Enhancing CMS data analyses using a distributed high throughput platform

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on behalf of the CMS Collaboration

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CMS Compact Muon Solenoid

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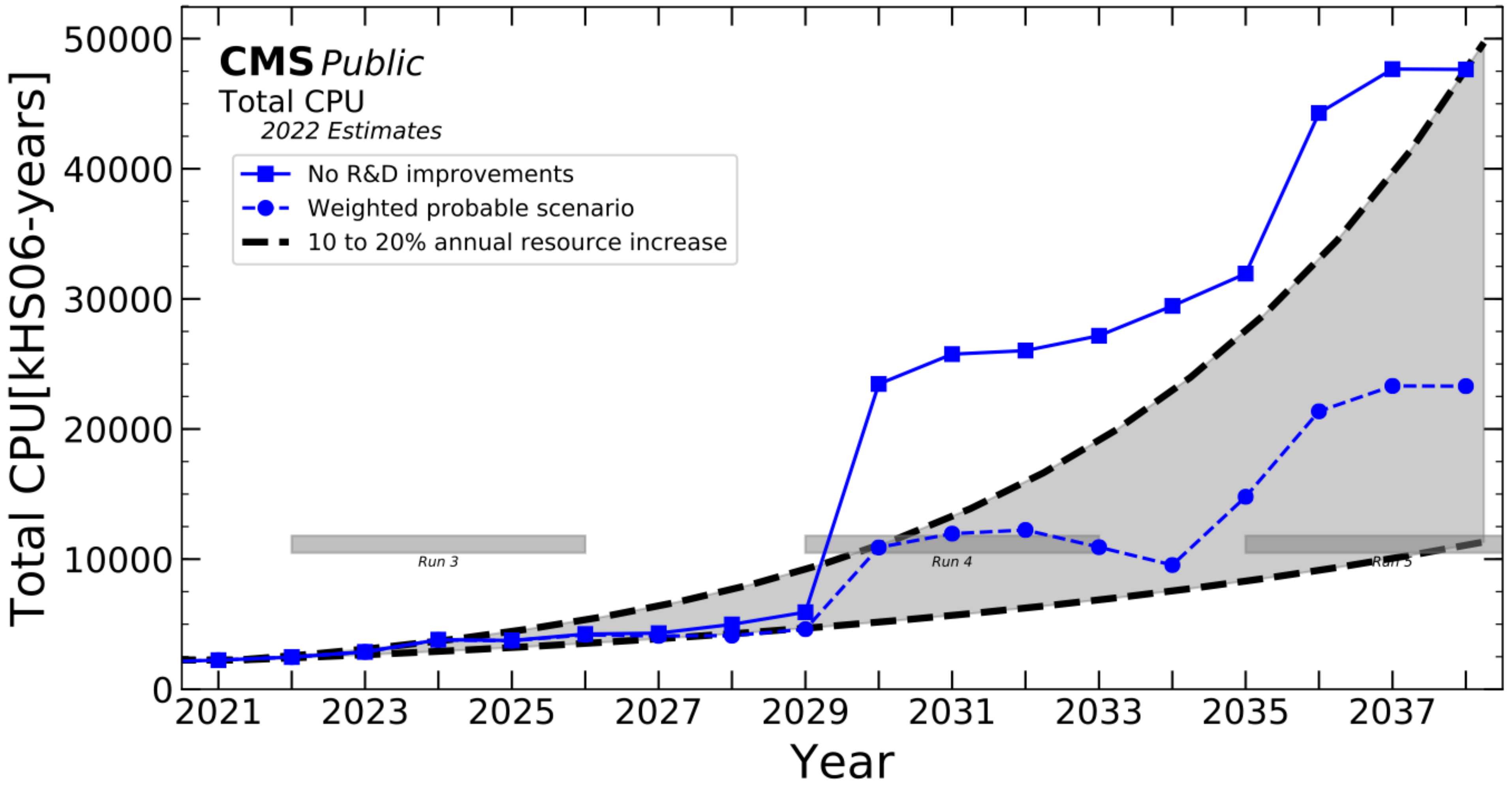
Introduction

- The upcoming high-luminosity phase at the CERN Large Hadron Collider (LHC), will require an increasing amount of computing resources;



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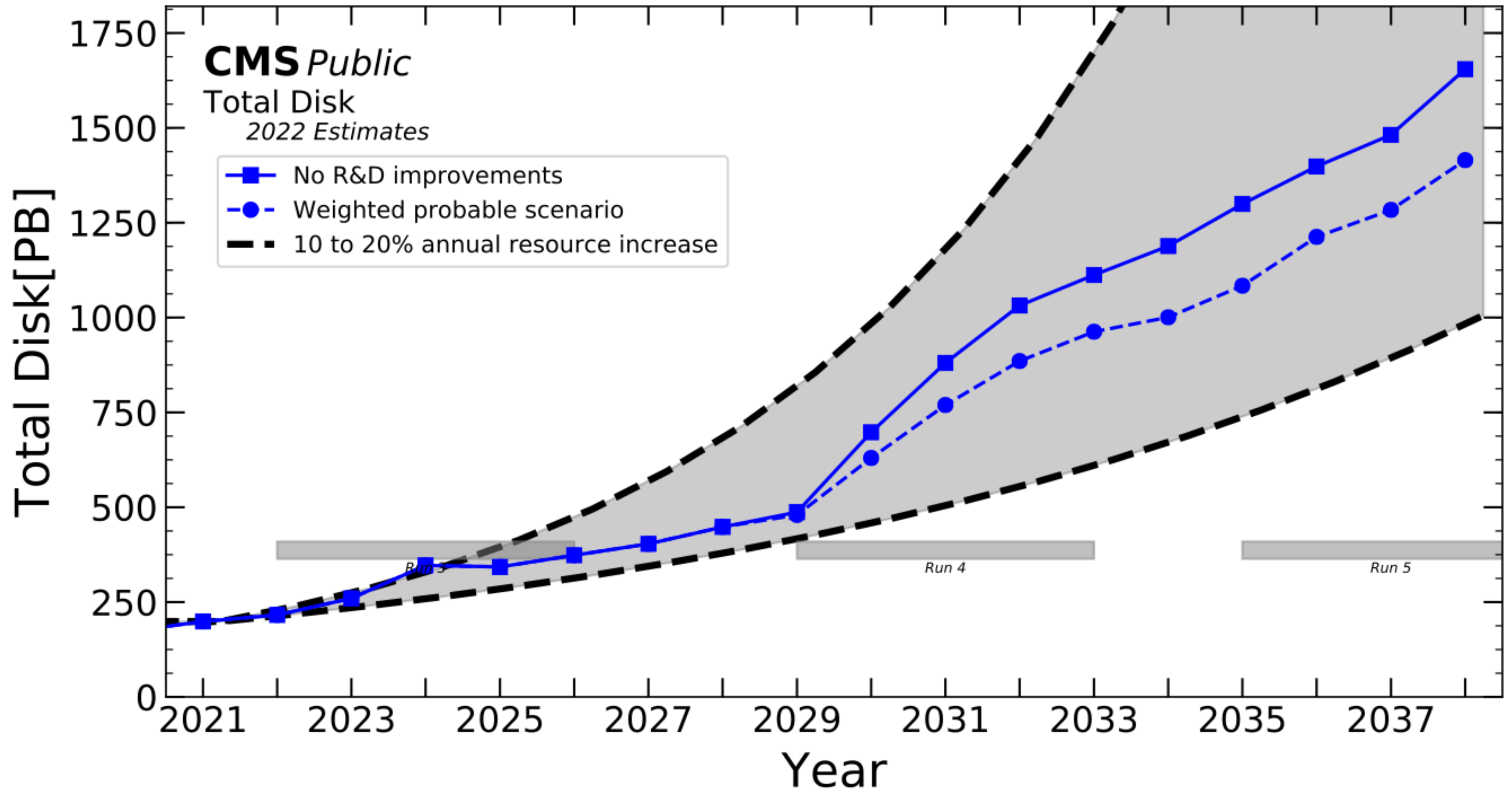

link

Higher rates of collision events → Higher demand for computing and storage resources

- To better analyse this increasing amount of Big Data:
  - Optimise the usage of CPU and storage;
  - Promote the usage of better data formats;
  - **Develop new analysis paradigms!**

→

- New software based on declarative programming and interactive workflows;
- Distributed computing on geographically separated resources.

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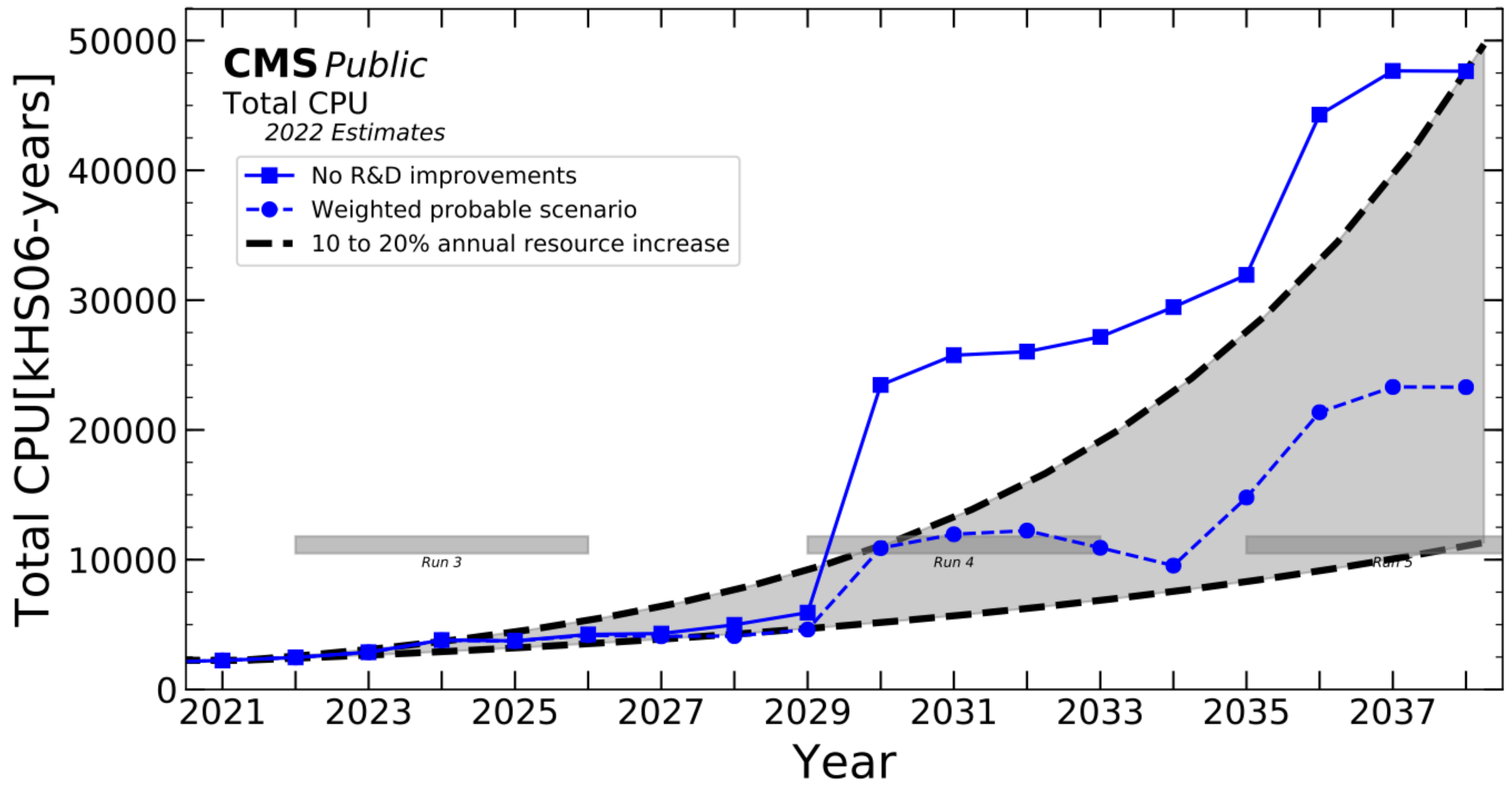

