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Testing RDataFrame in CMS analysis

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benchmark: W properties measurement using full Run2



**data taking
period**

2016

2017

2018

**number of
events into
acceptance**

35 fb^{-1}
 $\sim 100 \text{ M}$

45 fb^{-1}
 $\sim 130 \text{ M}$

65 fb^{-1}
 $\sim 185 \text{ M}$

x10 statistics in Montecarlo to have statistical error negligible

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do we have the tools to process such a huge number of events?

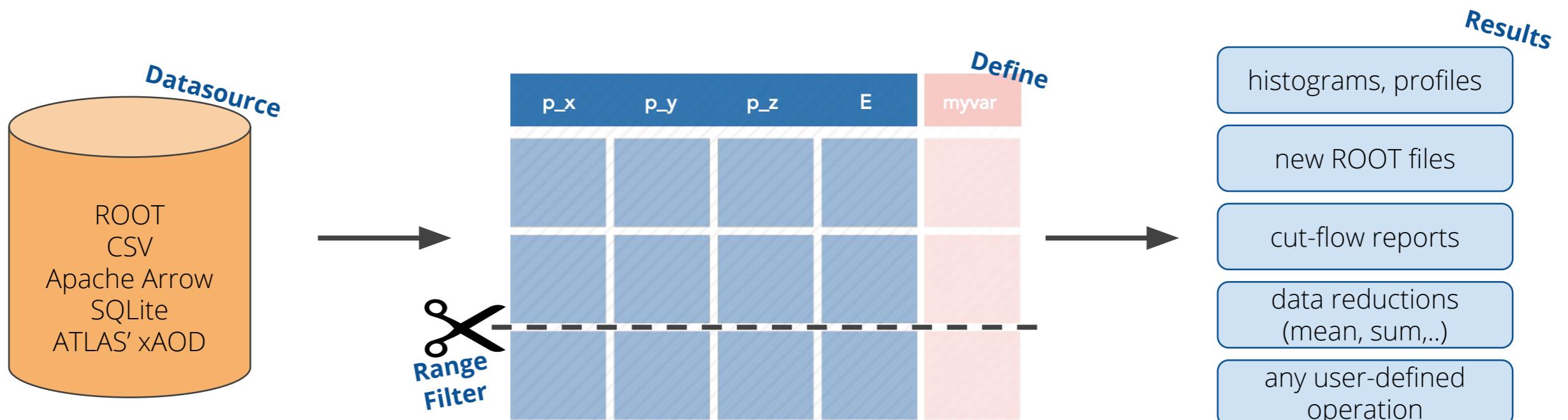
proposed solution: go multithread!

RDataFrame offers the possibility to
easily *parallelise* and *optimise* the
event loop

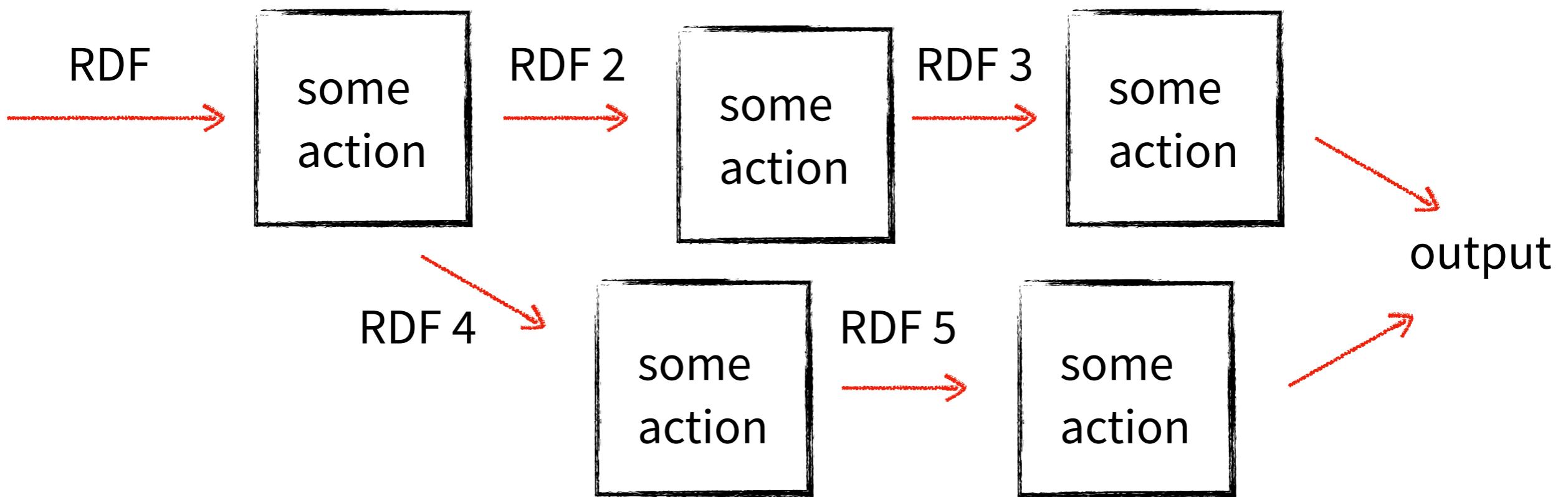
NanoAOD as a new data format
distributed by CMS as “centralised
ntuples”



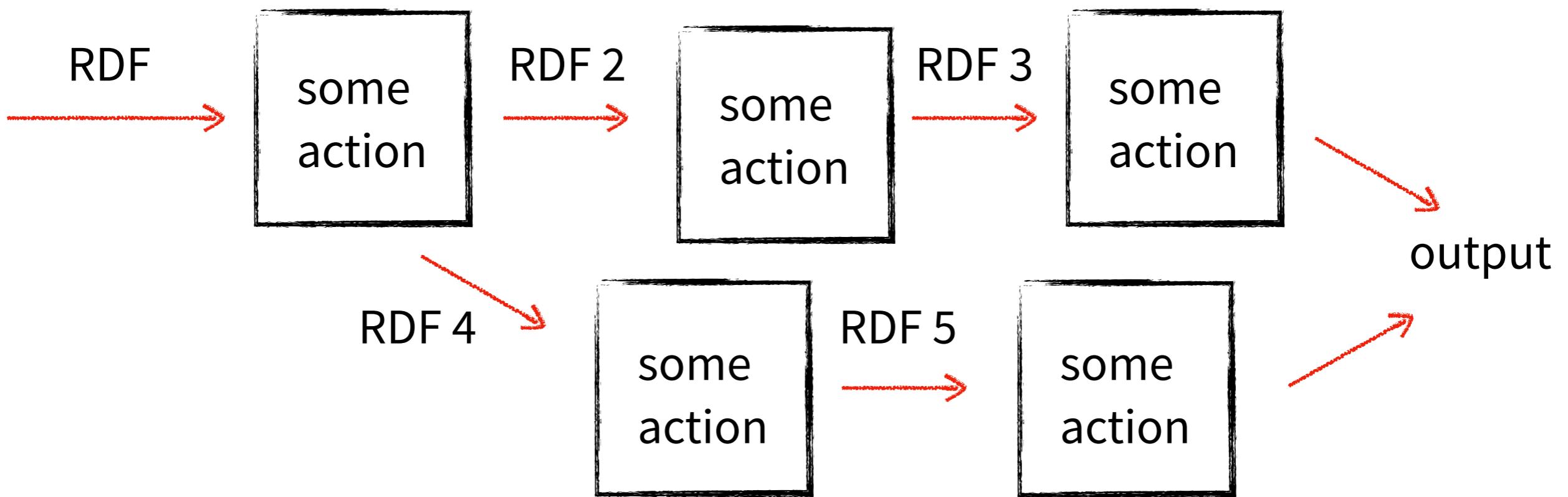
RDataFrame in a nutshell



the idea: wrap RDF into a mini-framework that executes some modules following a graph path



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RDataFrame transparently performs *data* parallelism
and the event loop is run only once
(due to RDF laziness and some output collection optimisation)

some
action

= a python class

= a C++ class (inherits from a virtual mother class)

```
class filter:  
    #include "filter.h"  
  
    def __init__(self, string):  
        self.myTH1 = []  
        self.myTH2 = []  
        self.myTH3 = []  
        self.string = string  
  
    def run(self,d):  
        self.d = d.Filter(self.string)  
        return self.d  
  
    def getTH1(self):  
        return self.myTH1  
  
    def getTH2(self):  
        return self.myTH2  
  
    def getTH3(self):  
        return self.myTH3  
  
RNode filter::run(RNode d){  
    auto d1=d.Filter("Mystring_");  
    return d1  
}  
  
std::vector<R00T::RDF::RResultPtr<TH1D>> filter::getTH1(){  
    return _h1List;  
}  
  
std::vector<R00T::RDF::RResultPtr<TH2D>> filter::getTH2(){  
    return _h2List;  
}  
  
std::vector<R00T::RDF::RResultPtr<TH3D>> filter::getTH3(){  
    return _h3List;  
}
```

an example of action: extraction of the “Angular Coefficients” from a WJets Montecarlo

task: compute

$$m = \frac{\sum P_k(\cos \theta, \phi) w_i}{\sum w_i}$$

↑
spherical harmonics 2nd order (W has spin 1!)

$$\sigma_m = \sqrt{\sigma_{P_k}^2 \frac{\sum w_i^2}{(\sum w_i)^2}}$$

for each bin of W p_T and y
for each harmonics $k = 0, \dots, 7$

implementation:

▶ 1 TH2 filled with w

for each harmonics (0 to 7):

▶ 1 TH2 filled with P_k and weighted with w

▶ 1 TH2 filled with P_k^2 (to compute variance)

in RDF language:
about 10 Filters and 10 Defines

an example of usage:

```
import ROOT

from RDFtreeV2 import RDFtree

ROOT.ROOT.EnableImplicitMT(64)

cut = 'pt1>22.0&&pt2>20.0&&abs(eta1)<2.5&&abs(eta2)<2.5&&mass>75&&mass<115'
inputFileD ='/scratch/emanca/WMass/MuonCalibration/KaMuCaSLC7/CMSSW_8_0_20/src/KaMuCa/Derivation/
run/Scale/muonTreeDataZ.root'

calibData = ROOT.string('DATA_80X_13TeV')

# data
pD = RDFtree(outputDir = 'TEST', outputFile = "beforeCalibData.root", inputFile = inputFileD, \
modules=[prepareSample(cut=cut, target=90.851, isMC=False), basicPlots(res='Z')], treeName = 'tree')

# execute run() method of a class
pD.run()

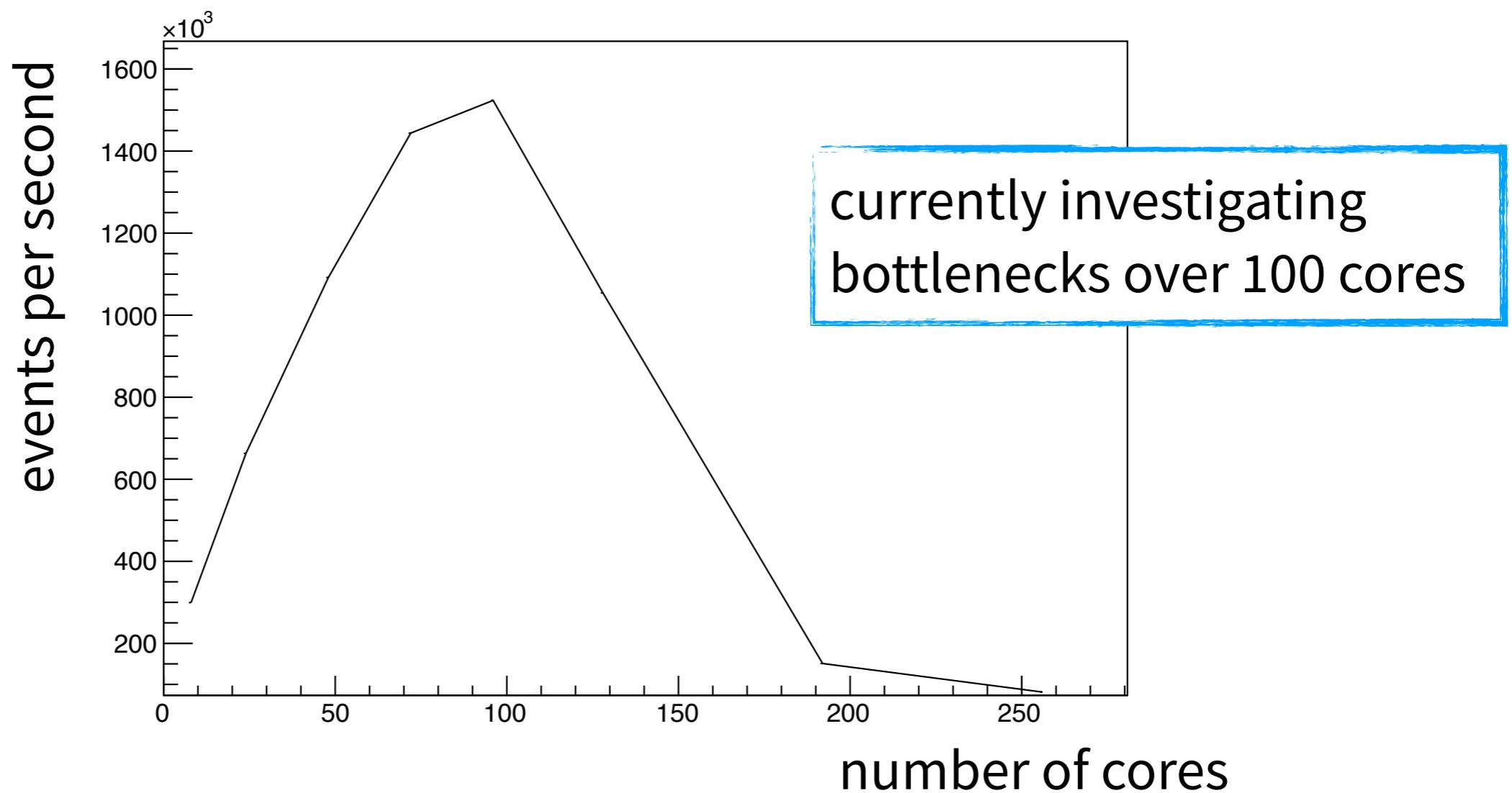
# add new classes

pD.branch([ROOT.applyCalibration(calibData), basicPlots(res='Z', \
calib=True), prepareSampleAfter(cut, res='Z')], outputFile="afterCalibData.root")

# collect output and trigger event loop
pD.getOutput()
```

a scaling plot: 384 cores Intel(R) Xeon(R) Platinum 8168 CPU @ 2.70GHz
Lots of SSD storage, bleeding edge hardware
@ Scuola Normale Superiore
27 GB input data (~4000 cluster)

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conclusions:

the combo RDF + NanoAOD (or any kind of flat tree) proved to be very successful in reducing execution time in multicore machines

mini-framework is a nice tool to perform an analysis in a compact way.
new features can be added:

*ex. can we treat systematic uncertainties
in an automatic and efficient way?*