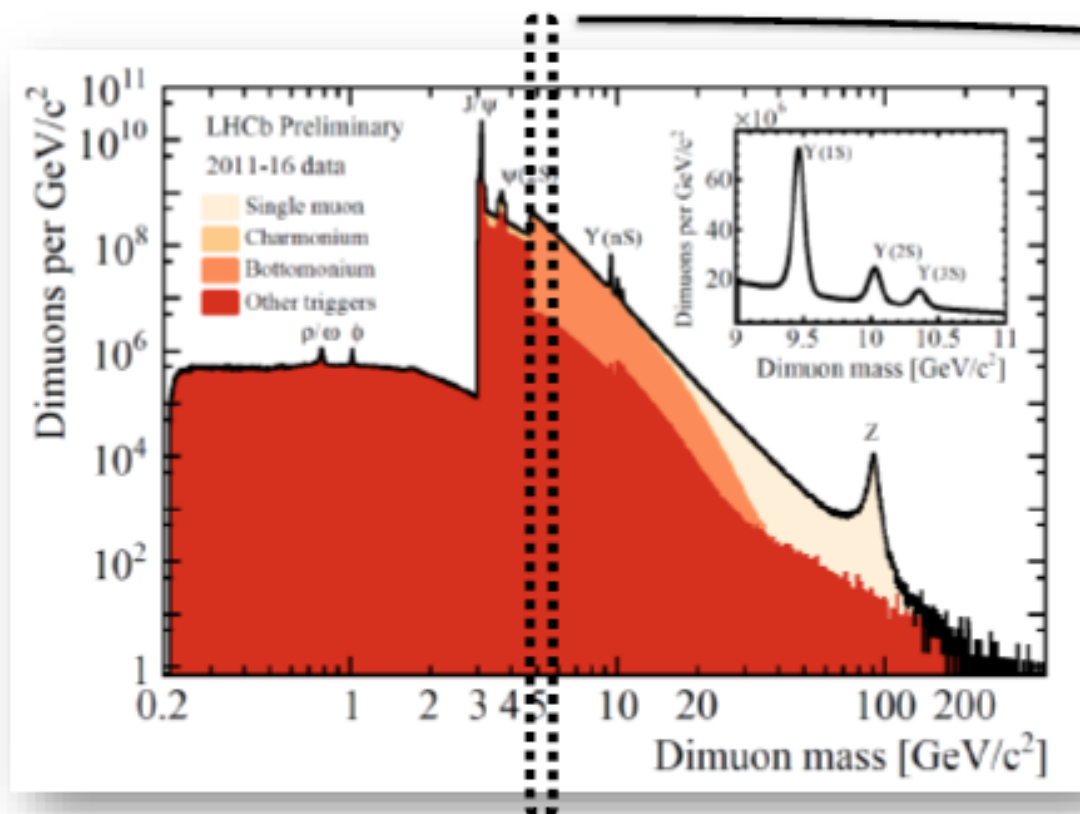
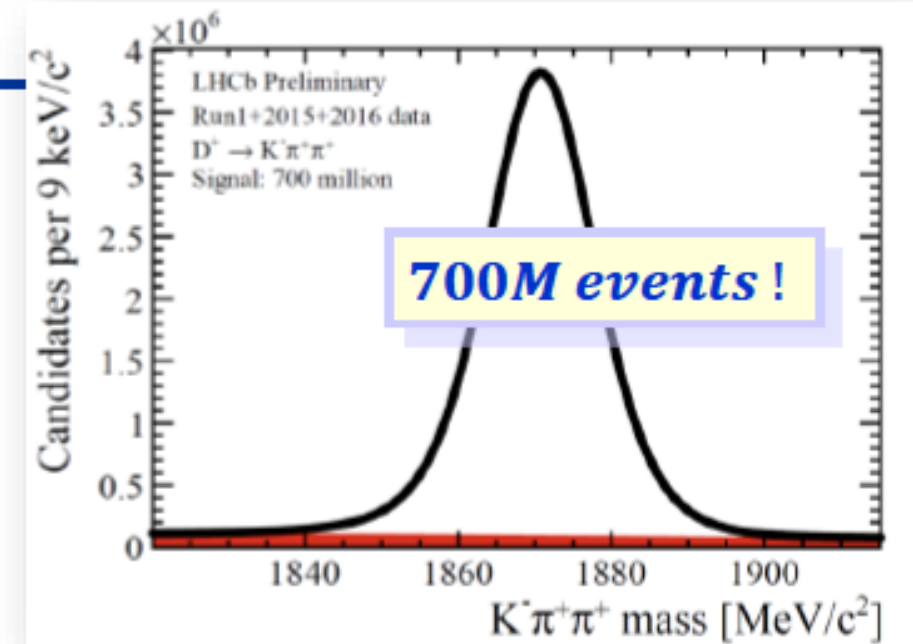
CSC 2016, MUI Belgium © CERN



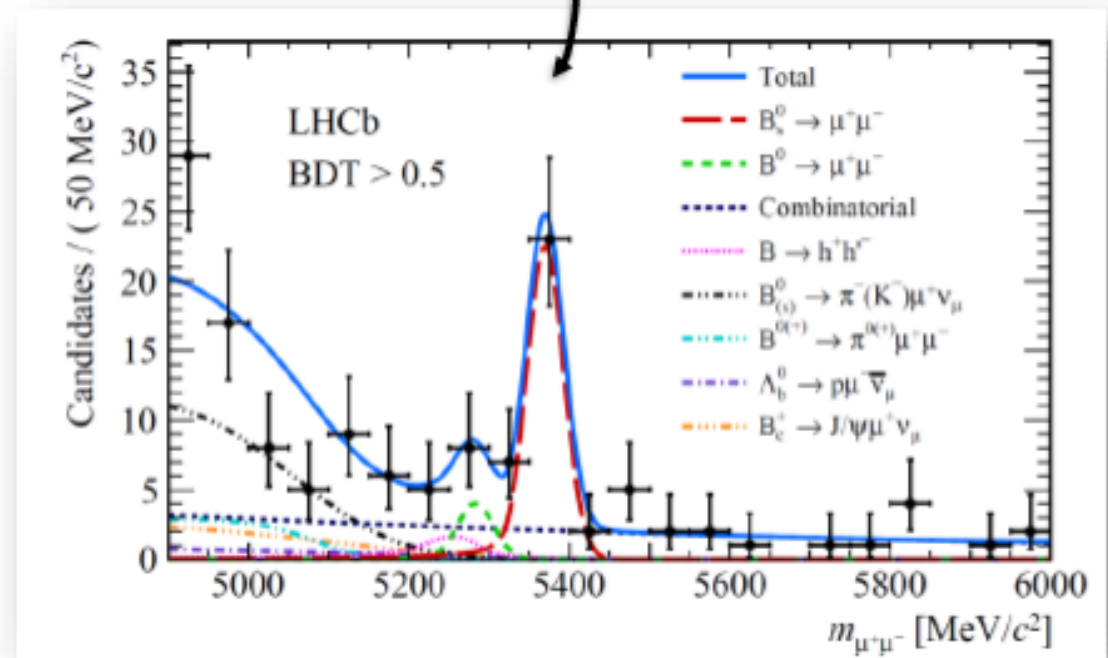
CSC 2016, Mol Belgium@CERN

A question of many scales

Wildly different Challenges !