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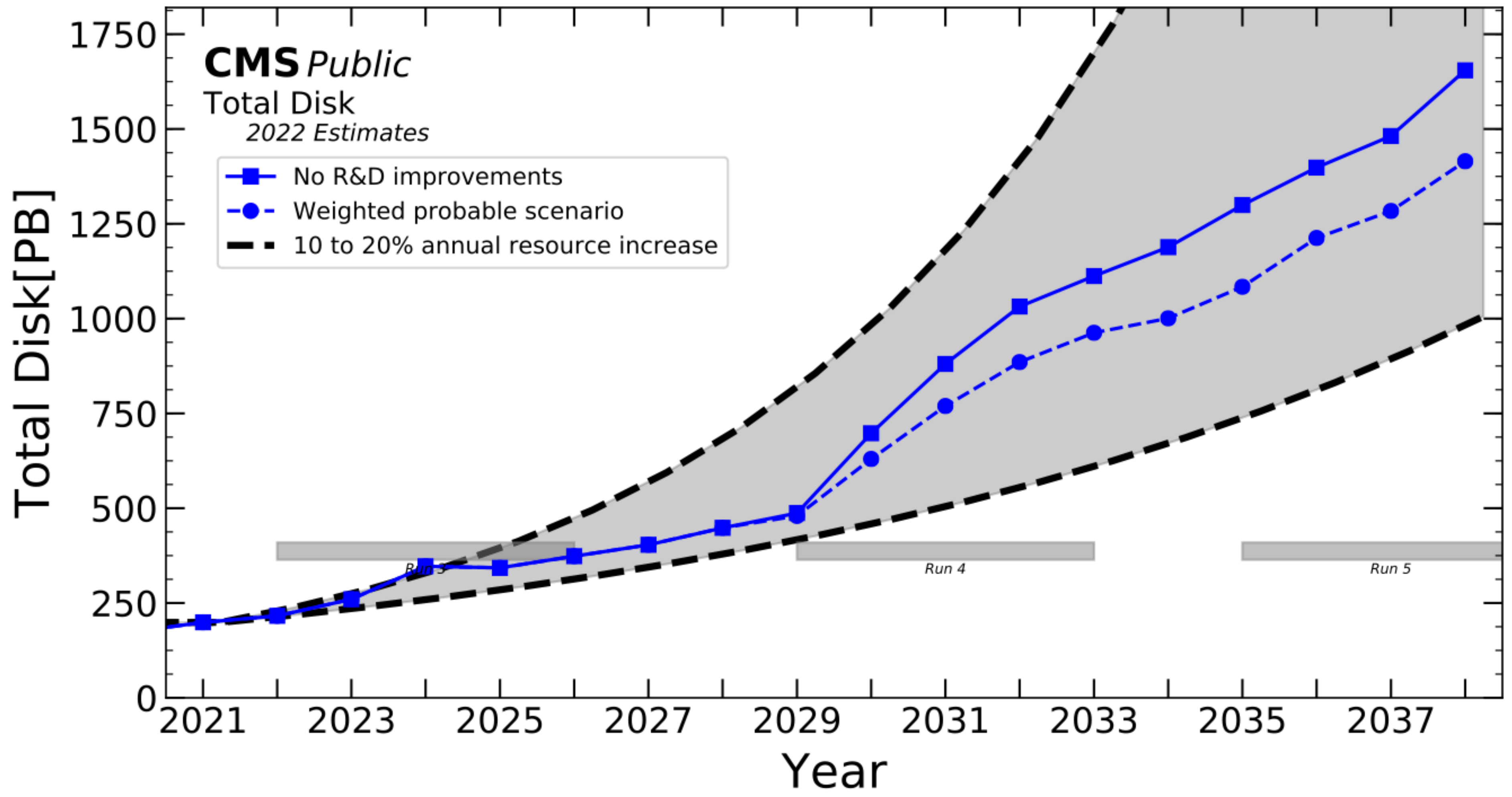

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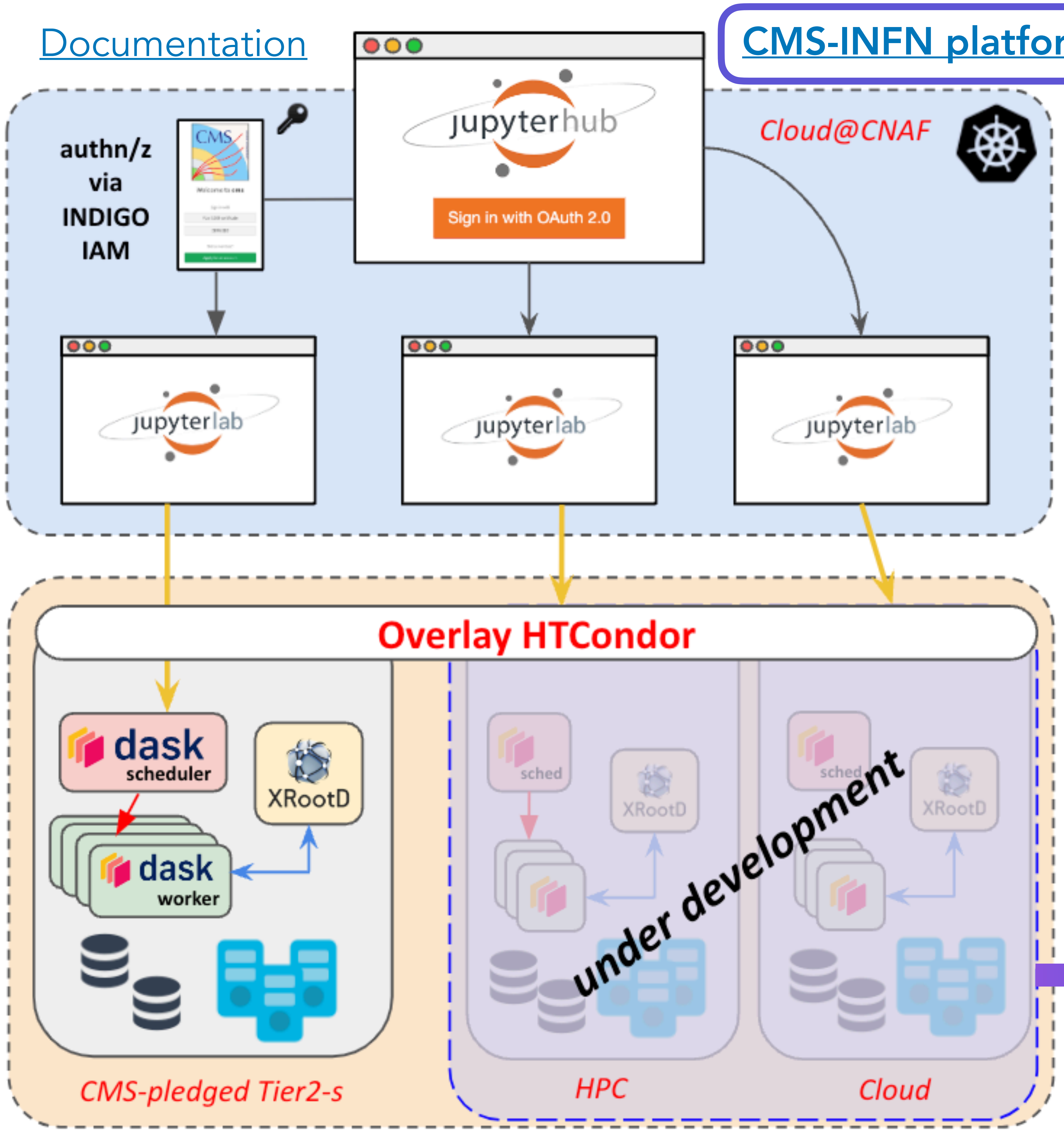
High-throughput platform!

What is a high throughput platform?

[Documentation](#) [CMS-INFN platform](#)



synergy with: Common Analysis Tools @ CMS

- Access to a single JupyterHub and authentication/authorisation token-based (Indigo-IAM);
- Based on industry standard technologies;
- Configurable kernel python (via containers), with specific working environment.

- HTCondor-based overlay (also available standalone);
- DASK library (python) for distributing the execution:
  - ✳ Scale from 1 to N cores (depending on resources availability)
- Interfaced with WLCG (using XRootD, WebDAV, …)

Offloading strategy:

synergy with: interTwin

- Schedule worker processes spawning on multiple remote sites dynamically and transparently:
  - Implementation on heterogeneous resources (HTC/HPC/Cloud)

What is a high throughput platform?

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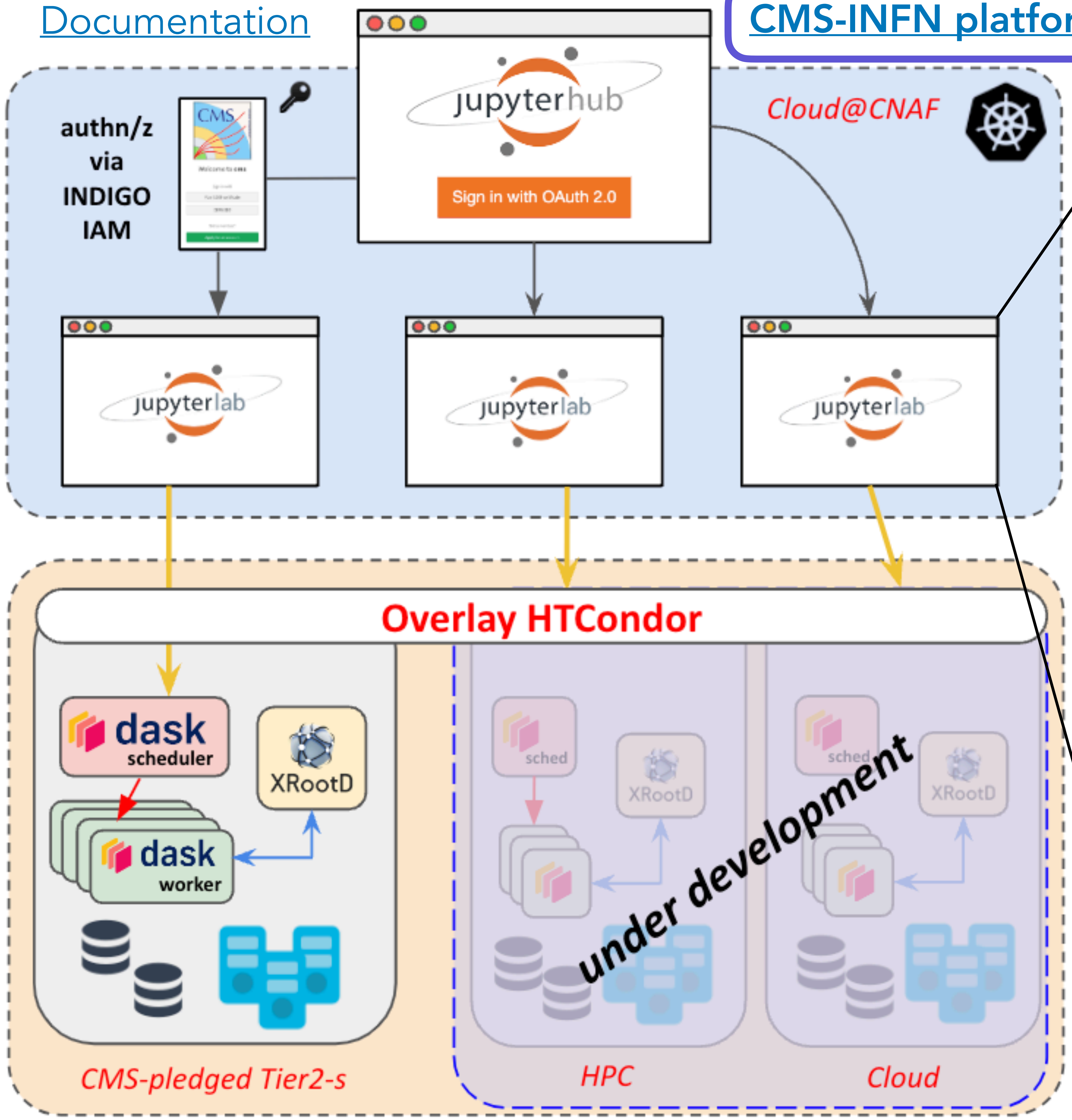

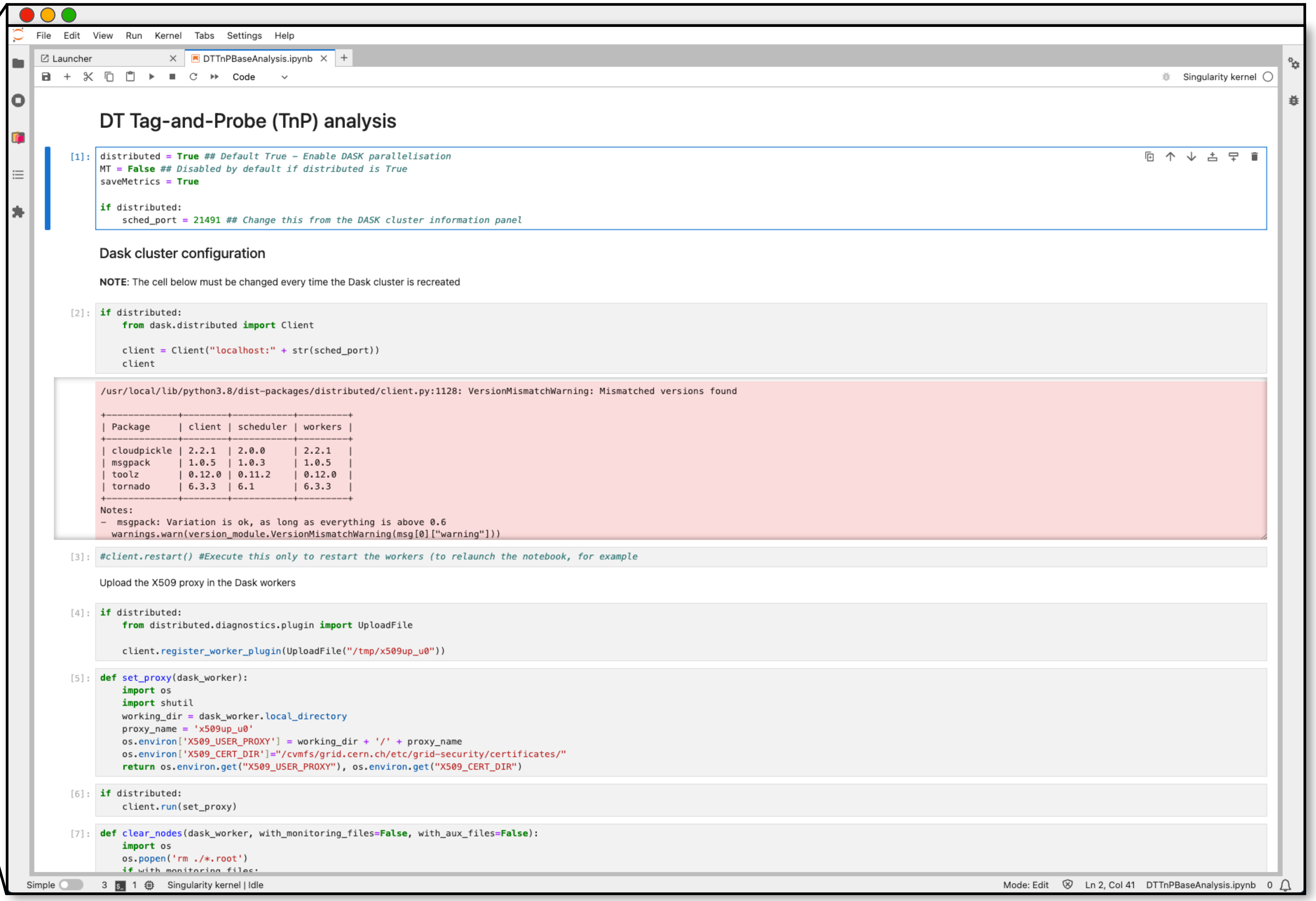

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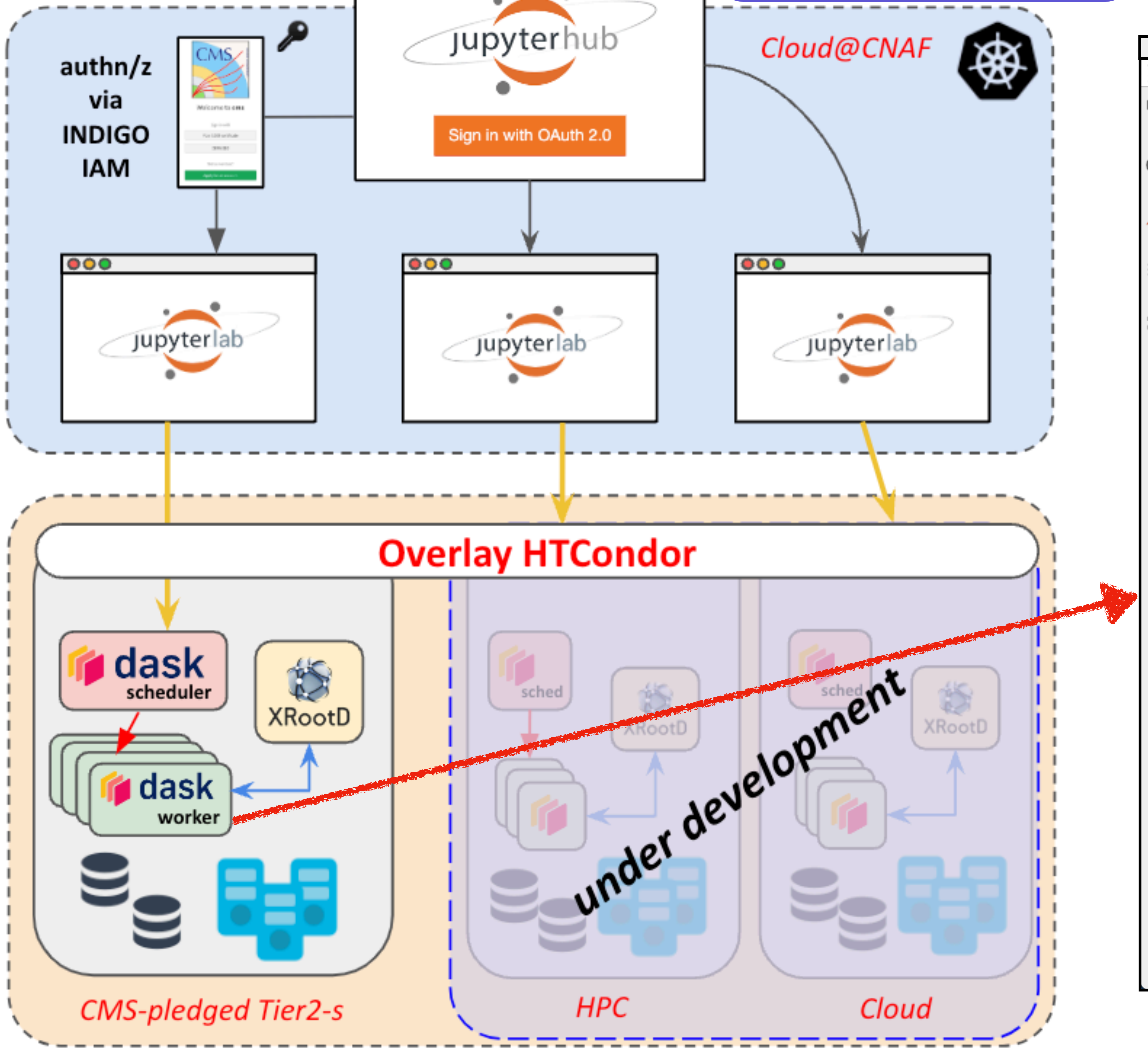
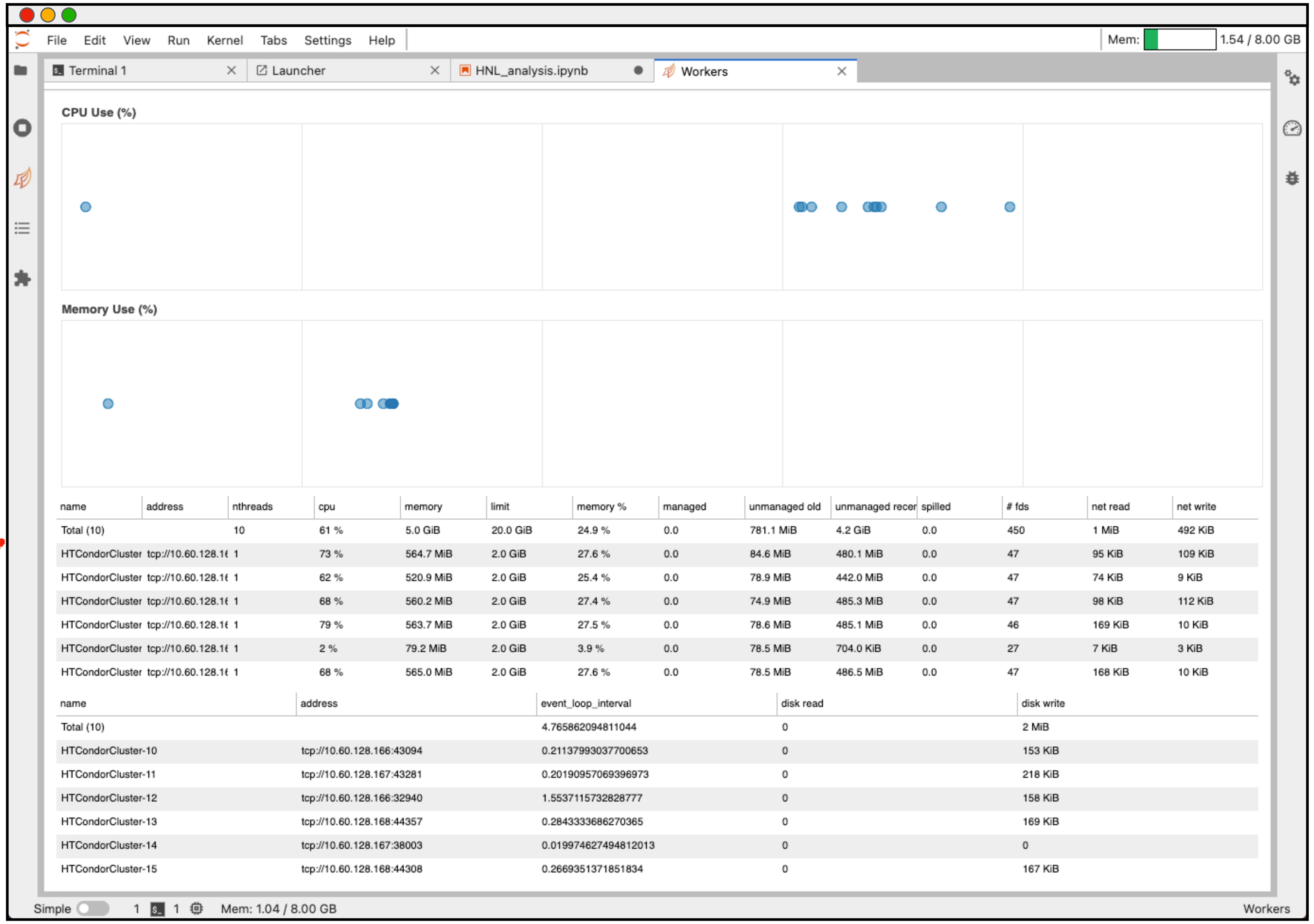




name	address	nthreads	cpu	memory	limit	memory %	managed	unmanaged old	unmanaged recer	spilled	# fds	net read	net write
Total (10)		10	61 %	5.0 GiB	20.0 GiB	24.9 %	0.0	781.1 MiB	4.2 GiB	0.0	450	1 MiB	492 KiB
HTCondorCluster	tcp://10.60.128.1(	1	73 %	564.7 MiB	2.0 GiB	27.6 %	0.0	84.6 MiB	480.1 MiB	0.0	47	95 KiB	109 KiB
HTCondorCluster	tcp://10.60.128.1(	1	62 %	520.9 MiB	2.0 GiB	25.4 %	0.0	78.9 MiB	442.0 MiB	0.0	47	74 KiB	9 KiB
HTCondorCluster	tcp://10.60.128.1(	1	68 %	560.2 MiB	2.0 GiB	27.4 %	0.0	74.9 MiB	485.3 MiB	0.0	47	98 KiB	112 KiB
HTCondorCluster	tcp://10.60.128.1(	1	79 %	563.7 MiB	2.0 GiB	27.5 %	0.0	78.6 MiB	485.1 MiB	0.0	46	169 KiB	10 KiB
HTCondorCluster	tcp://10.60.128.1(	1	2 %	79.2 MiB	2.0 GiB	3.9 %	0.0	78.5 MiB	704.0 KiB	0.0	27	7 KiB	3 KiB
HTCondorCluster	tcp://10.60.128.1(	1	68 %	565.0 MiB	2.0 GiB	27.6 %	0.0	78.5 MiB	486.5 MiB	0.0	47	168 KiB	10 KiB

name	address	event_loop_interval	disk read	disk write
Total (10)		4.765862094811044	0	2 MiB
HTCondorCluster-10	tcp://10.60.128.166:43094	0.21137993037700653	0	153 KiB
HTCondorCluster-11	tcp://10.60.128.167:43281	0.20190957069396973	0	218 KiB
HTCondorCluster-12	tcp://10.60.128.166:32940	1.5537115732828777	0	158 KiB
HTCondorCluster-13	tcp://10.60.128.168:44357	0.2843333686270365	0	169 KiB
HTCondorCluster-14	tcp://10.60.128.167:38003	0.019974627494812013	0	0
HTCondorCluster-15	tcp://10.60.128.168:44308	0.2669351371851834	0	167 KiB

Use case: Detector Performance Analyses

Typically, **Detector Performance Group** (DPG) analyses are run on a reduced amount of data (e.g. one run or fill), but processing of large dataset, at once, might be needed:

- To assess/improve systematics of high precision analyses, when they are dominated by the response of a specific detector;
- To reprocess multiple year data, e.g. for detector stability studies (ageing).

Use case:

Porting of a well established Drift Tubes (DT) Tag-and-Probe analysis [CMS-DP-2023-049]

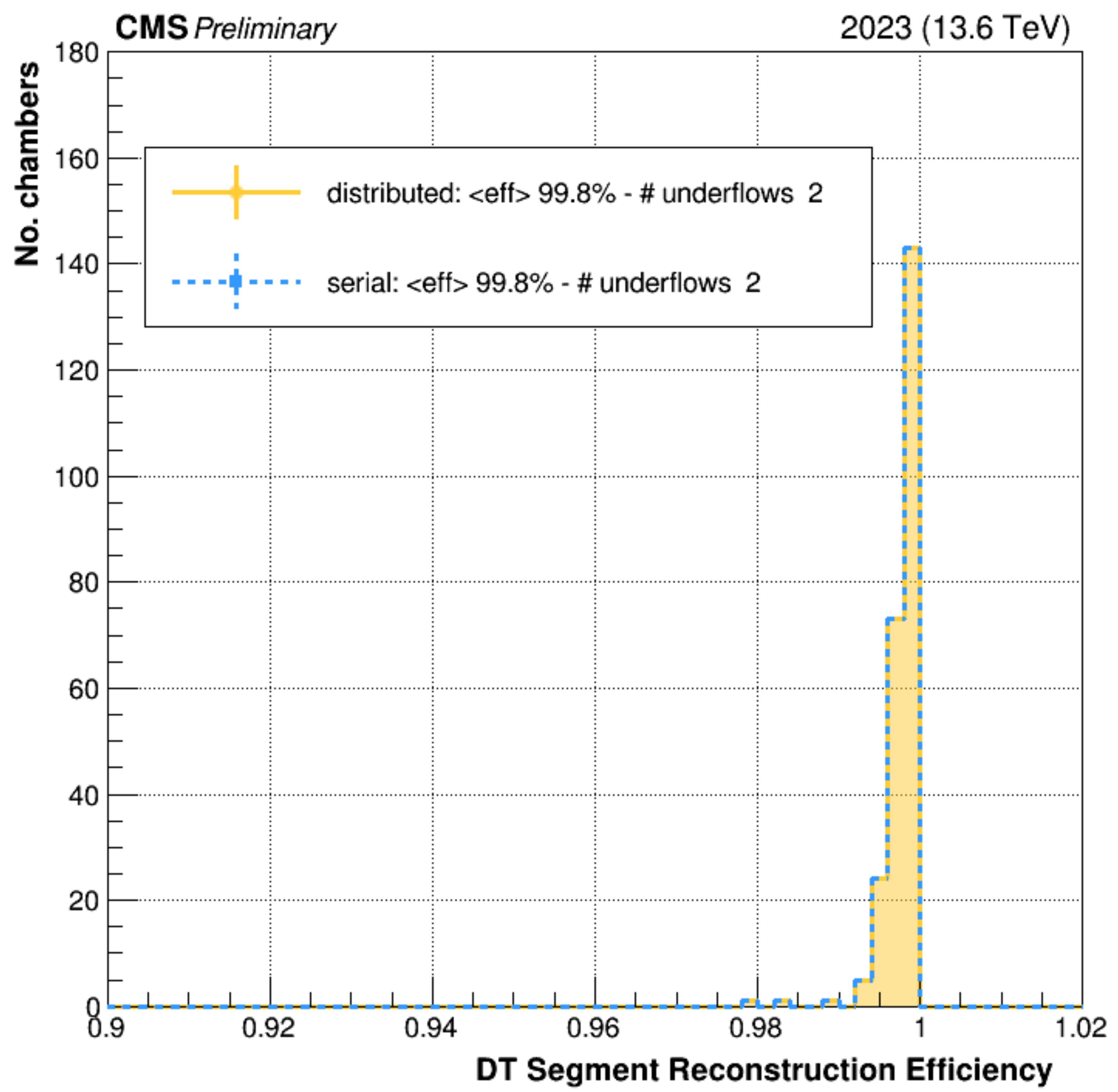
A **data sample** consisting in a skim of $Z \to \mu\mu$ **decay candidates** collected by CMS over **2023**, corresponding to ~27fb^{-1} was explored for the study. Size: 224GB

- The original code running mainly on C++, for the base histograms and computing the segment efficiencies.
    - The ported code is running on Jupyter notebook (in Python), using **ROOT RDataFrame**. The Tag-and-Probe libraries are stored in a dedicated header file.
    - The execution is off-loaded remotely (CMS Tier-2 - LNL) and the results are retrieved directly on the platform.

Use case: Detector Performance Analyses
Porting results

- Tag-and-Probe method [CMS-DP-2023-049]:
    - Two oppositely-charged well-reconstructed tracker muons;
    - Tag muon: $p_T > 27\text{GeV}$ passing HLT for isolated muons. TightID criteria in the muon detector reconstruction.
    - Probe muon: track with segment matching in at least a chamber other than the one under study. $p_T > 20\text{GeV}$.
- A DT chamber is efficient if reconstructed segment is near the extrapolated probe muon track.
- The **efficiency is computed in fiducial regions** (ignoring probes whose tracks falls near the chambers borders).
- The changes applied to the Tag-and-Probe program to run on the High Throughput Platform (distributed) do not affect performance, which is consistent with the original program (serial).

(one entry per chamber)



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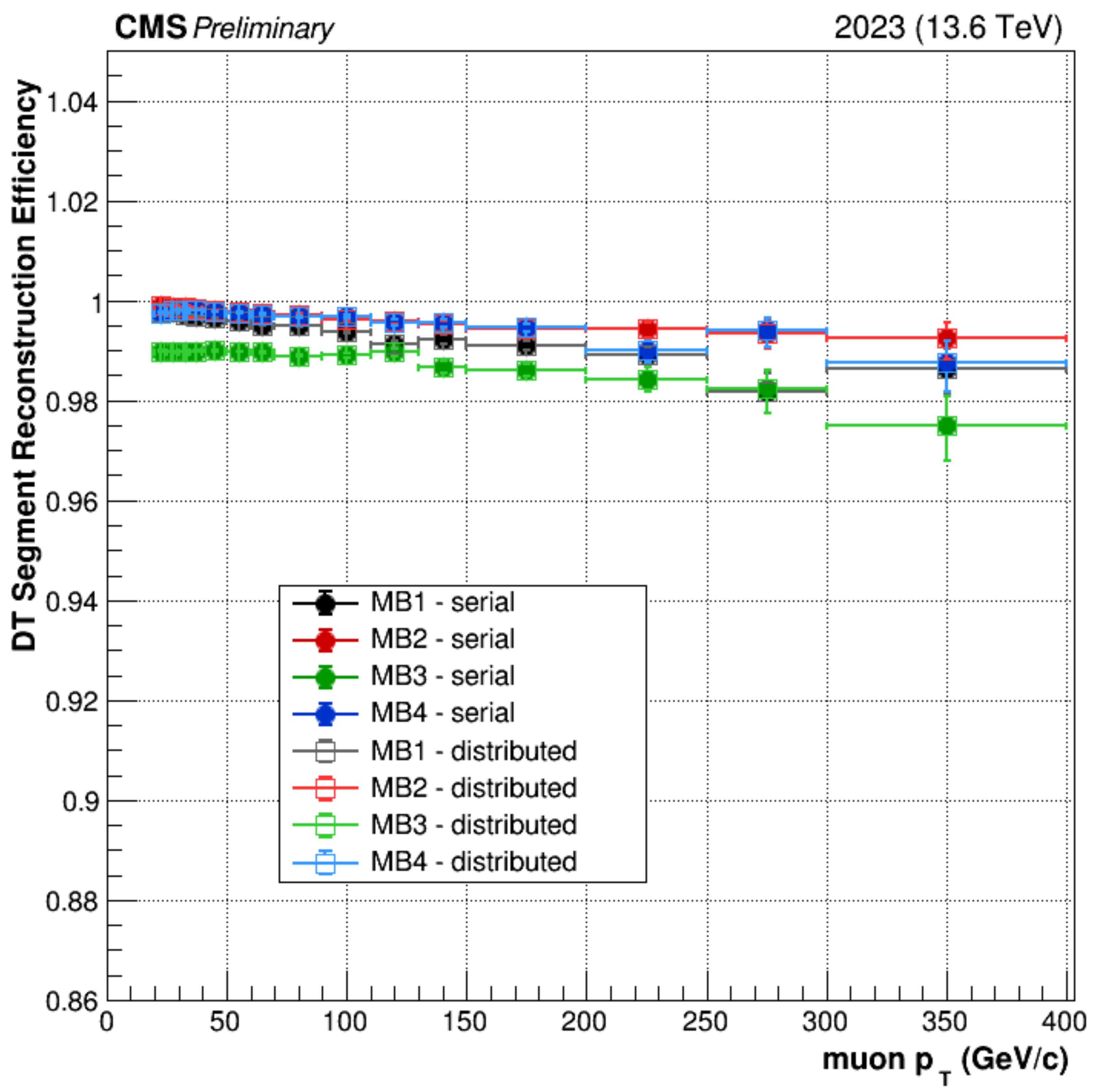
- The changes applied to the Tag-and-Probe program to run on the High Throughput Platform (distributed) do not affect performance, which is consistent with the original program (serial).
    - Including **high-energy muons**.

(measurement as function of muon p_T)



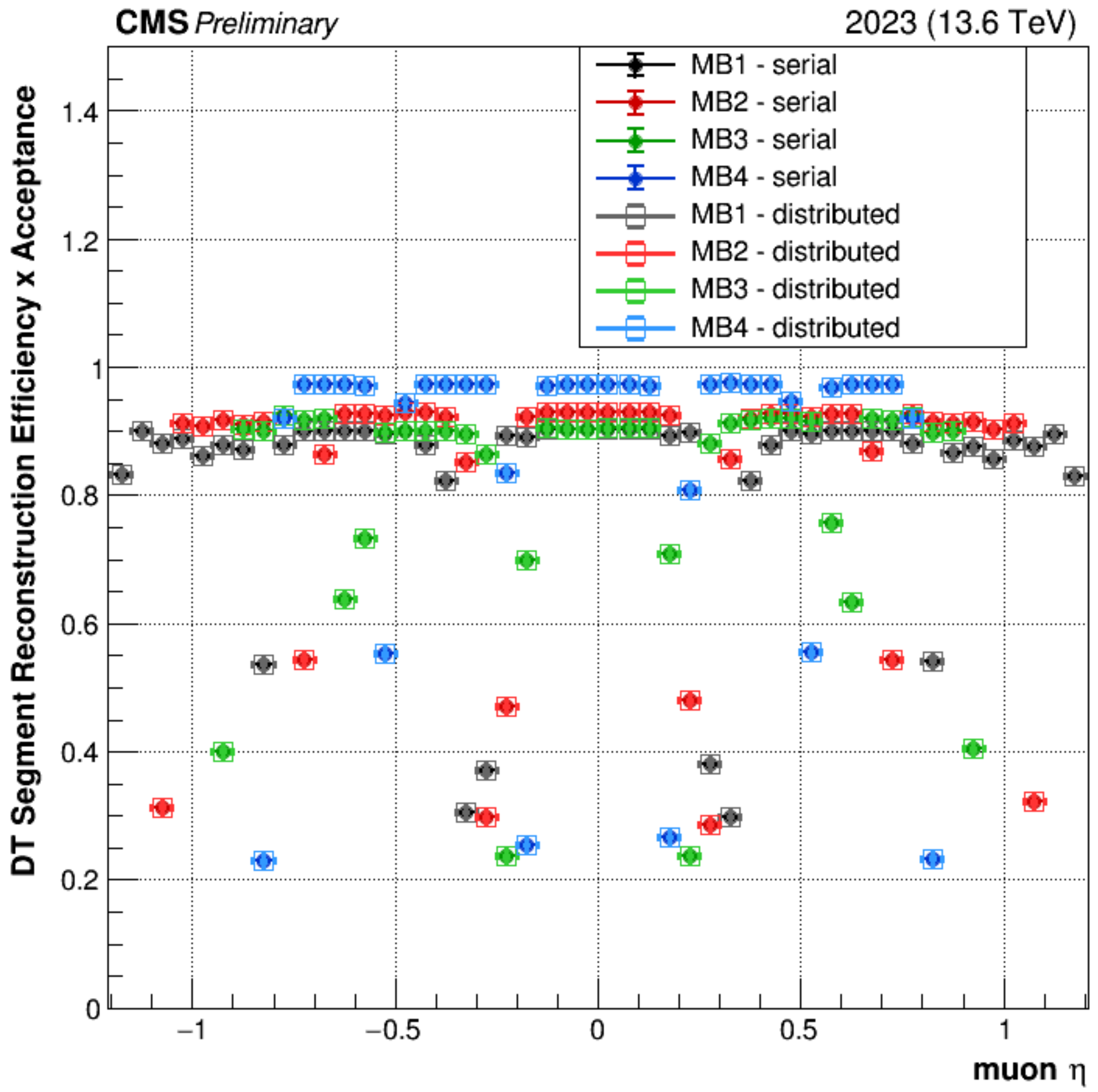
Use case: Detector Performance Analyses
Porting results

(efficiency x acceptance vs muon η)

- **The efficiency is computed**, this time, **without applying fiducial region selections** (convoluting reconstruction efficiency with detector acceptance) using the Tag-and-Probe method [CMS-DP-2023-049]

- The changes applied to the Tag-and-Probe program to run on the High Throughput Platform (distributed) do not affect performance, which is consistent with the original program (serial).

- Acceptance is the dominant effect observable in the plots:
    - Significant **efficiency drops** appearing in the boundaries between muon barrel wheels.
    - The impact of the cracks between barrel sectors varies among stations, explaining the differences in the regions where efficiency is maximal.



Use case: Detector Performance Analyses
Technical performance

- To evaluate the technical performance, the **available statistics has been processed 3 times**, mimicking an integrated luminosity of **~82fb^{-1}**, consisting of **~77M events** in total. Size: 224*3 = 672GB

- Serial processing (as a single job on HTCondor)

Wall time: ~120 minutes

1 CPU on a AMD EPYC 7302 16-Core Processor, with 2GB memory

- Distributed processing on the platform:

Wall time: ~6 minutes

Up to 92 CPUs (46 physical), on two AMD EPYC 7413 24-Core Processor, with 2GB memory per CPU. Resources hosted at T2_IT_LNL.

- The remote resources are monitored using in-site metrics, gathered and displayed using an **InfluxDB instance**.

- Quasi-interactivity is now reached:
  - Every time a re-execution of the analysis is needed (e.g. tweaking some thresholds or using different selection criteria), running a few Jupyter Notebook cells will do the trick (transparently accessing more resources)!!
  - This can result in a **great improvement** for any detector performance analysis application.

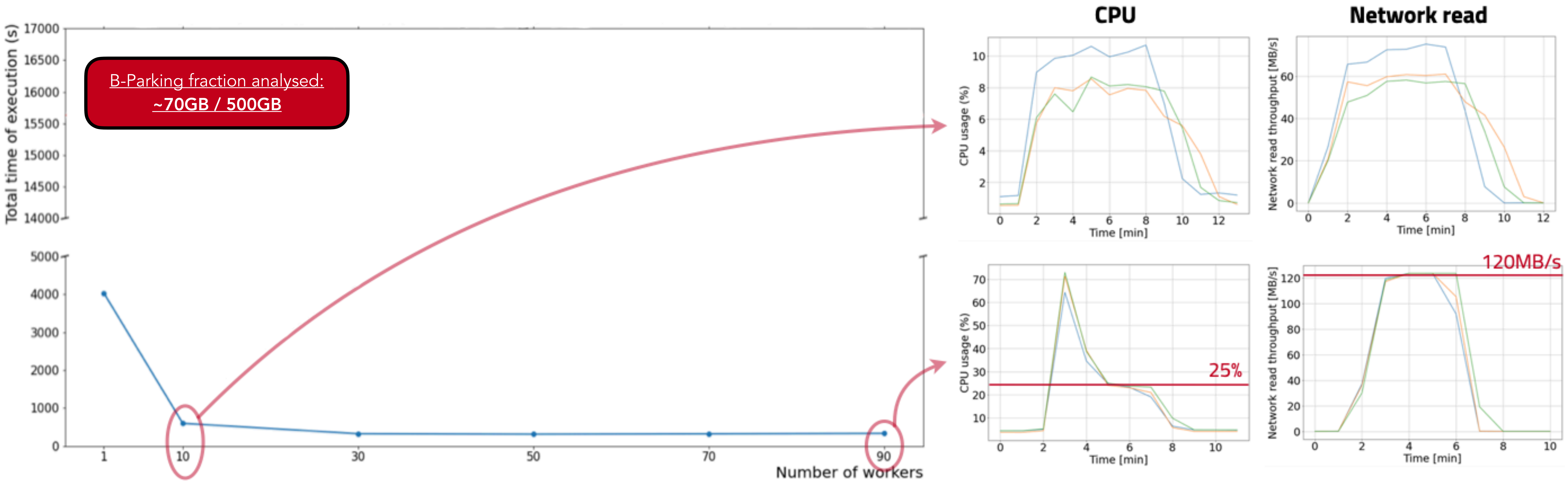
Use case: Physics data analysis
Technical performance

- The performances of the high-rate platform have been investigated also on a CMS physics data analysis.

Use case:

Analysis on a high amount of data, coming from the b-parking dataset gathered by CMS in 2018.

- The same analysis workflow, running on an increasing number of workers shows a decrease in execution time.



- As expected, low number of workers show a CPU usage saturation;
- For a high number of workers, network access becomes the main bottleneck (due to I/O access, via protocols like xRootd/WebDAV).

Moving towards a DataLake infrastructure

synergy with: ICSC Centro Nazionale di Ricerca in HPC, Big Data and Quantum Computing [1]

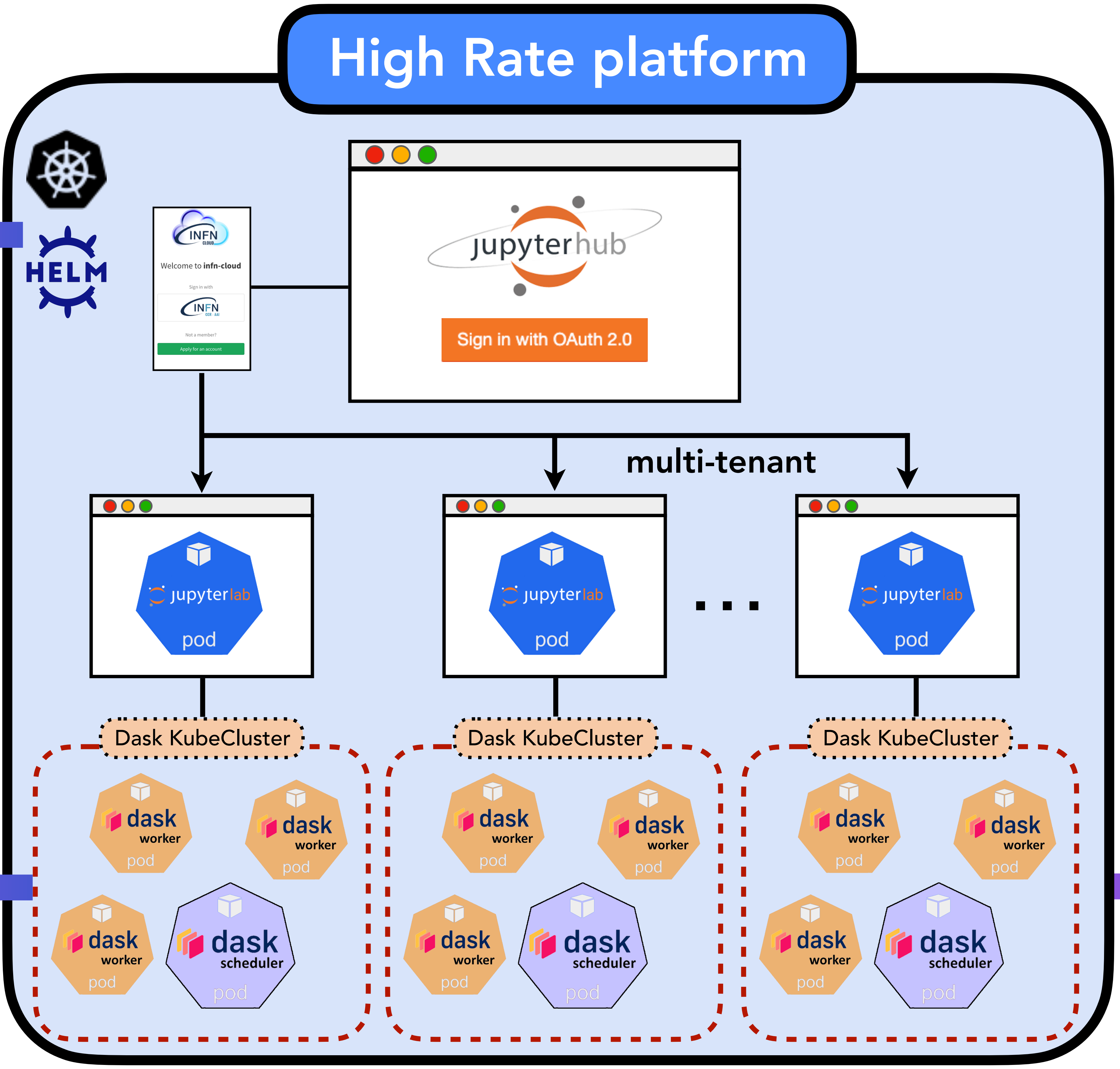
- Extending the entire infrastructure towards a multi-tenant platform, capable of intercepting the needs of data analysts from different scientific collaborations.

Deployment of the **Kubernetes** resources handled via **HELM charts**.

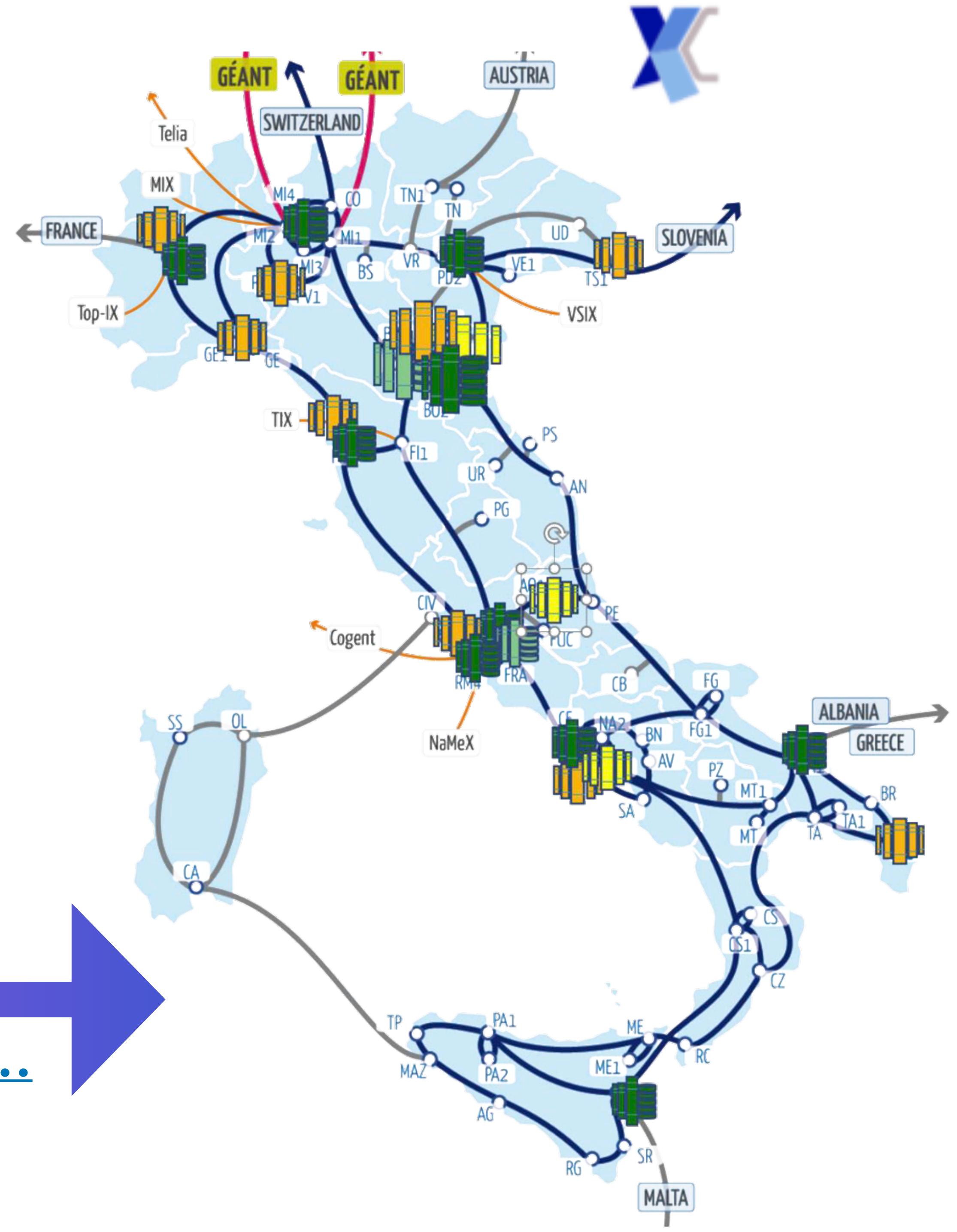
↓

Scalable deployment on the available resources

Also the **Dask cluster** is deployed on the K8s cluster, through the `KubeCluster` class, providing a Python API to manage the cluster.



offloading to...



[1] ICSC - Spoke 2 "Fundamental Research & Space Economy"

Conclusions

- In view of the R&D efforts for the next phases of LHC, new tools are required for making data analysis as efficient as possible;
- New **high-throughput platforms** have been developed:
    - Based on *interactive workflows* and *declarative programming* solutions;
    - Running on *distributed (and heterogeneous) resources*.
- Physics analysts already started the porting of their code, for testing and measuring the up-scaling performances:
- A **Detector Performance Group (DPG)** use case, coming from DT Tag-and-Probe analysis, has been successfully ported:
    - The changes applied to the source code are **not affecting performance**, and show an optimal consistency with the original analysis;
    - A **noticeable reduction in execution time** has been observed. In this way, analysts can re-run their applications multiple times (running on entire years of data-taking and/or performing multiple code changes).
- A performance speed-up of a physical data analysis has also been shown. For an increasing number of workers, the parallelisation of the workflow results in a faster execution. Some bottlenecks can be observed for massive I/O ops.

This work is partially supported by ICSC – Centro Nazionale di Ricerca in High Performance Computing, Big Data and Quantum Computing, funded by European Union – NextGenerationEU.

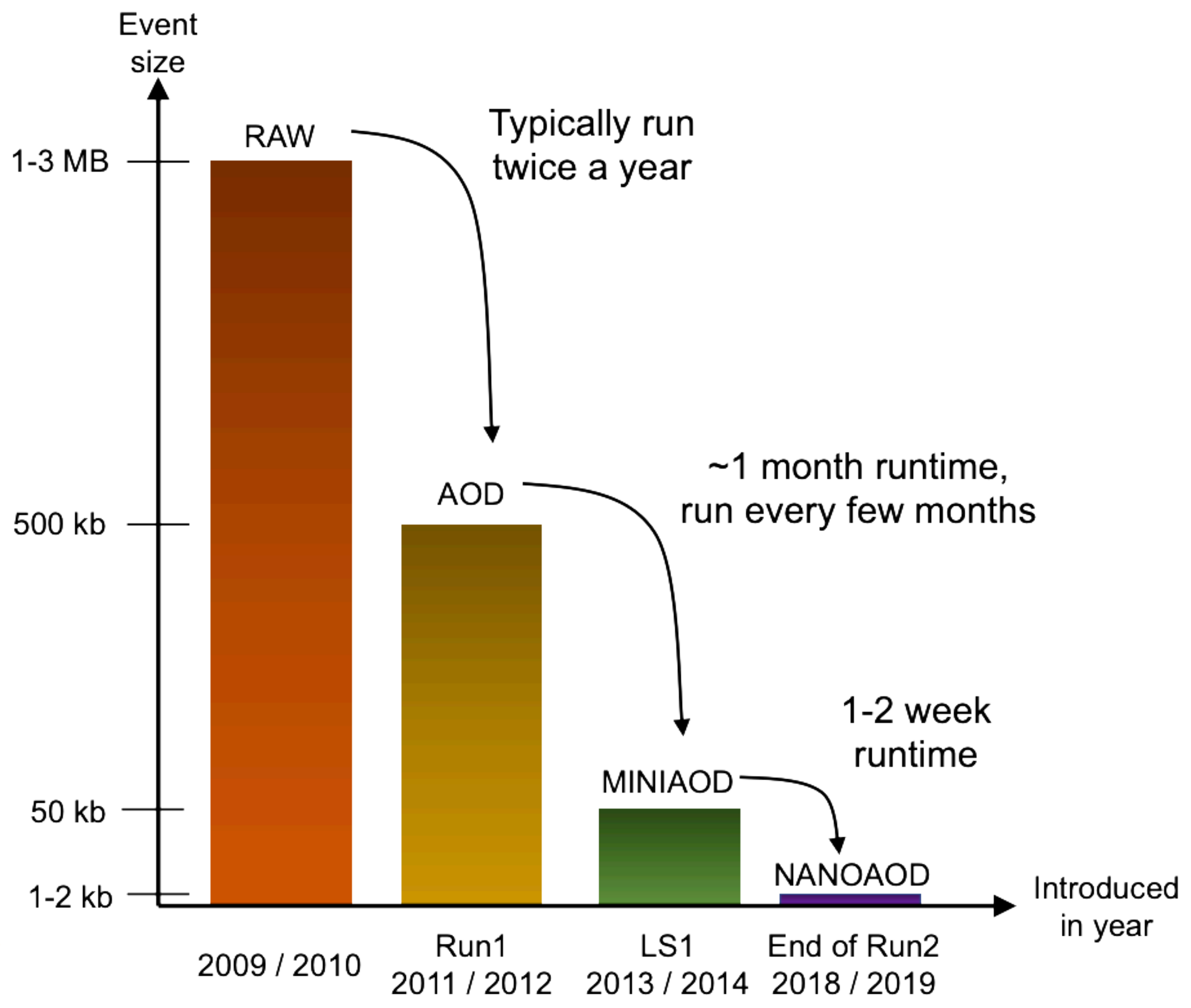
Finanziato dall'Unione europea NextGenerationEU | Ministero dell'Università e della Ricerca | Italiadomani | ICSC

BACKUP

Data processing in CMS

The entirety of CMS data, centrally produced, are saved in ROOT files, in different data formats:

- **RAW**: A collection of the detector electronics output. Event size: 1-3 MB
- **AOD**: Analysis Object Data. Transforming RAW data in analysis objects (used by analysts) like jets, muons, electrons, etc… Event size: 500kB
- **MiniAOD**: Reducing the size of AODs, making them more compact with the downside of losing some information (e.g. zeroing floating-point numbers bit). Event size: 50kB
- **NanoAOD**: Further reduction of MiniAODs, saved as a columnar ROOT file. This new format, using fundamental data types (int, float), exits from the CMS ecosystem and requires a small amount of dependencies to be analysed. Event size: 1-2 kB.



(image taken from: link to CHEP19 contribution)

DT Tag-and-Probe dataset:

Dataset used, based on muon DPG common NANO flavour: a NanoAOD-like dataset, with 410 physical variables, tailored for DPG-based analyses.

ROOT RDataFrame

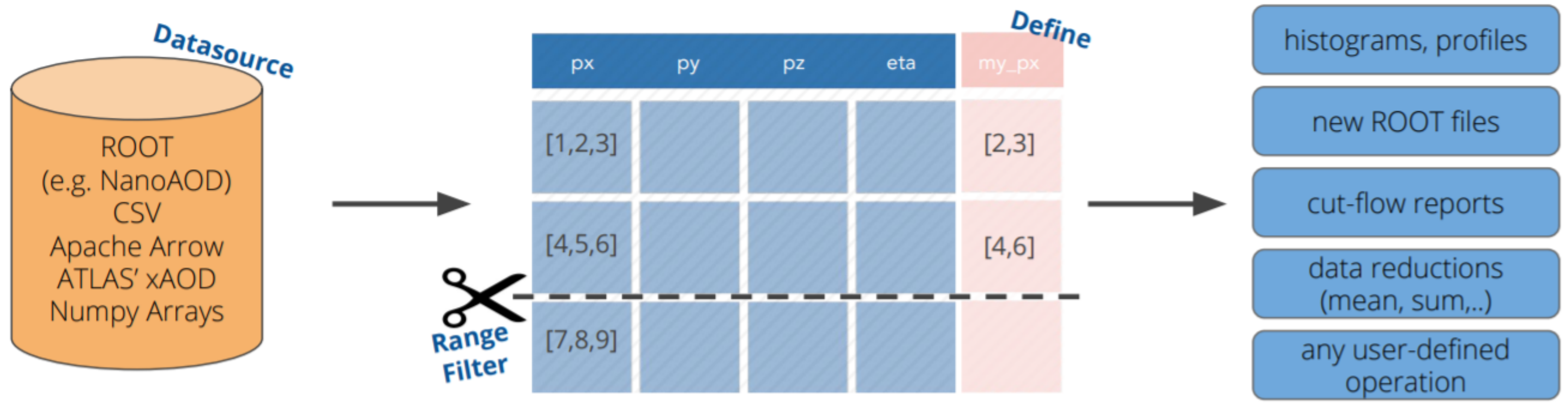
RDataFrame (RDF) is the high-level interface of ROOT for the data analysis saved in TTree, CSV and many other data formats. It is based on:

- multi-threading;
- low level optimisations (parallelism and caching).

Computations are expressed in terms of actions and transformations chain, constituting a computational graph.

The execution of such graph can be made also distributed, exploiting backends such as Dask and Spark.

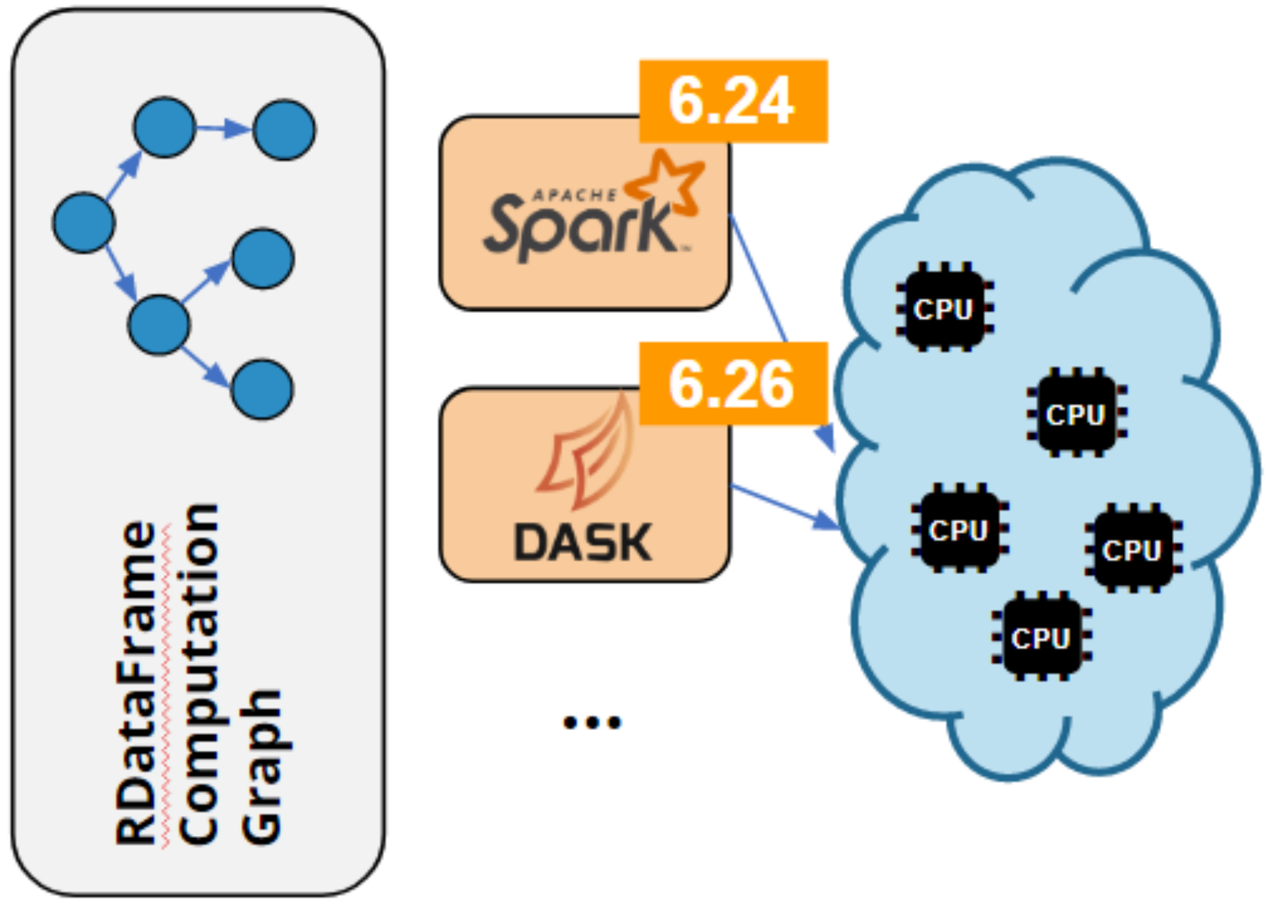
Thanks to the "distributed" extension of RDF, available experimentally.




```
# enable multi-threading
ROOT.EnableImplicitMT()
df = ROOT.RDataFrame(dataset)

df = df.Range(2)
       .Define("my_px", "px[eta > 0]")

# filled in a single loop
h1 = df.Histo1D("my_px", "w")
h2 = df.Histo1D("px", "w")
```

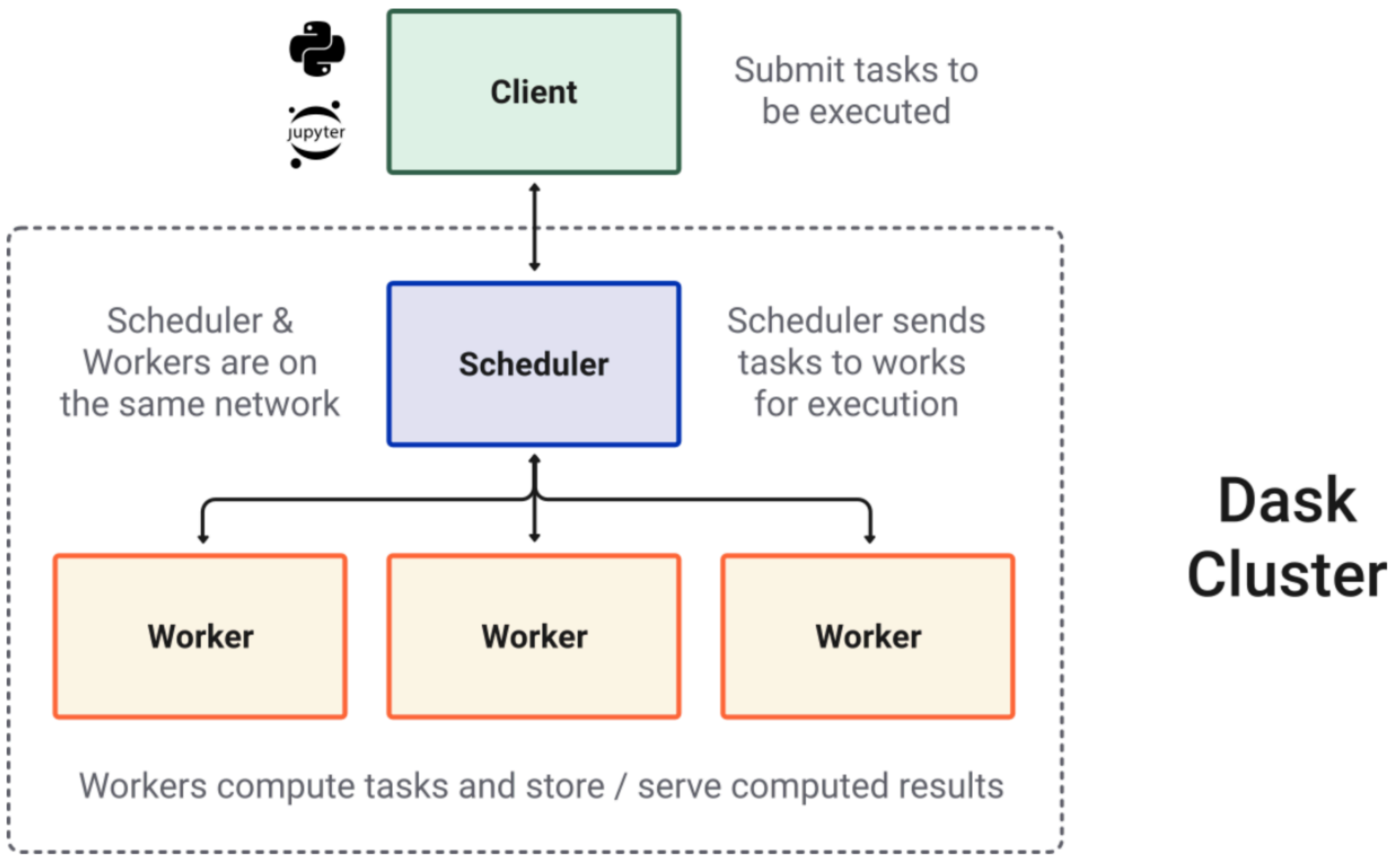


Images taken from: PyHEP 2021

Dask

There are many parts to the "Dask" cluster:

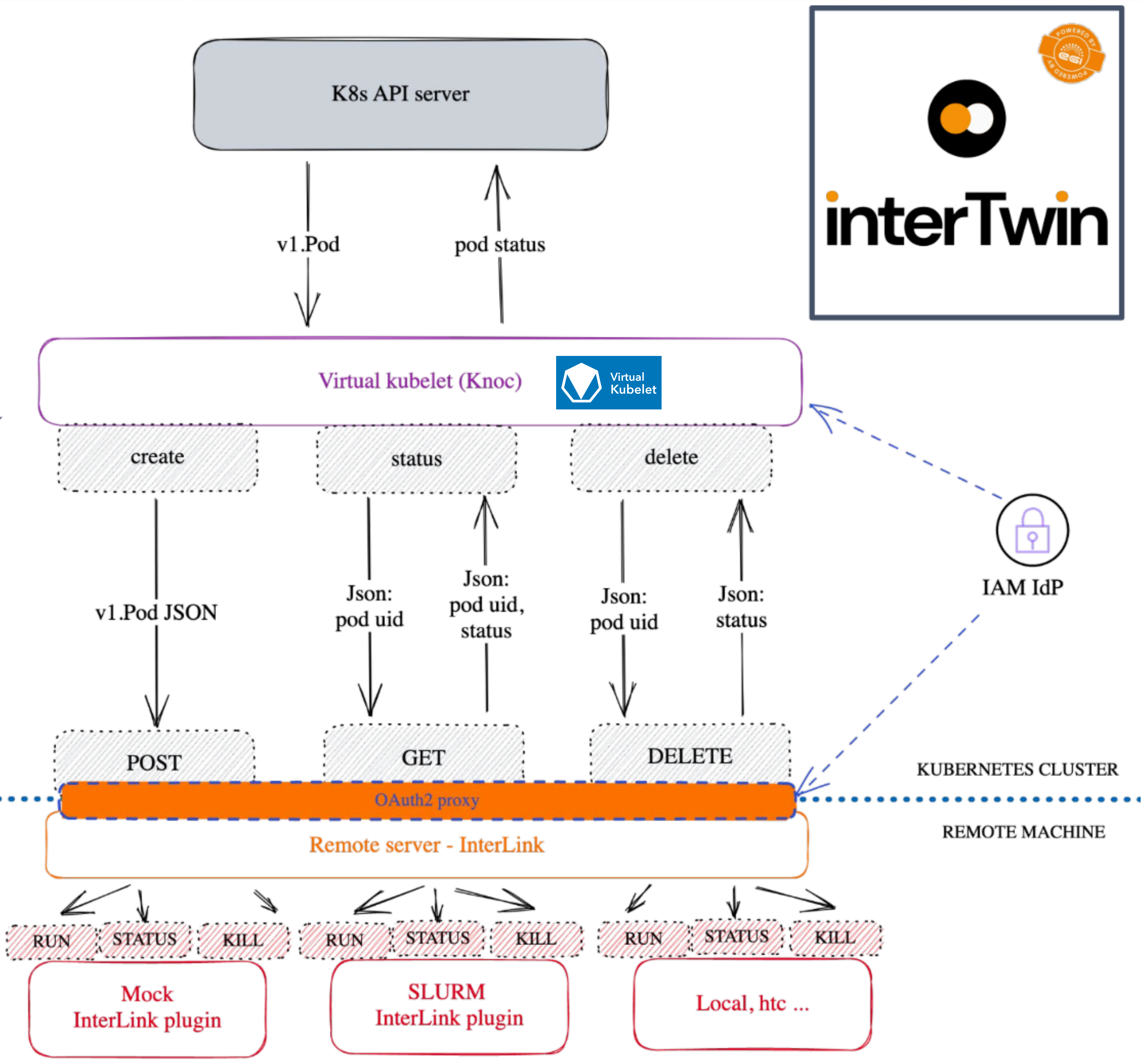
- Collections/API also known as "core-library".
- Distributed – to create clusters
- Integrations and broader ecosystem



The offloading strategy

Scheduling worker processes, spawning on multiple remote sites dynamically and transparently:

- Virtual Kubelet (open-source Kubernetes kubelet implementation that masquerades as a kubelet): registers as a virtual node and pulls work to run;
  - "It takes your pod and executes it wherever"
- InterLink + **HTCondor Sidecar (Plugin)**: pods are translated into HTCondor jobs:
  - Translating interlink create/status/delete calls interacting with the proper HTCondor schedd via CLI
    - `POST /create` call -> `condor_submit`
    - `GET /status` call -> `condor_q`
    - `POST /delete` call -> `condor_rm`
- In future, this strategy can be also applied to other job scheduling systems (e.g. Slurm/HPC)



DT local reconstruction efficiency

The DT efficiency to reconstruct a local track segment was defined and measured using a Tag & Probe method.

Events were selected to contain a pair of oppositely charged reconstructed muons.

Muon tracks were required to be well reconstructed in the tracker detector (≥ 6 hits in the strip detector and ≥ 1 hit in the pixel detector) and to be well isolated in η and ϕ from other tracks. Moreover the muon tracks were required to have a separation between each other $\Delta R = \sqrt{\Delta\eta^2 + \Delta\phi^2} > 0.3$.

- To ensure that they come from the same interaction vertex, their distance at the point of closest approach to the interaction point should be $\Delta z < 0.1$ cm.
- Their invariant mass should be within 10 GeV of the Z_0 mass.

The track used as tag is also required to be well reconstructed in the muon detector, by satisfying the Tight-ID criteria described in JINST 13 (2018) P06015. Furthermore, it is required to have a transverse momentum $p_T > 27$GeV and also to pass the High-Level Trigger selection of isolated muons with $p_T > 27$GeV.

The inner component of track used as probe is propagated inside-out to each station of the DT detector and must have segments matched in ≥ 2 muon stations different from the one under study. It also must have $p_T > 20$GeV.

A DT chamber crossed by a probe track is considered efficient if a reconstructed segment is found within 15 cm distance of the extrapolated track in the R-ϕ plane.

The DT Segment Reconstruction Efficiency can be computed:

- within the full solid angle, in this case it also includes detector acceptance
- within fiducial regions i.e. discarding probes that cross a chamber within 15 cm of its edges.