Analysis on LHC-Managed Facilities: Coffea-Casa

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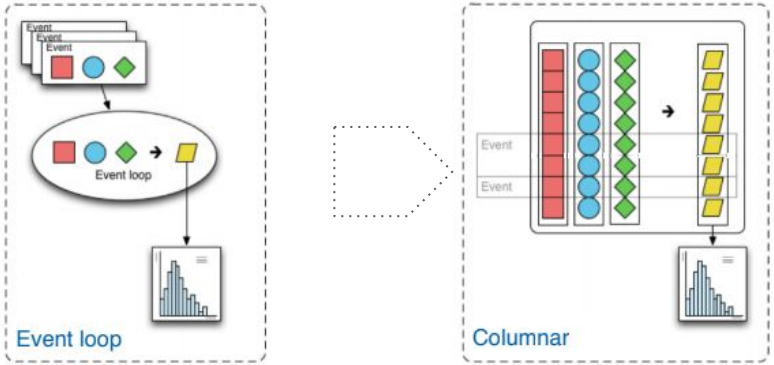
Analysis facilities:
how we understand it?

We need to look into a new services and resource types!

- **People, software / services, and hardware**
- **Services** includes:
  - Access to experimental data products
  - Storage space for per-group or per-user data (often ntuples)
  - Access to significant computing resources
- Physics **software**: ROOT and the growing Python-based ecosystem
- **Computing hardware:** available/new CPUs and disks (maybe GPUs)

B.Bockelman, Analysis Facilities for the HL-LHC, Snowmass 2020

Trending towards column-wise (tidy/big data) analysis:



One of examples: https://github.com/CoffeaTeam/coffea

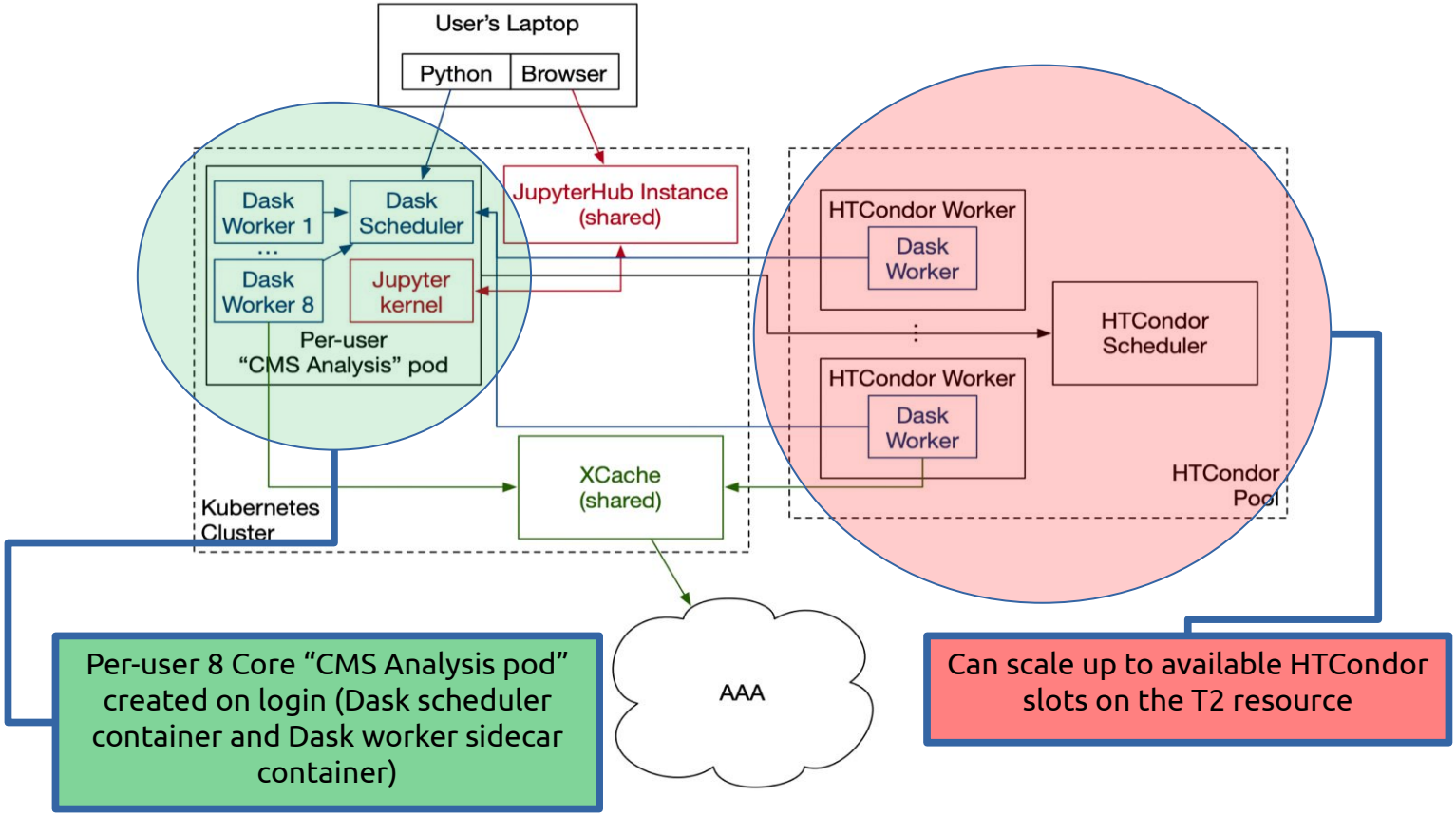
Analysis facilities: prototypes

- **Two AF facilities** with the possible outcome of adding more sites as soon as we gain experience

CMSAF @T2 Nebraska
“Coffea-casa”
https://cmsaf-jh.unl.edu

Elastic AF @ Fermilab

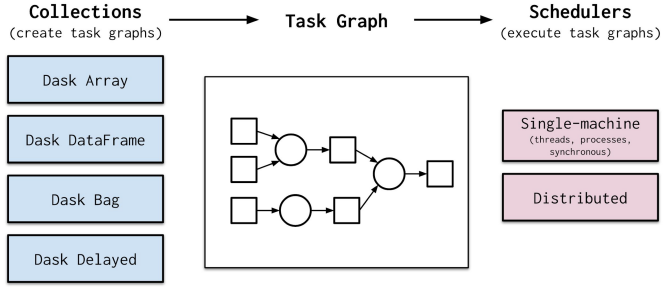
Analysis Facility @ T2 Nebraska

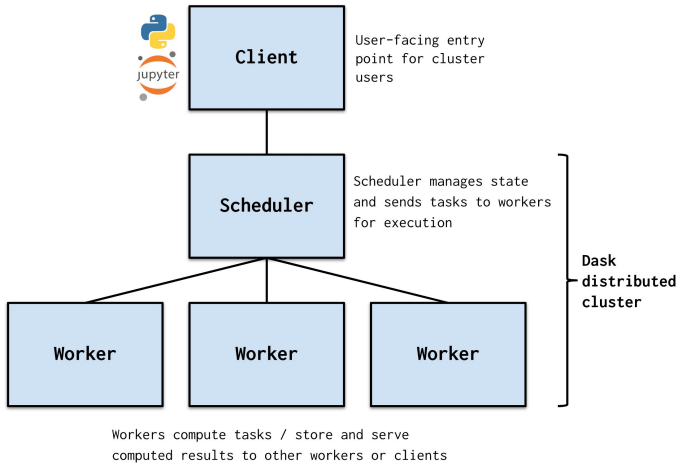


Analysis facilities: why we use Dask?

- Dask provides flexible library for parallel computing in Python
- Builds on top of the python ecosystem (e.g. Numpy, Pandas, Scikit-Learn and etc.)
- Dask exposes lower-level APIs letting to build custom systems for in-house applications (!)
- Integrates with HPC clusters, running a variety of schedulers including SLURM, LSF, SGE and *HTCondor via "dask-jobqueue"*
- ***This allows us to create a user-level interactive system via queueing up in the batch system***

Dask can be used inside Jupyter or you can simply launch it through Jupyter and connect directly from your laptop





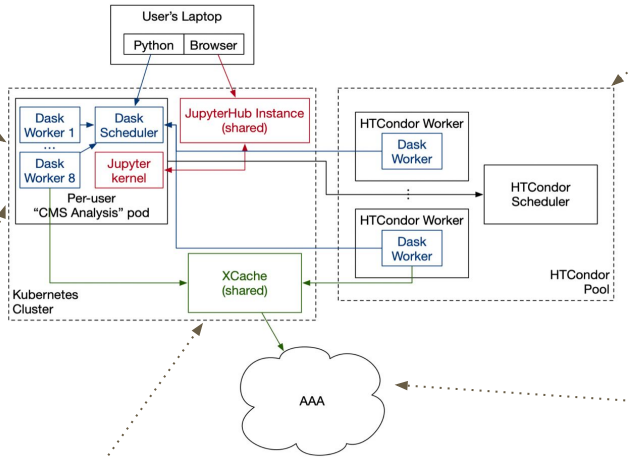
Current status of Analysis Facility @ T2 Nebraska

Enabled token authentication in HTCondor infrastructure

Security - TLS enabled communication between workers and scheduler

CoffeaCasaCluster: HTCondorCluster integration for Dask to allow auto-scaling out to the local HTCondor pool

We are using **a highly customized "CMS Analysis" container** with all the necessary dependencies



All of this is being *incorporated into a Helm chart* - many rough edges, but it will be portable to other sites

Pod customization hook to create secrets and services **-** pod can expose the Dask scheduler to the outside world and can authenticate with services like HTCondor and XRootD

Integration of XRootD - each pod's unique secret includes and **auto-generated macaroon *authorizing the pod to access files at the site XCache server***

Developed a custom XRootD client plugin enabling whenever the prefix *root://xcache/* is used, hostname is replaced with the correct one for the local site (using environment variables) and token authorization is automatically used & embedded in the URL

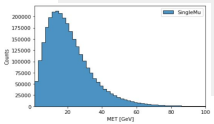
Analysis facilities: “ideal” workflow

Request data “over night” via data delivery service *(filter, add specific columns, optimise data layout for columnar analysis in AF)*

Request addition to existing NanoAOD *(request info from MiniAOD /correct existing branches)*

Analyse custom NanoAOD in AF (as well in a batch from AF)

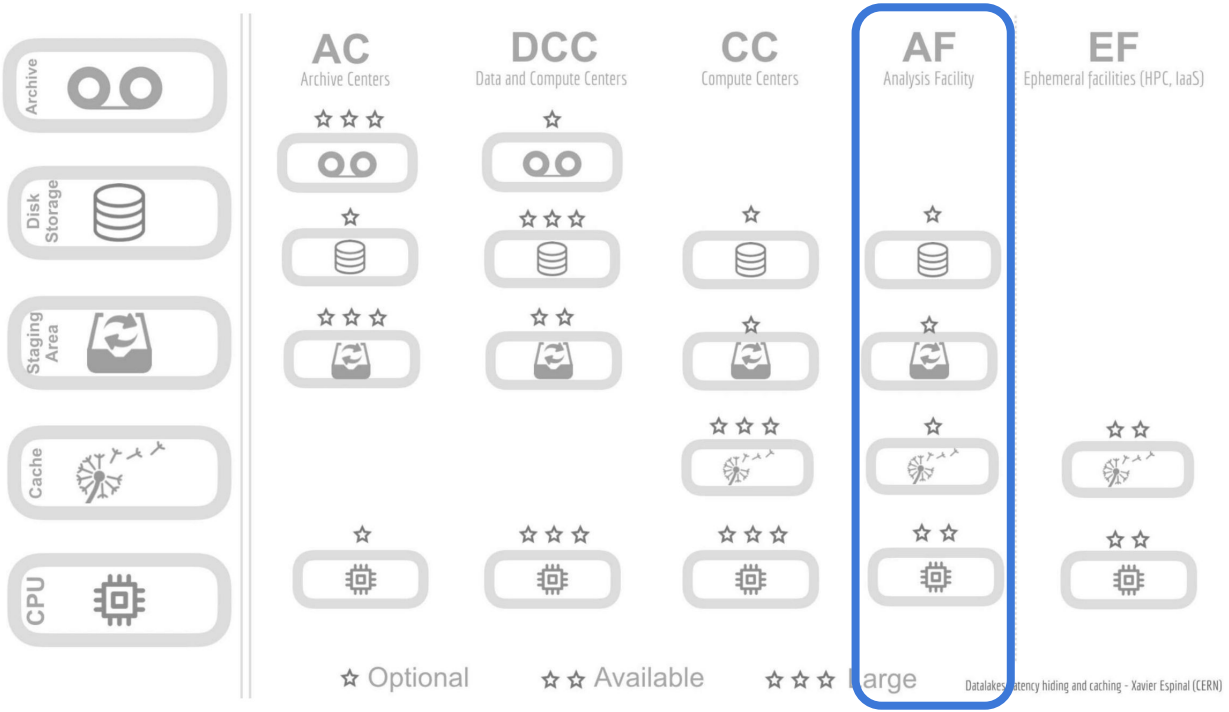
Get results on your laptop from AF



The AF should help to assist with 90% of analyses using NanoAOD by merging parts or derived from MiniAOD into Nano (automatically, without the intervention of the end-user)

Analysis facilities: Datalake's distribution model

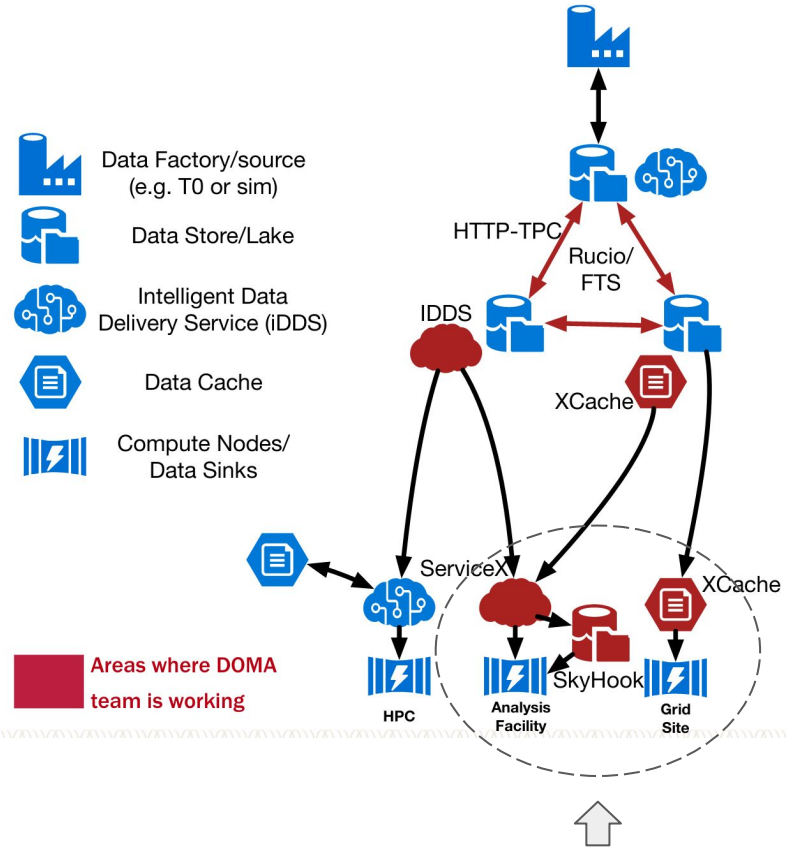
Datalake draft model: components



Analysis facilities: data lake data transfer

- For AF access to data from processing elements inside the lake is mediated either via *caches (implemented via XCache) or streaming directly from one of the data lake origins*

B.Bockelman, IRIS-HEP WLCG DOMA F2F

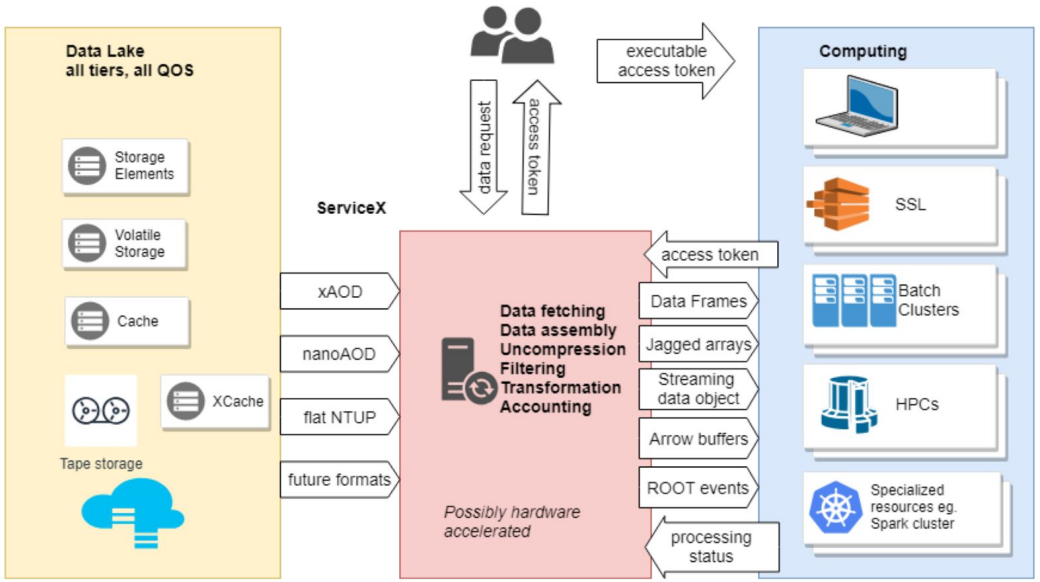


CMSAF @T2 Nebraska “Coffea-casa”
https://cmsaf-jh.unl.edu

Data delivery services: Service X

Testing deployment of **ServiceX@coffea-casa**

- **ServiceX provides user level ntuple production**
- Converts experiment-specific datasets to columns
- Extracts data from flat ROOT files
- Enable simple cuts or simple derived columns, as well as specified fields
  - Heavy-weight analysis will still happen via some separate processing toolchain (like CRAB)
- ServiceX already supports NanoAODs, and will also support MiniAOD extension to end-user “ntuples” derived from NanoAOD



IRIS-HEP Scalable System Laboratory https://iris-hep.org/ssl

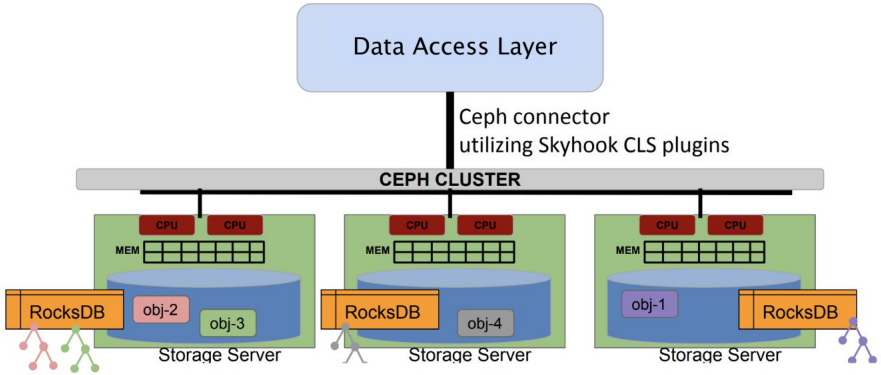
Data delivery services: Servicex + Skyhook

Next to be deployed **@coffea-casa**

iris hep

SkyhookDM

- The Skyhook DM project has shown the ability to ingest ROOT files (particularly, CMS NanoAOD) and convert event data to the internal object-store format
- Ceph-side C++ plugins transition from on-disk format to desired memory format
- **Uses Dask workers to distribute data to clients**
- **Data delivered as Arrow tables** and (optionally) presented as dataframes



B.Bockelman, IRIS-HEP WLCG DOMA F2F

CROSS, UCSC https://github.com/uccross

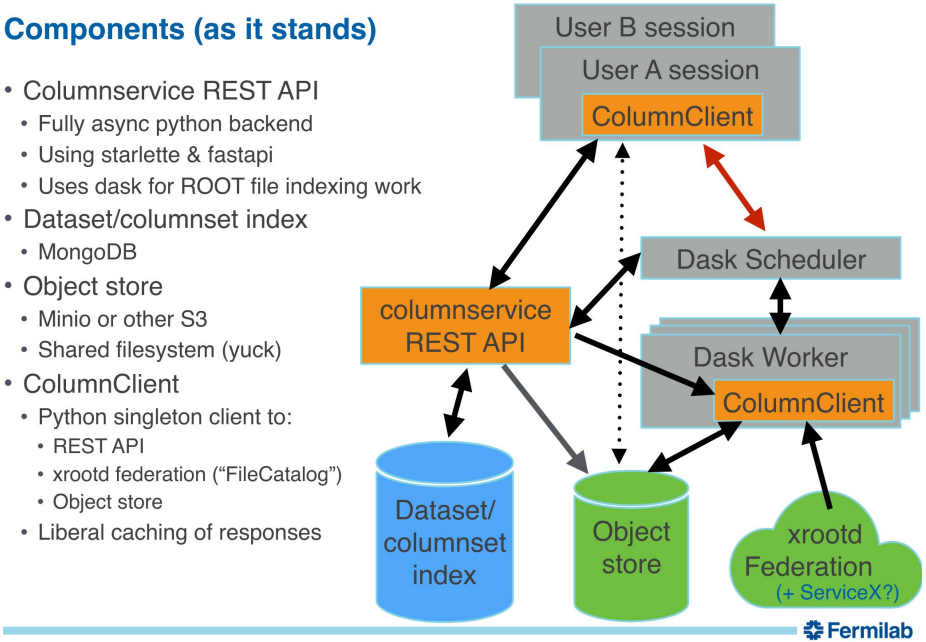
Data delivery services: columnservice

We are looking forward to test it**@coffea-casa**

- **Coffea Team has an idea to design a scale-up mechanism for coffea users** that removes the need to curate skims and re-run expensive algorithms over and over
  - Shared input cache at column granularity
  - Derived columns declared, only constructed and cached on access
  - Unified metadata and dataset schema database

Components (as it stands)

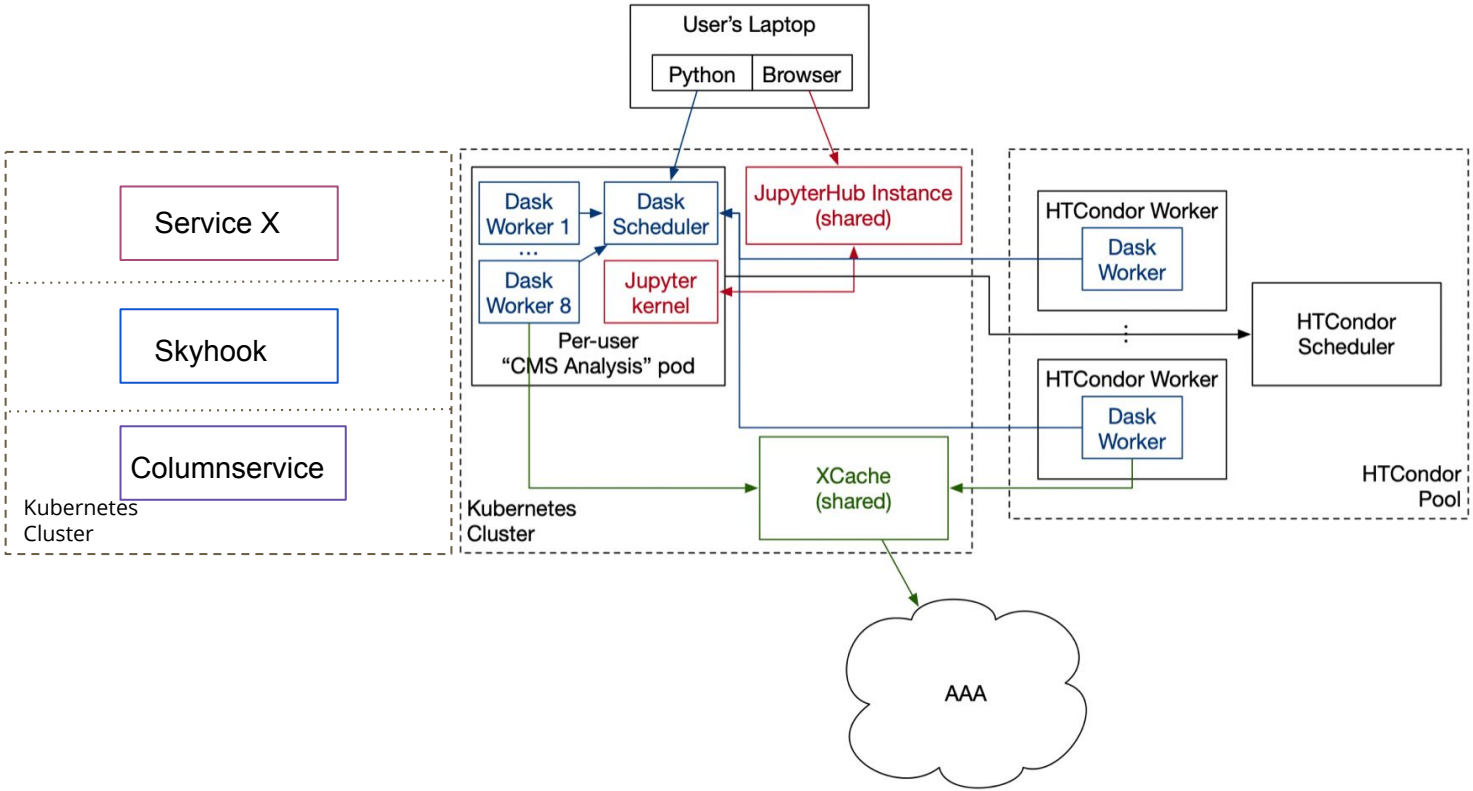
- Columnservice REST API
  - