SWAN usage at COMPASS

SWAN workshop 2019

Brian Ventura

SWAN usage at COMPASS *Summary*

1. Study of the DVCS process at COMPASS
2. The current analysis softwares
3. Post analysis using SWAN

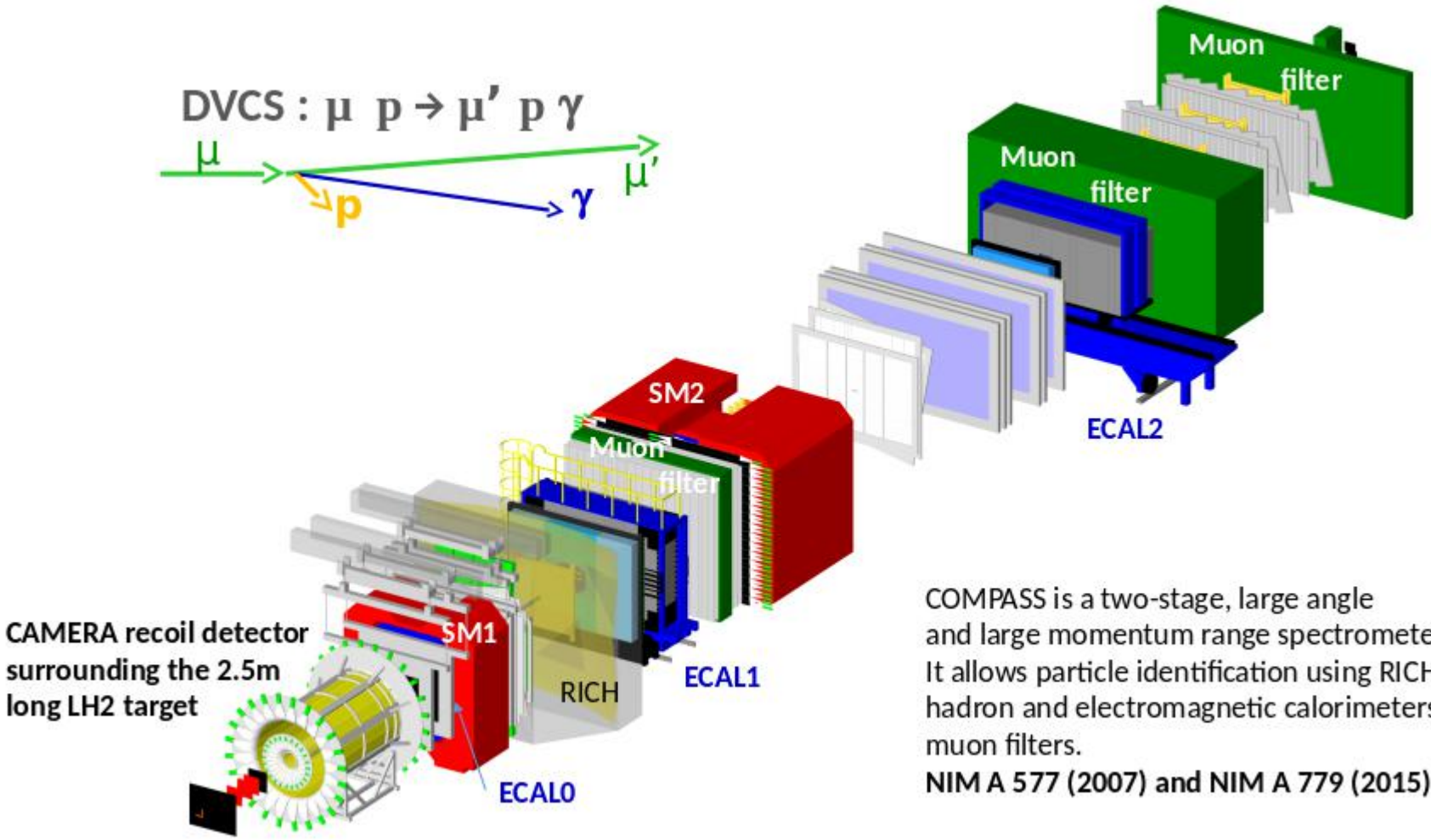
The COMPASS experiment & the DVCS process

μp→μpγ

SWAN usage at COMPASS

Study of the DVCS process at COMPASS

- Exclusive process with small cross section compared with large background
- Detection of the complete initial and final state.
- Remove background using the overdetermined kinematics



COMPASS is a two-stage, large angle and large momentum range spectrometer. It allows particle identification using RICH, hadron and electromagnetic calorimeters and muon filters.

NIM A 577 (2007) and NIM A 779 (2015) 69

The current chain of analysis softwares

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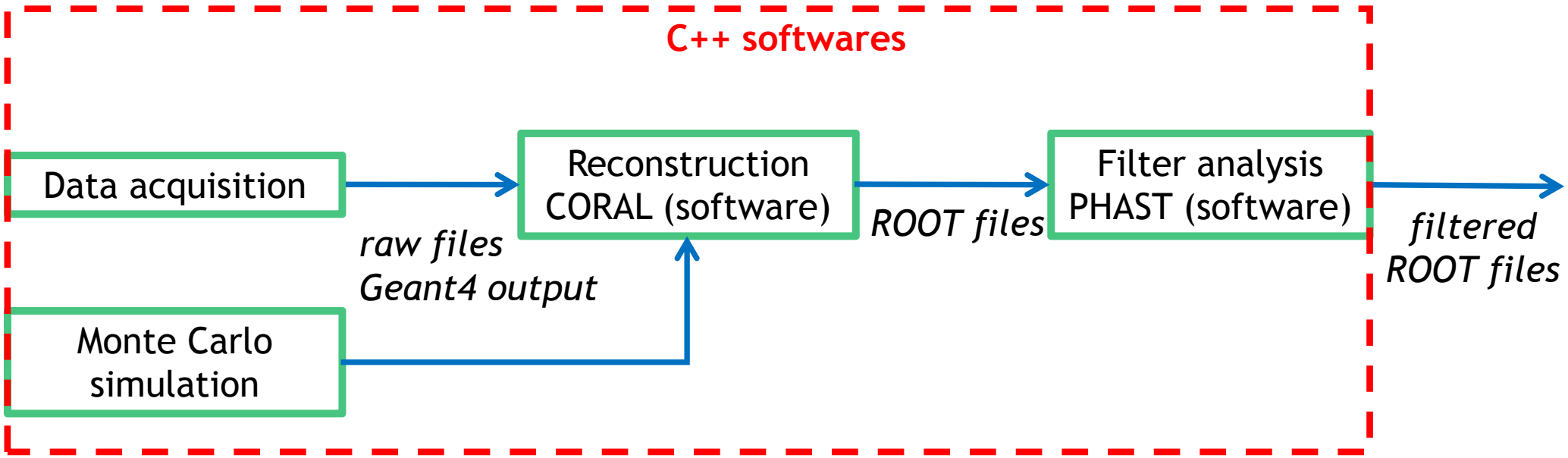
Current chain of analysis softwares



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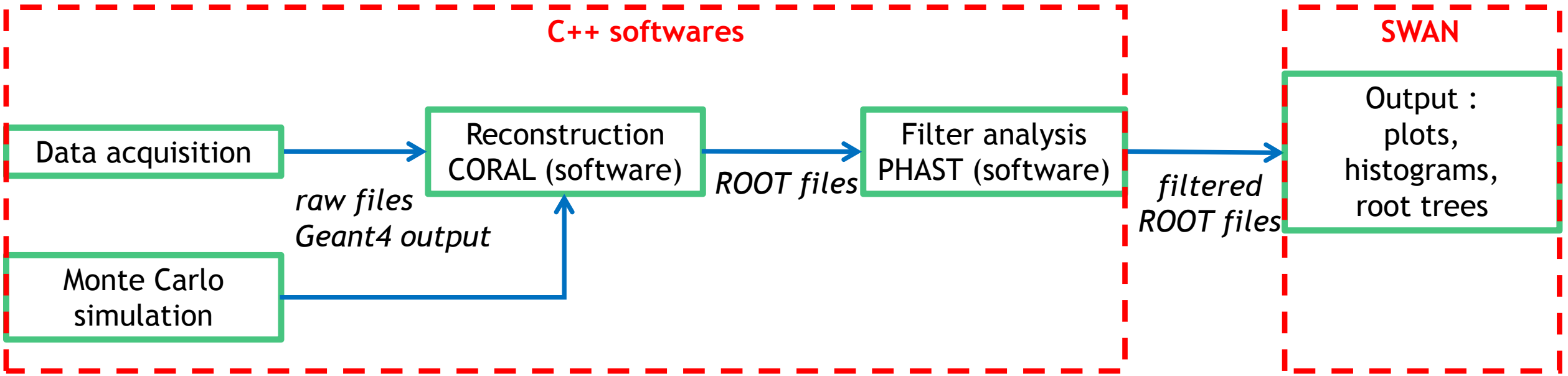
Current chain of analysis softwares



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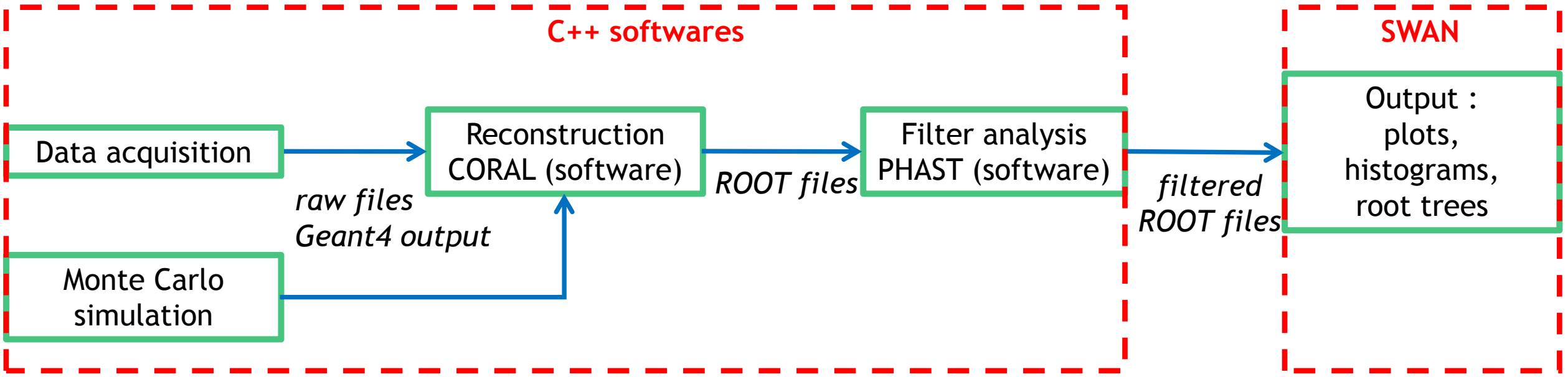
Current chain of analysis softwares



At the end of the C++ part : DVCS events candidates + background using first well determined cuts on target, triggers, radiation lengths, etc.

$$\text{DVCS} : \mu\ p \rightarrow \mu'\ p\ \gamma$$

Second cuts performed to get the DVCS exact topology (exclusivity) and remove the background

Post analysis using SWAN

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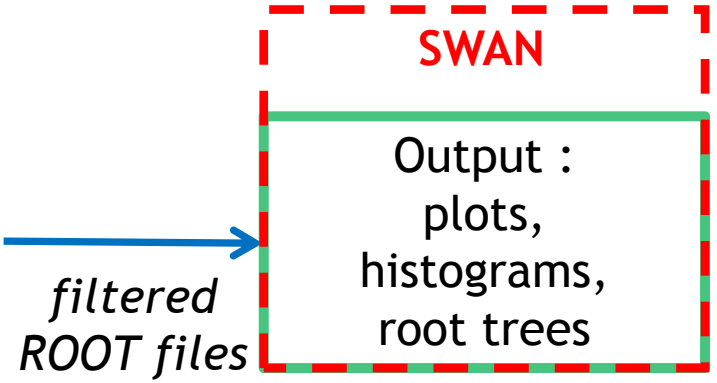
Study of the DVCS process at COMPASS



For all the events candidates, extract the DVCS exact topology

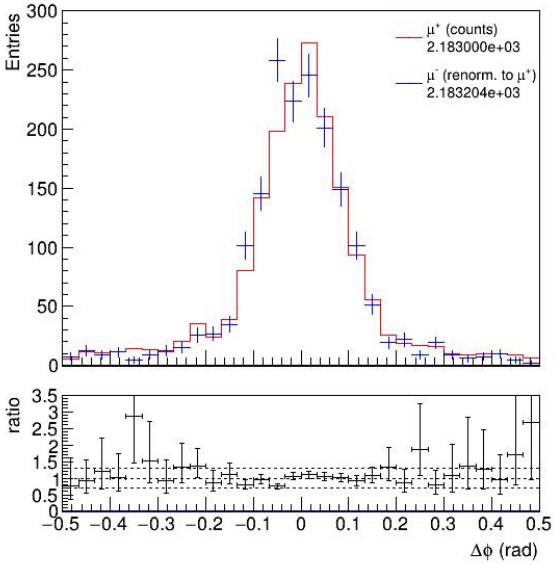
$$DVCS : \mu\ p \rightarrow \mu'\ p\ \gamma$$

+ plot many other physics observables

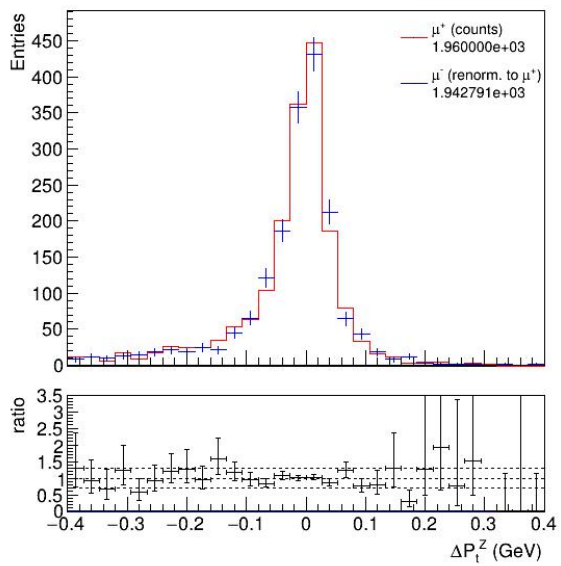
Pros & cons of SWAN

- Well organised analysis in notebooks using sections (use of markdown, latex, etc)
- Flexible enough to make systematic studies: use SWAN to adjust some cuts
- Drawback of interactivity: can be slow with too many events

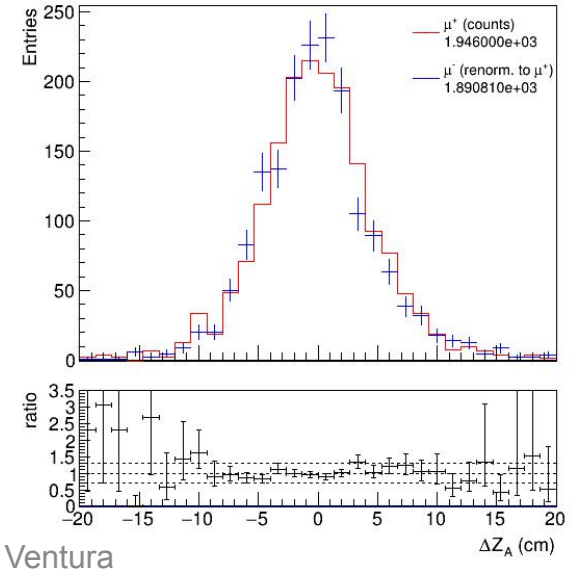
$\Delta\varphi = \varphi^{cam} - \varphi^{spec}$



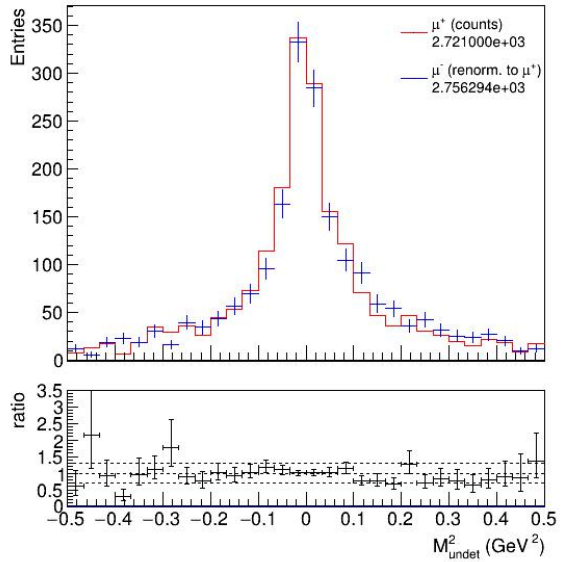
$\Delta p_T = p_T^{cam} - p_T^{spec}$



$\Delta z_A = z_A^{cam} - z_A^{Z_B}$ and vertex



$M^2_{Undet} = (k+p-k'-q'-p')^2$



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But How to use ROOT & spark clusters in SWAN ?

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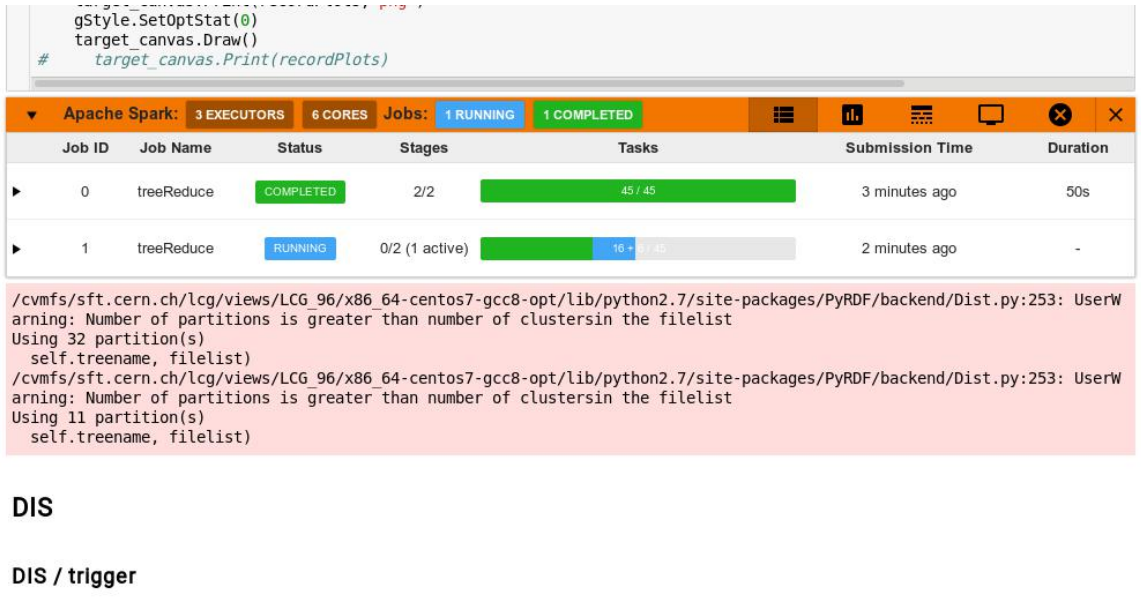
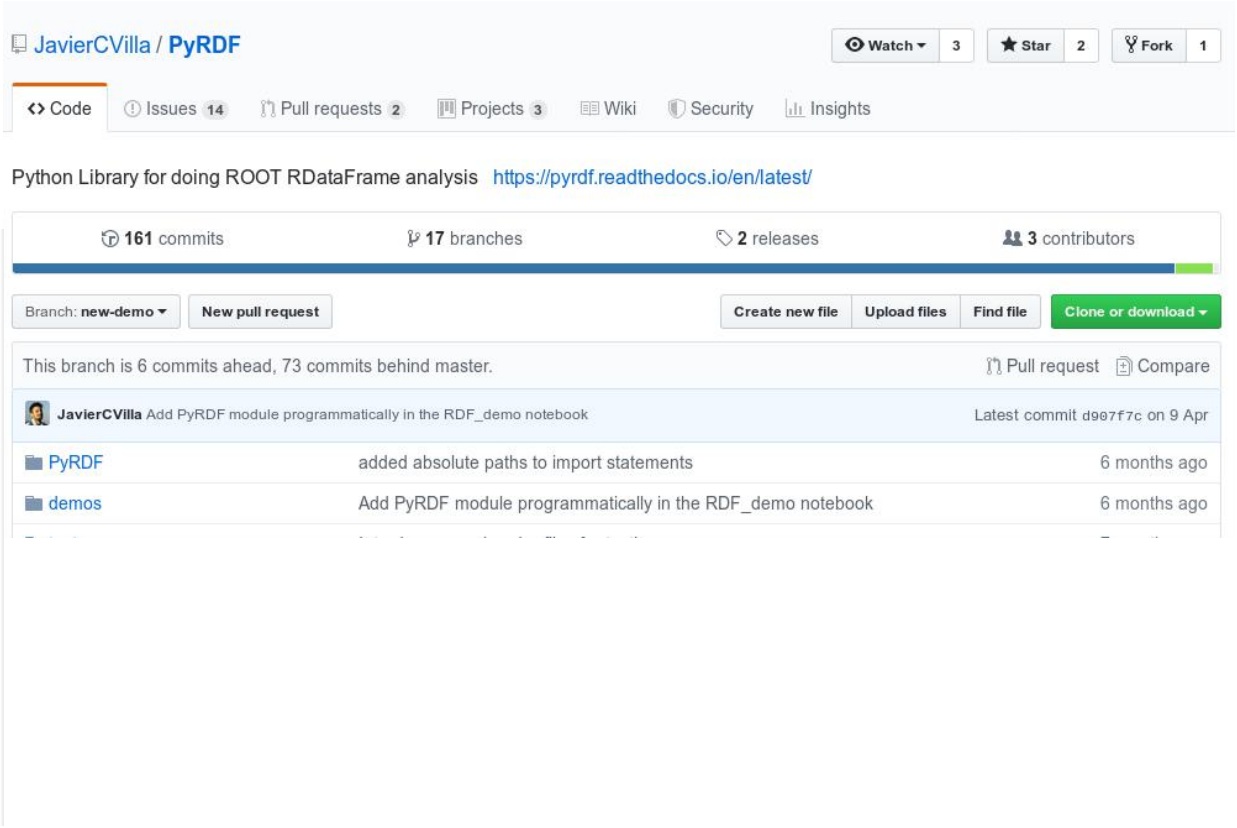
https://github.com/JavierCVilla/PyRDF/tree/new-demo





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https://github.com/JavierCVilla/PyRDF/tree/new-demo

```
    gStyle.SetOptStat(0)
    target_canvas.Draw()
#     target_canvas.Print(recordPlots)
```

Apache Spark: 3 EXECUTORS 6 CORES Jobs: 1 RUNNING 1 COMPLETED

Job ID	Job Name	Status	Stages	Tasks	Submission Time	Duration
0	treeReduce	COMPLETED	2/2	45 / 45	3 minutes ago	50s
1	treeReduce	RUNNING	0/2 (1 active)	16 + 7 / 45	2 minutes ago	-

```
/cvmfs/sft.cern.ch/lcg/views/LCG_96/x86_64-centos7-gcc8-opt/lib/python2.7/site-packages/PyRDF/backend/Dist.py:253: UserW
arning: Number of partitions is greater than number of clustersin the filelist
Using 32 partition(s)
  self.treename, filelist)
/cvmfs/sft.cern.ch/lcg/views/LCG_96/x86_64-centos7-gcc8-opt/lib/python2.7/site-packages/PyRDF/backend/Dist.py:253: UserW
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Using 11 partition(s)
  self.treename, filelist)
```
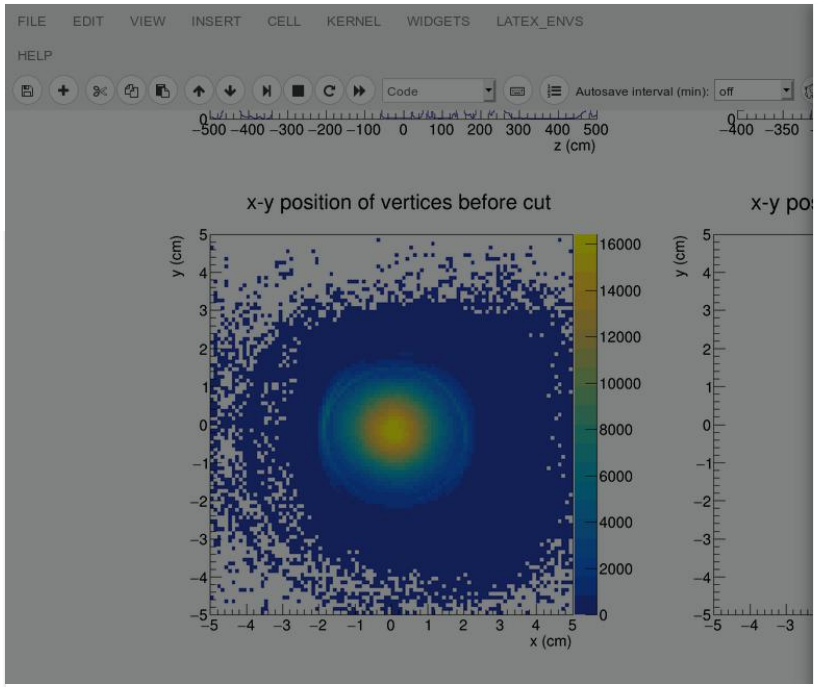

DIS

DIS / trigger



Spark clusters connection

You are connected to **k8s**

The following variables were instantiated

- sc = SparkContext
- spark = SparkSession

Connection details

- Spark version is 2.4.3
- Spark History Server is available here
- Spark Metrics are available here
- Spark driver logs of the running application show/hide

Go to the notebook | Restart Spark session

SWAN usage at COMPASS Study of the DVCS process at COMPASS

The **PyRDF** module provides a pythonic wrapper of the existing ROOT **RDataFrame** class

```
import PyRDF

# Initialize RDataFrame object
df = PyRDF.RDataFrame(dataset)

# Define operations
df2 = df.Filter("x > 0")
        .Define("r2", "x*x + y*y")
rHist = df2.Histo1D("r2")

# Display histogram
rHist.Draw()
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J. Cervantes and E. Tejedor, "ROOT RDataFrame and Spark", HSF Software Forum

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ROOT::EnableImplicitMT();                    Run a parallel analysis
ROOT::RDataFrame df(dataset);                on this (ROOT, CSV, ...) dataset
auto df2 = df.Filter("x > 0")                only accept events for which x > 0
             .Define("r2", "x*x + y*y");     define r2 = x² + y²
auto rHist = df2.Histo1D("r2");              plot r2 for events that pass the cut
df2.Snapshot("newtree", "out.root");         write the skimmed data and r2
                                             to a new ROOT file
```

Lazy execution guarantees that all operations are performed in **one event loop**

E. Guiraud, "RDataFrame", CHEP 2018

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Thanks a lot, for RDataFrames and PyRDF !

Thanks to Javier Cervantes Villanueva for his reactivity regarding PyRDF !

SWAN usage at COMPASS Conclusion

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Propositions of improvements

- RDataFrames: always have to define classes members as columns before using them.

  df.Define("rho0_mass", "rho0.M()")
  for rho0 a TLorentzVector

- SWAN: sometimes really slow connection or kernel not responding. Stability ?