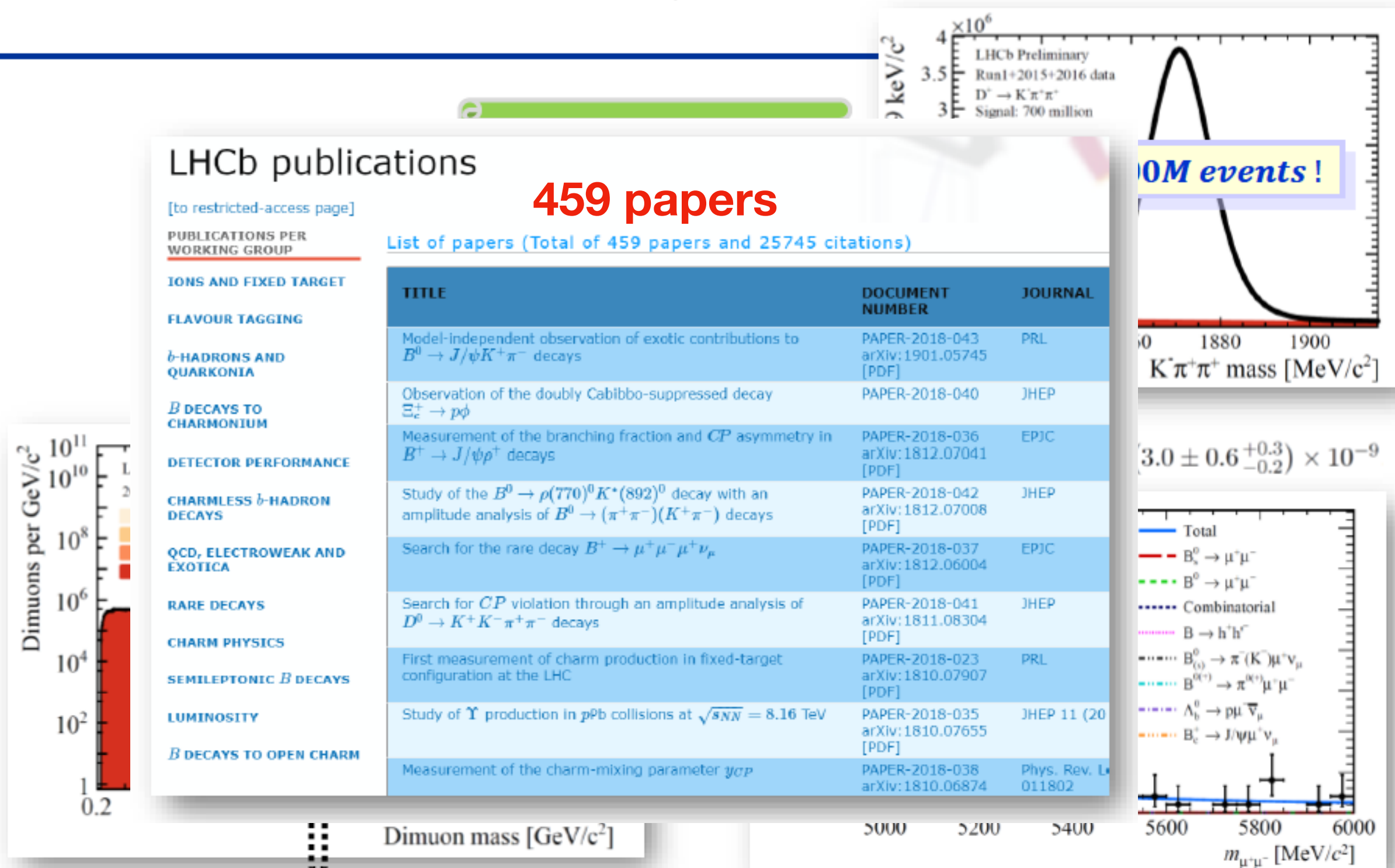


$$\mathcal{B}(B_s^0 \rightarrow \mu^+ \mu^-) = (3.0 \pm 0.6^{+0.3}_{-0.2}) \times 10^{-9}$$



Note : structure given the numerous “trigger lines” with different requirements

A question of many scales

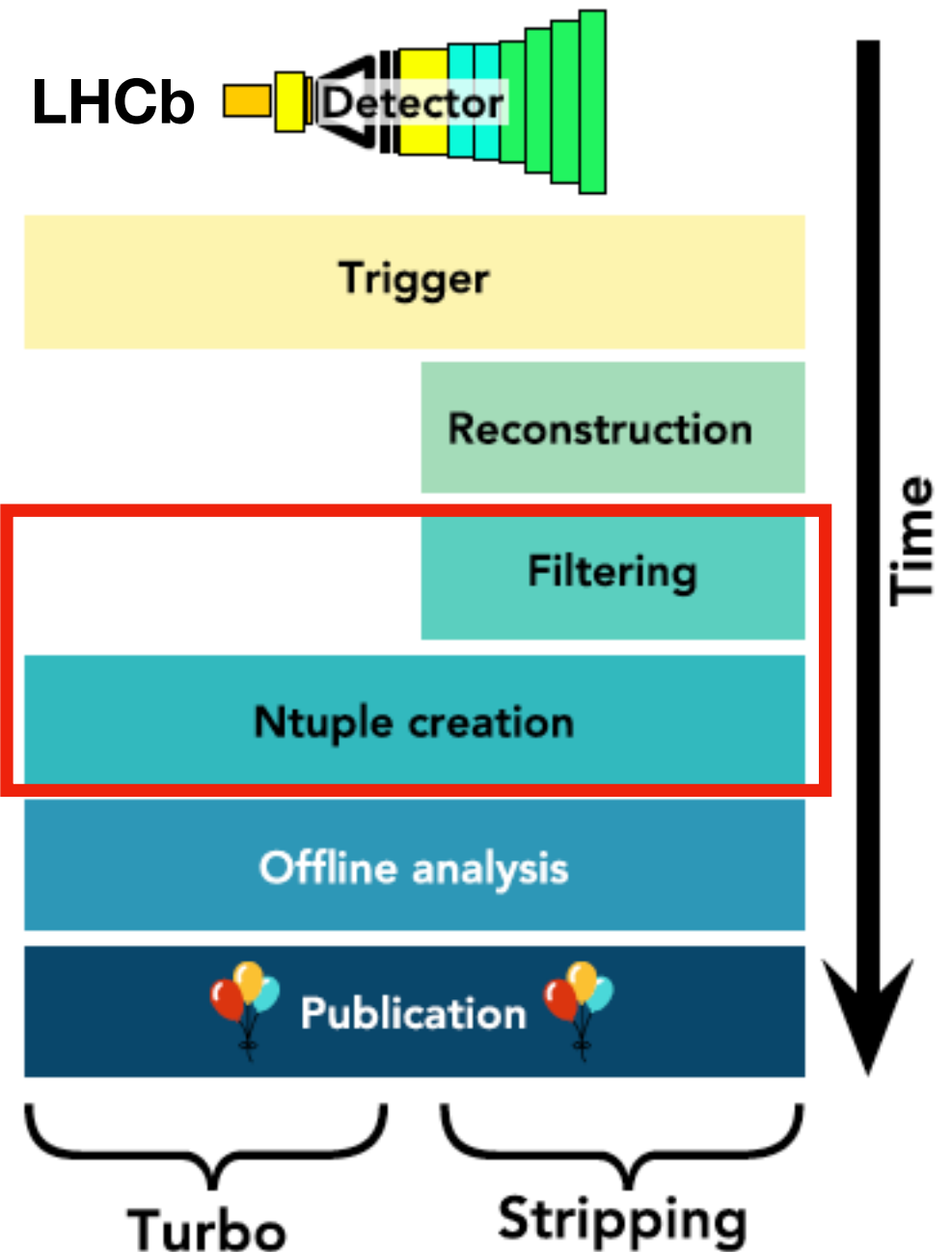
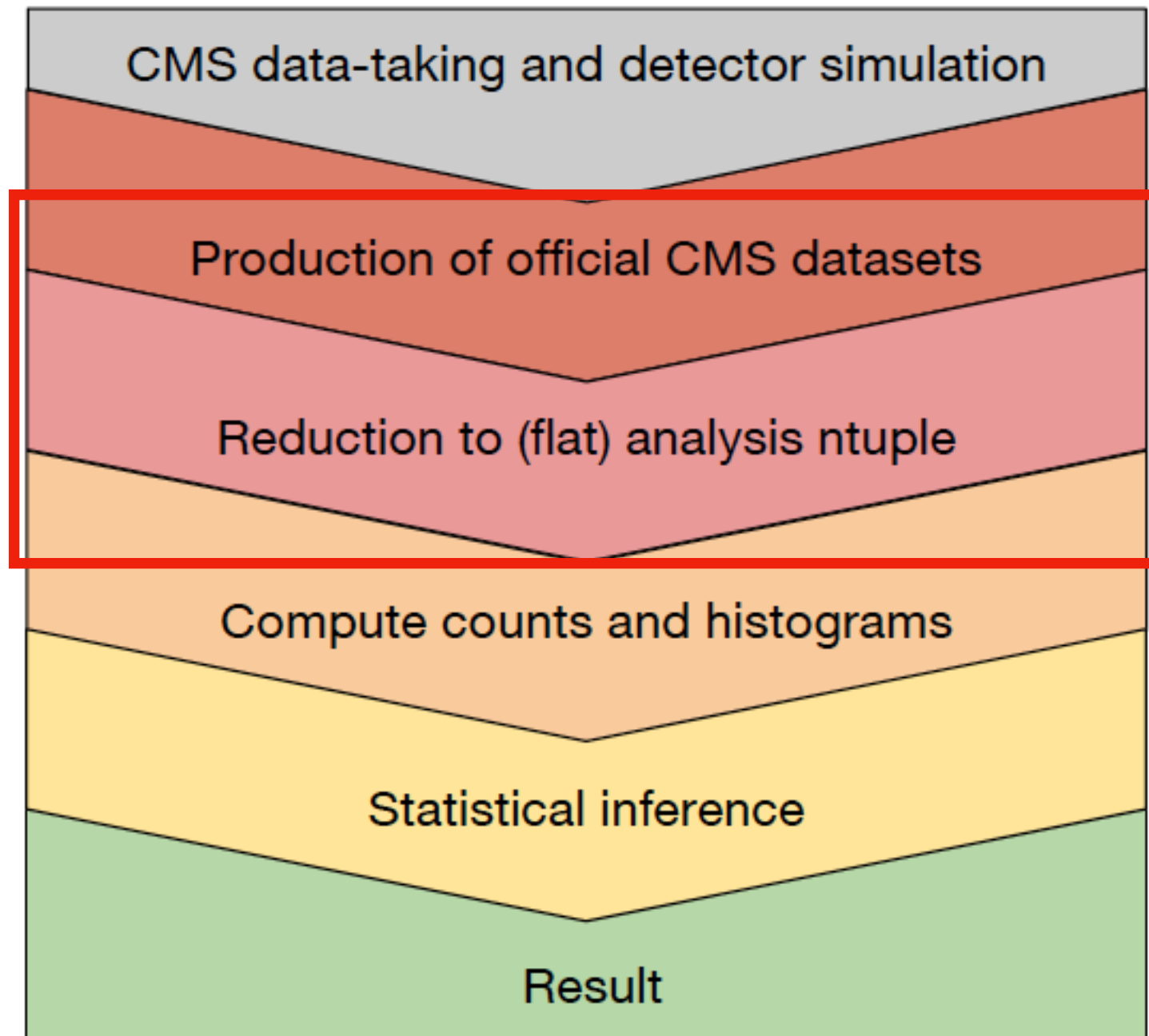


Note : structure given the numerous “trigger lines” with different requirements

Eduardo Rodrigues

HSF Data Analysis WG Meeting, CERN, 23rd Jan. 2019

Analysis workflows

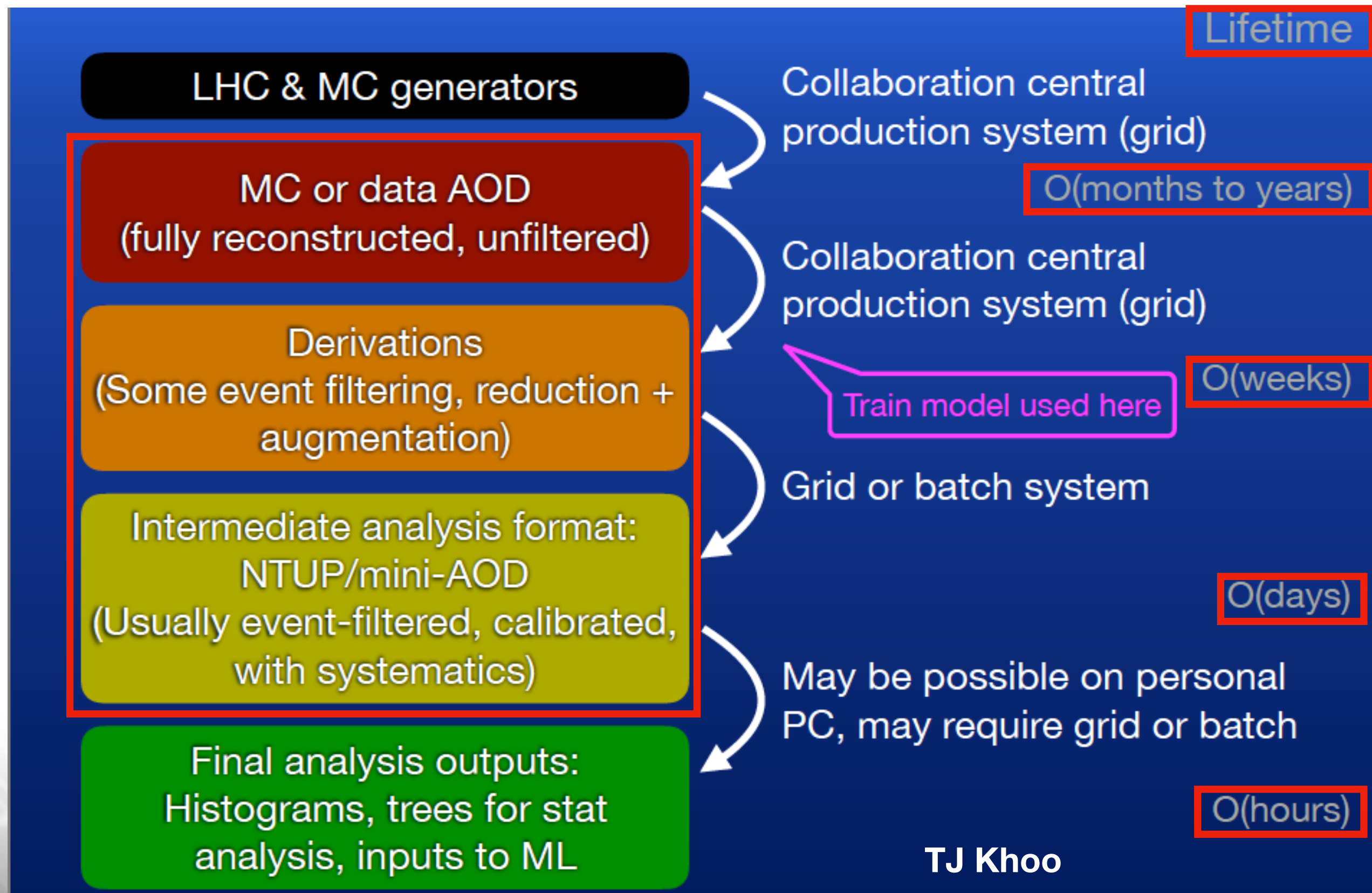


- Tend to focus on **heavy lifting** here rather than the final stages
 - More on statistical inference et al in **Andrea's** talk

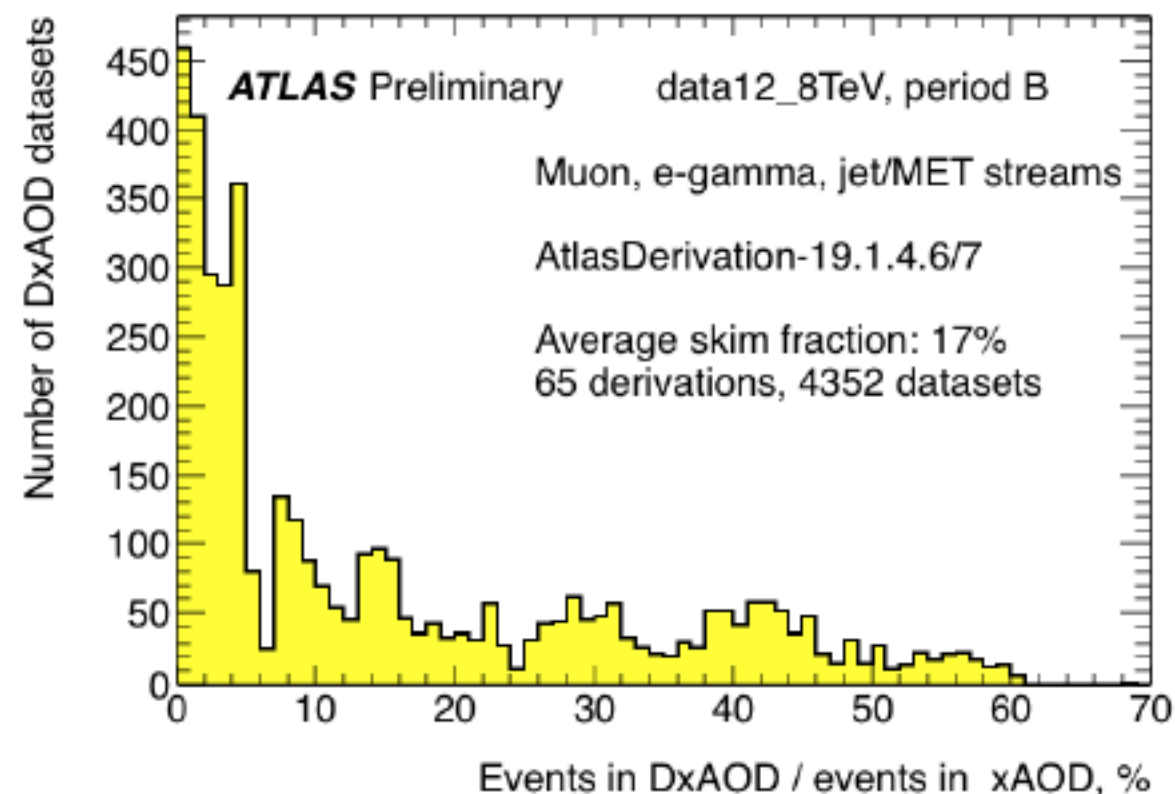
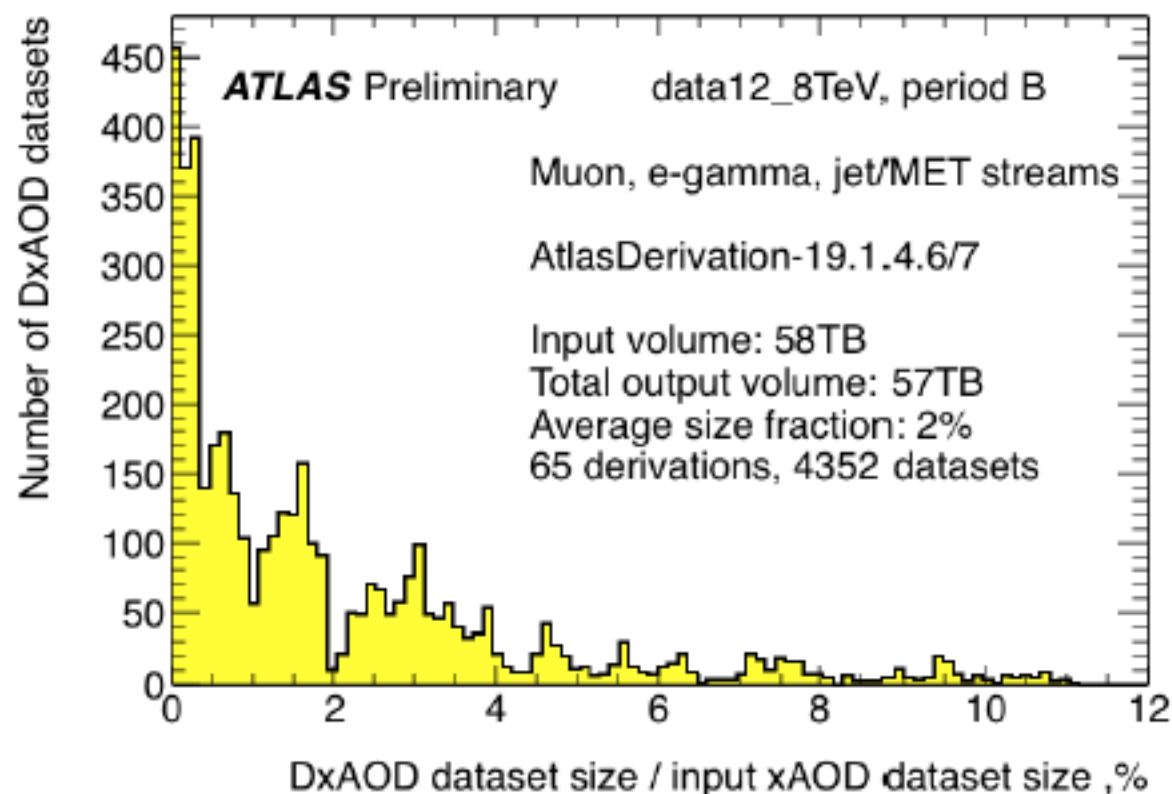


SYAHRUL RAMADAN photography

Repeated heavy lifting



Data reduction trains - Fact and fiction



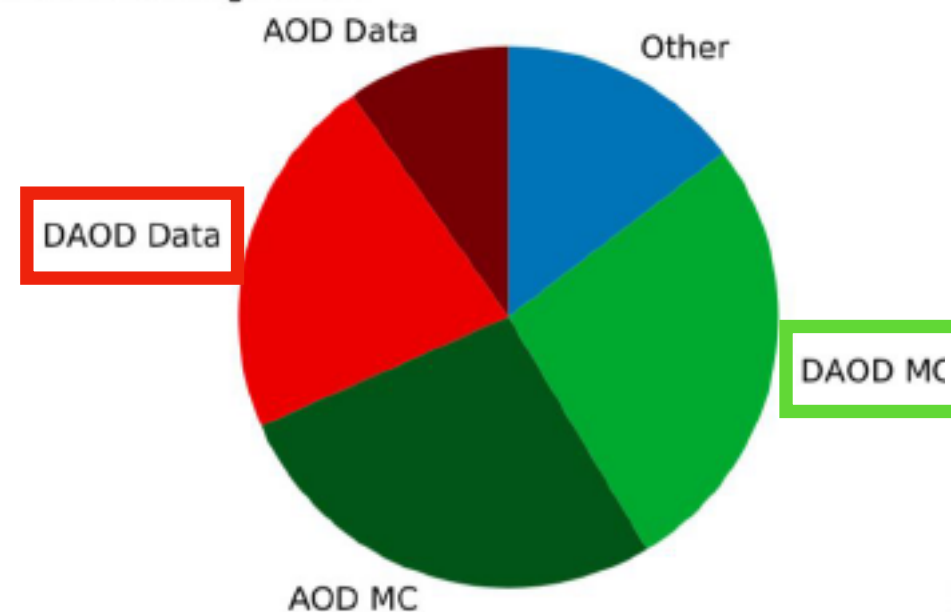
CMS nano-AOD ~1kB/event

- expected to cover > 50% of analyses

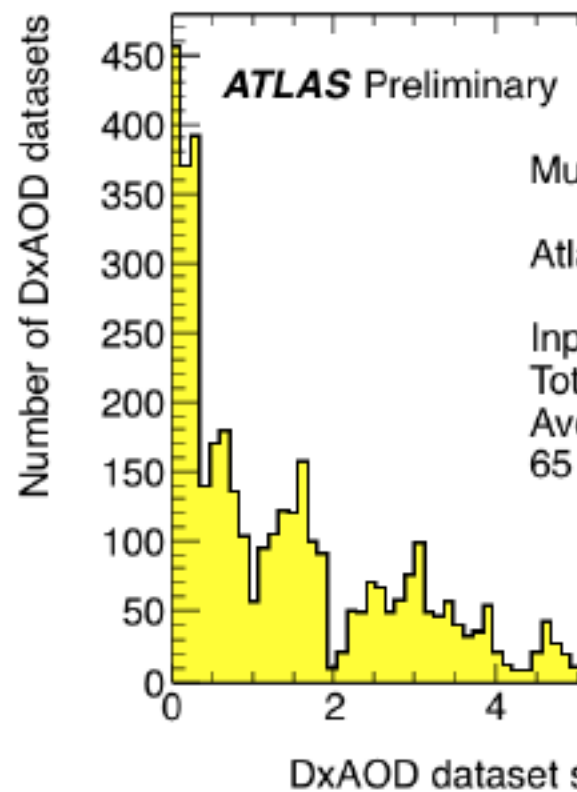
ATLAS derivations

- 2014 (*top*): small efficient data format
- 2028 (*right*): more than half the storage

ATLAS Preliminary. 2028 Disk resource needs
Reduced storage model

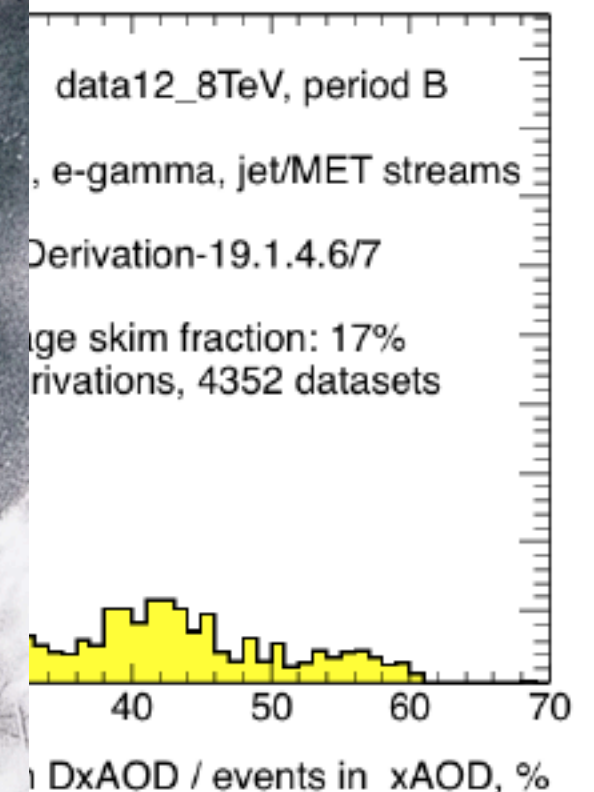


Data reduction trains - Fact and fiction

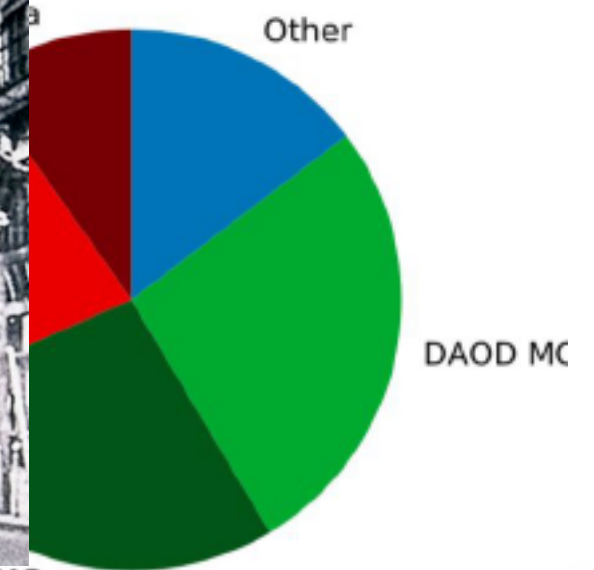


ATLAS derivation

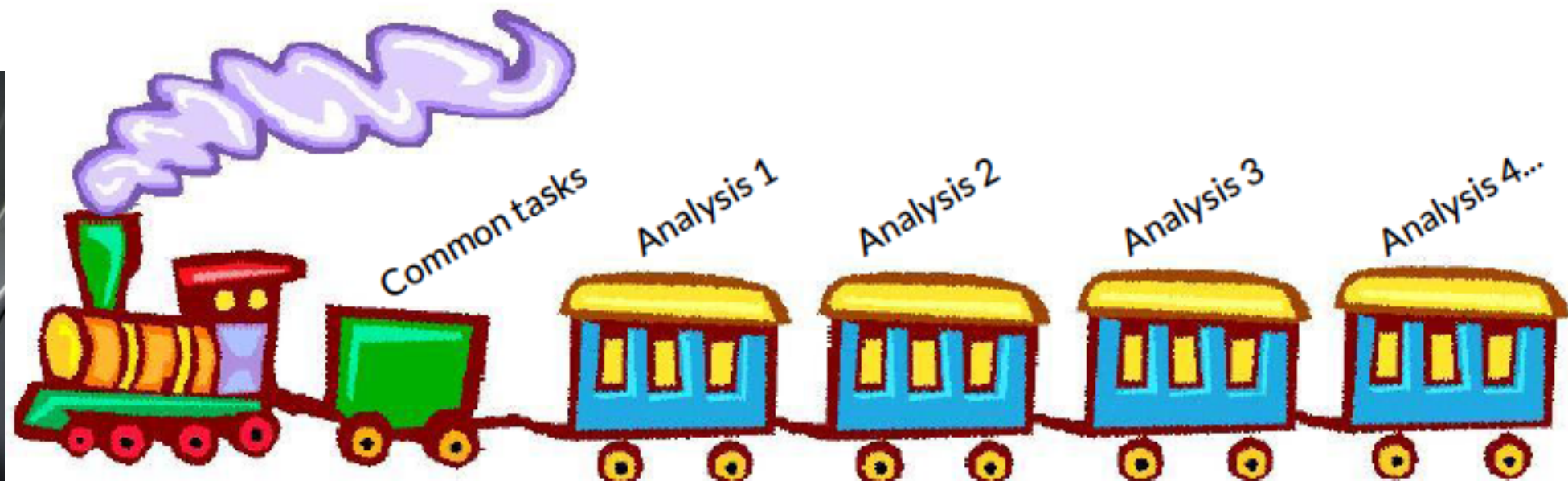
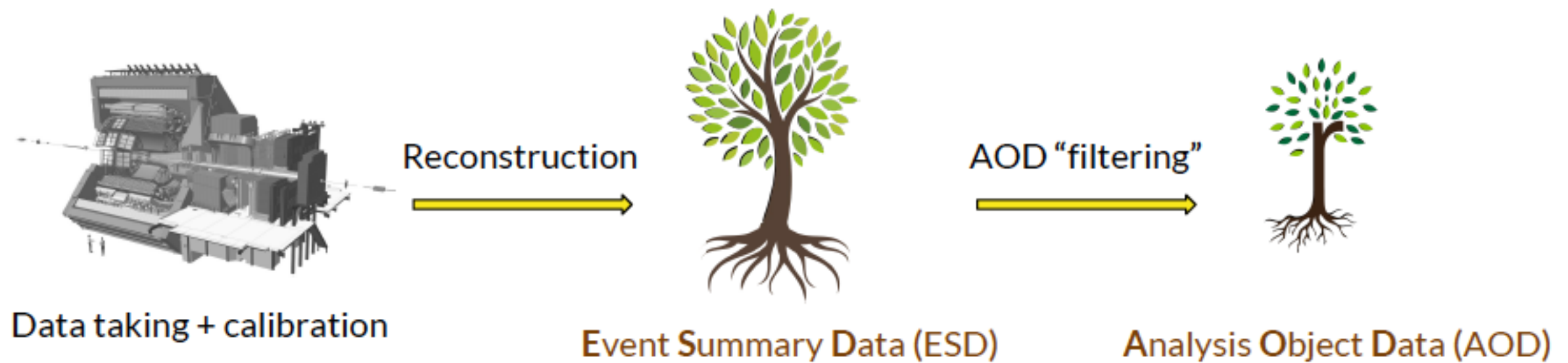
- 2014 (*top*):
 - small efficiency
- 2028 (*right*):
 - more than 100 datasets



Disk resource needs

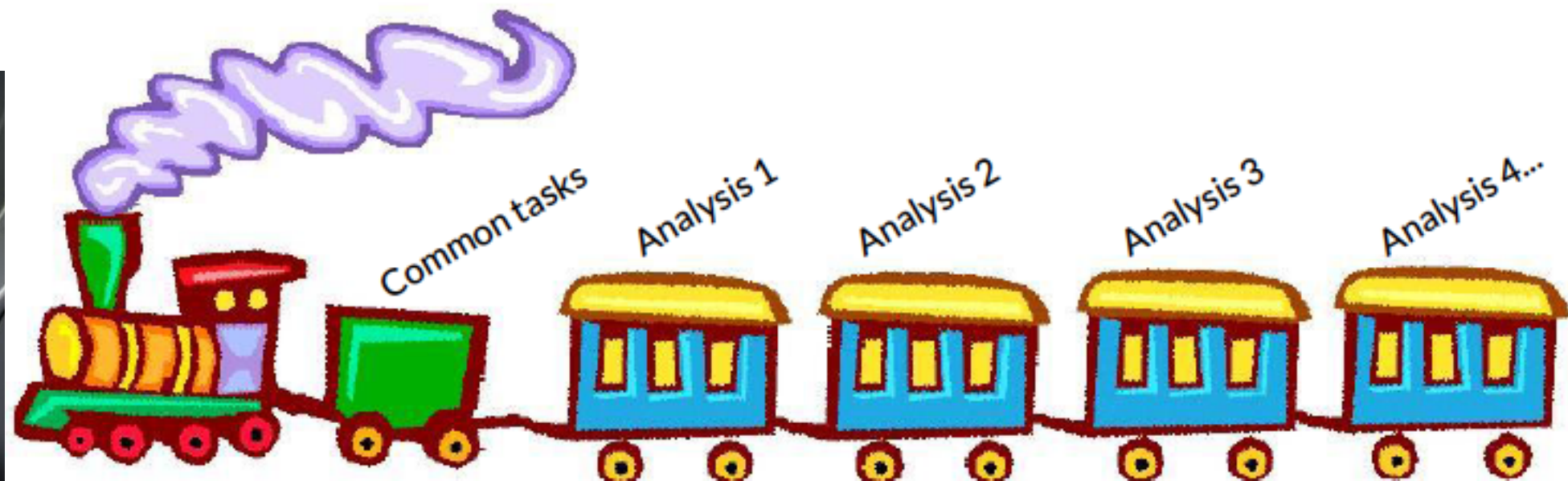
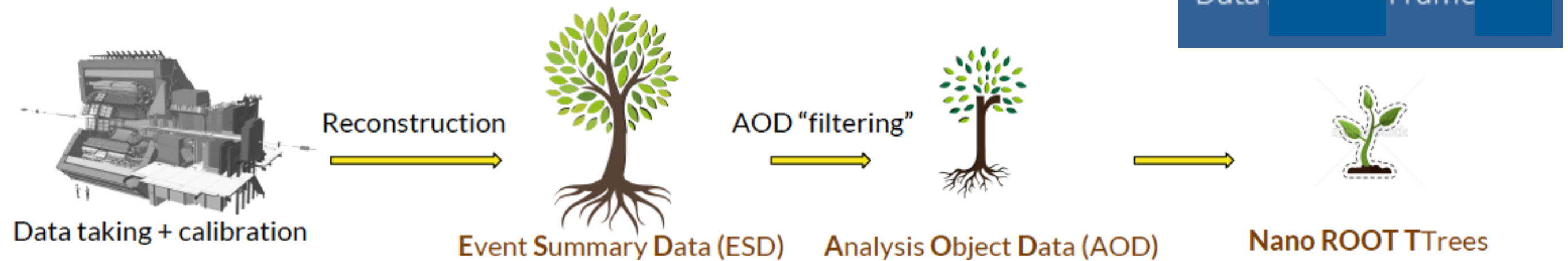
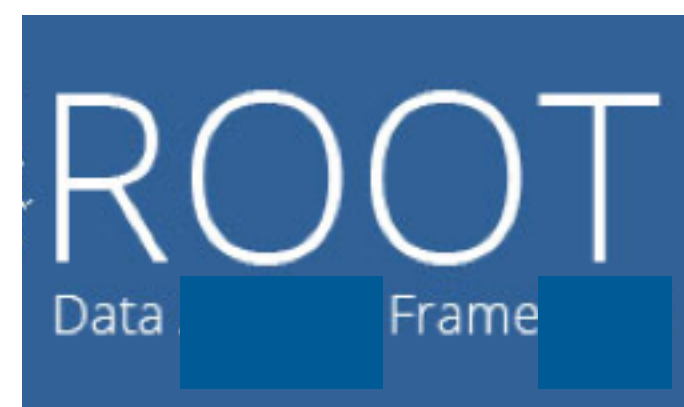


ALICE analysis trains



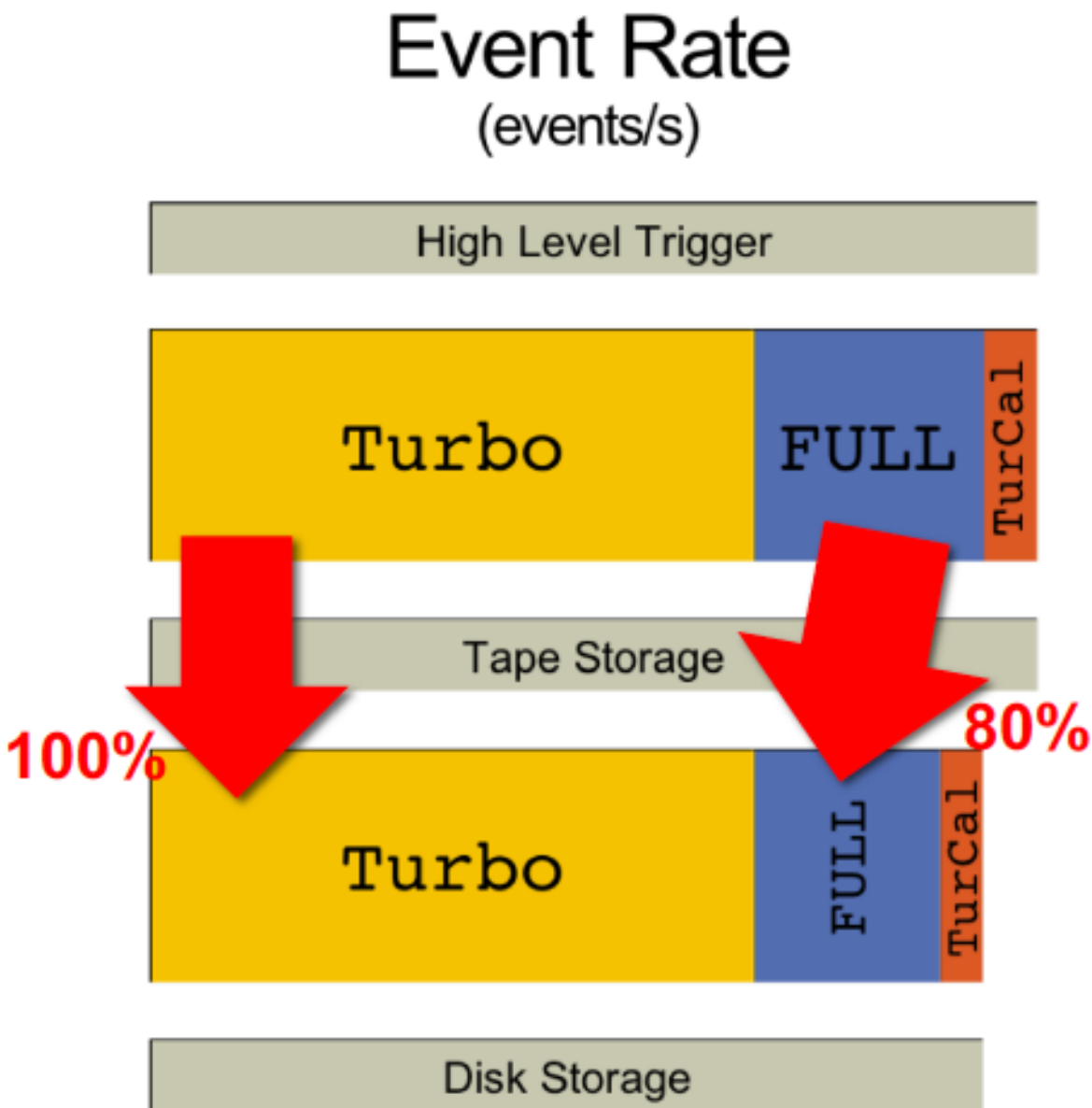
ALICE successfully driving analysis trains over **AOD** input

Going nano



ALICE plans to go nano like **CMS**, while **ATLAS** aiming for **10-50 kB/event**

Analysis workflows - best practice?



- ***Turbo stream analysis (data scouting):***
reco and calibration done once in HLT
no more reprocessing!
 - in reality for LHCb, two HLT passes
 - TDAQ to record events to a big buffer
 - then prompt calibration
 - then second pass for data reduction
- ***Q. How much physics bandwidth can go this route for other experiments?***
- ***Centrally produced nano-format:***
no more reinventing the wheel for producing a data analysis format
 - in reality, cannot accommodate all analyses, BUT important to use where it is possible (maybe even for ATLAS)
- ***Q. How much physics bandwidth can go this route for all experiments?***

Where: Power vs control

- Grid

- Portability
- Dataset sharing
- Dataset access
- Reliability

How easy for collaborator B to use collaborator A's submission scripts?

How easy for collaborator B to use collaborator A's job outputs?

How easy for collaborator A to use own job outputs?

How long before job outputs 100% available?

- Local cluster

- Dataset access
- Reliability
- Portability
- Dataset sharing

Wherever: Power and control?

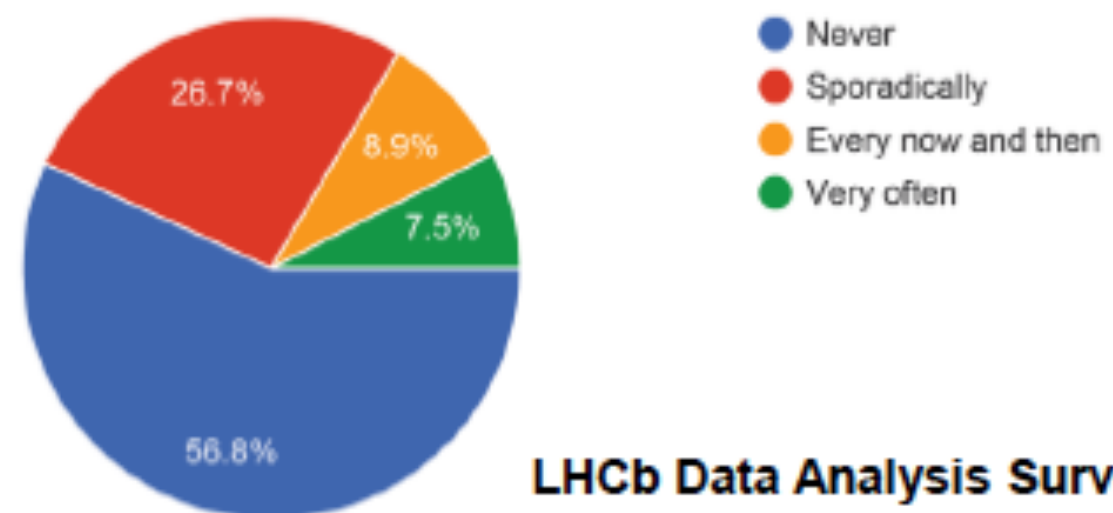
- Grid
 - Portability
 - Dataset sharing
 - Dataset access
 - Reliability
- Local cluster
 - Dataset access
 - Reliability
 - Portability
 - Dataset sharing

Hiding the “how” is a common theme

see declarative analysis in Andrea’s talk

Do you use notebooks, whether standard Jupyter notebooks, or within JupyterLab?

146 responses



LHCb Data Analysis Survey, 2018

Analysis platforms

LSST Science Platform



Portal

Jupyter Notebooks

Web APIs

- Data access via IVOA-standard protocols
- Same interfaces that support other aspects

- See also Lukas's [talk](#) from Tuesday

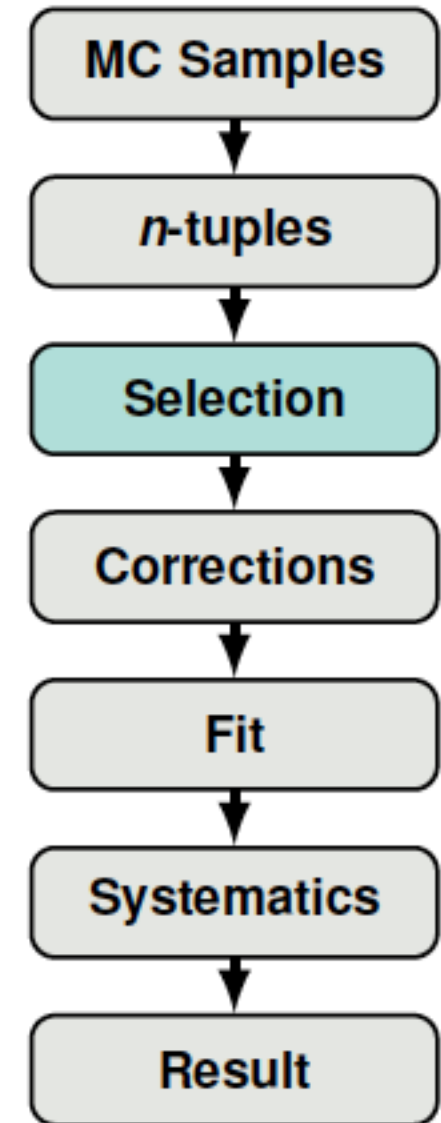
Belle II analysis software stack

Analysis of the n -tuples is done with Python:

- *Pandas* and *numpy*
- *root_pandas* or *uproot* to load ROOT files
- *scikit-learn* or *basf2* MVA package for MVA methods
- *matplotlib* for plots
- convert n -tuples to hdf5 files (these are loaded ~ 10 times faster)
- data analysis in *jupyter notebooks*

Why Python?

- Well documented!
- Easy to integrate into the rest of the analysis
- Modern and nice interface...



Belle II - best practice analysis code

UI

A simple example

```
import basf2
from modularAnalysis import inputMdst, reconstructDecay, fitVertex, variablesToNtuple
from stdCharged import stdPi
from stdPhotons import stdPhotons

mypath = basf2.Path()

# configure modules
inputMdst("default", basf2.find_file('analysis/tests/mdst.root'), path=mypath)
stdPi("good", path=mypath)
stdPhotons("good", path=mypath)
reconstructDecay('rho0:myrhos -> pi+:good pi-:good', '0.5 < M < 1.0', path=mypath)
fitVertex('rho0:myrhos', path=mypath)
reconstructDecay('B0:myBs -> rho0:myrhos gamma:good', '5.0 < M < 6.0', path=mypath)

# output modules
momenta = ['px', 'py', 'pz']
variablesToNtuple('B0:myBs', momenta, path=mypath)

basf2.process(mypath)
```

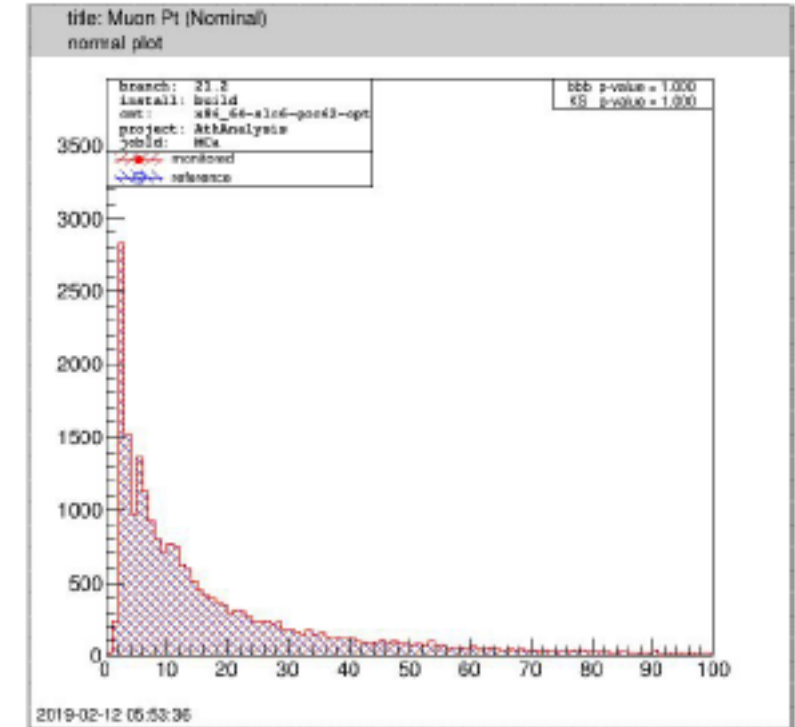
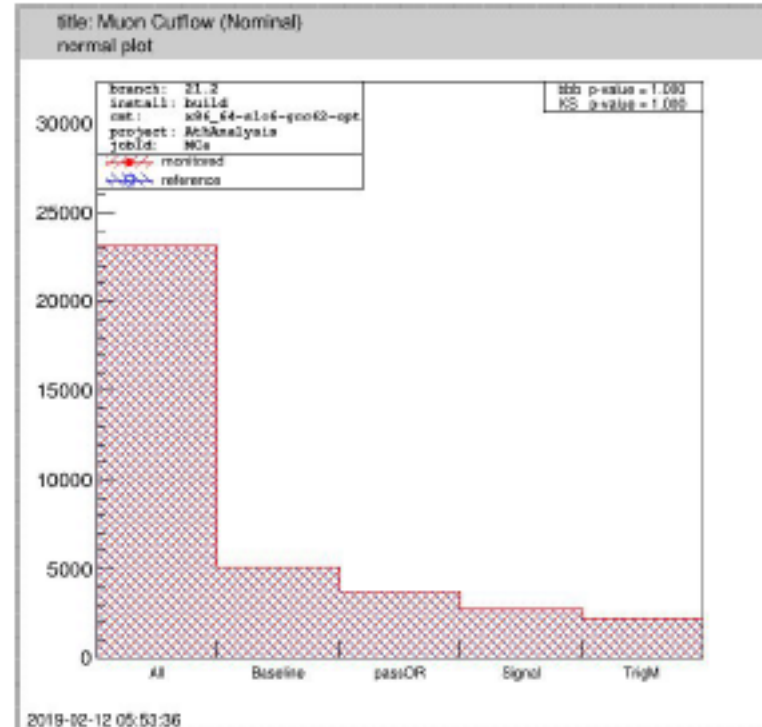

Beyond analysis functionality

SUSYTools @ Hass AbouZeid

Configuration diff
High-level analysis comparison

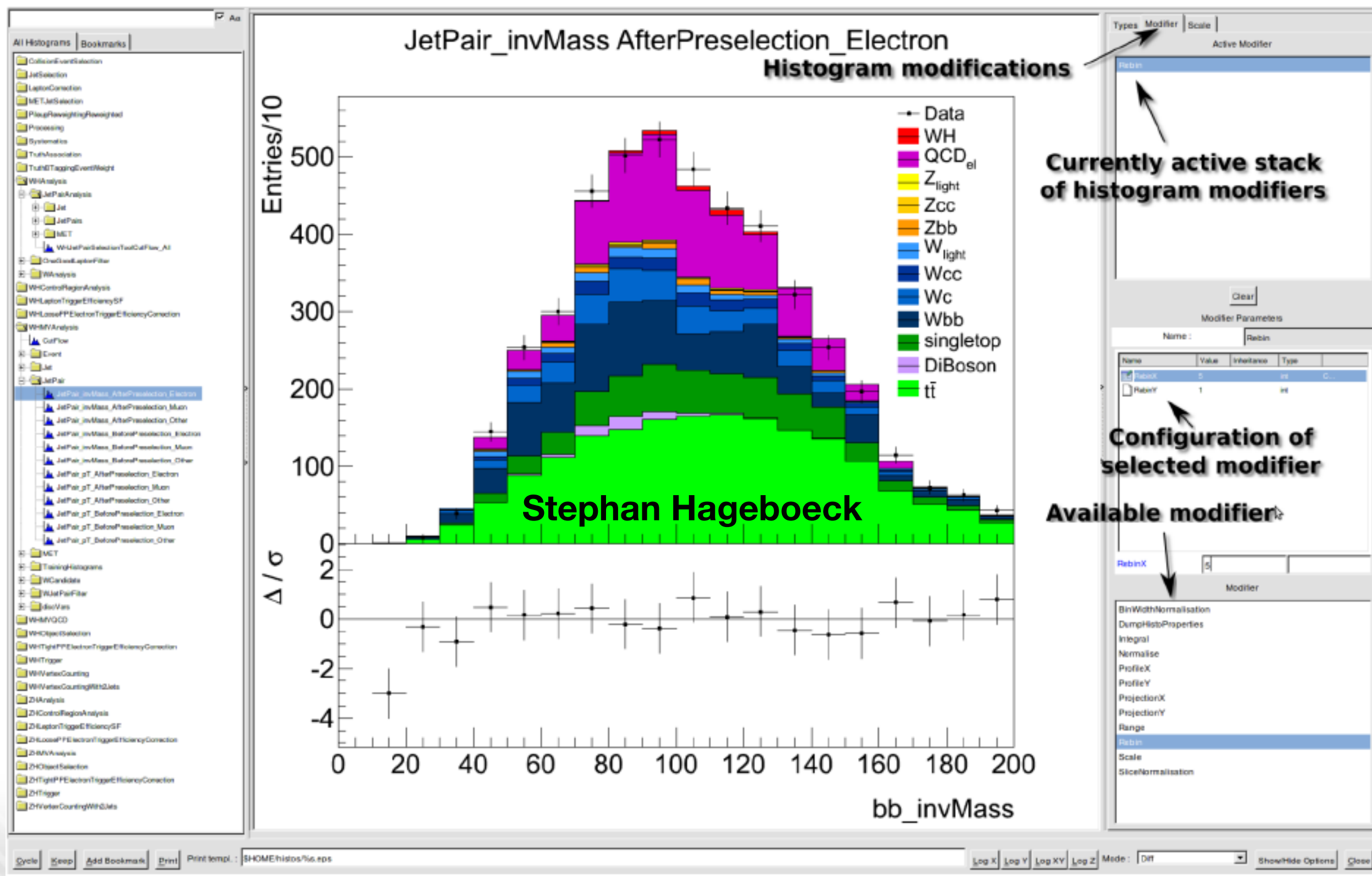
	Default	Analysis 1	Analysis 2
EleBaseline.Pt	10000.	10000.	7000.
EleBaseline.Eta	2.47	2.47	2.47
EleBaseline.Id	LooseAndBLayerLLH	LooseAndBLayerLLH	VeryLooseLLH
EleBaseline.CrackVeto	false	true	false
EleBaseline.z0	0.5	0.5	
Ele.Et	25000.	10000.	20000.
Ele.Eta	2.47	2.47	2.47
Ele.CrackVeto	false	true	false
Ele.Iso	Gradient	FCTight	Gradient

CI pipeline
Carefully control code



Reference histogram updated automatically every night

GUI Overkill



Observations / Questions

- Analysis is diverse, but we see recurring themes and solutions
- Reducing I/O for heavy lifting:
- **Trains** an accepted solution, can more workflows use this concept?
- **Common nano-AOD** centrally produced, less reinventing the wheel on format
 - Q. How much bandwidth can go this route?
- **Turbo stream** calibrate once
 - Q. How much bandwidth can go this route? How strong is the physics case to justify not doing that?
- Convergence on **Jupyter** notebooks as analysis platform, **hiding the how is good**
- Trend towards **declarative analysis**, especially for **LHCb/Belle II**
 - Does anything prevent other experiments?
- Addressing **systematics** is still a challenge, see **Andrea's** talk
 - Can we attack (some of) this as a community? What is best practice?
 - Not covered - **Monte Carlo**

But first, the next talk



Winter is comin'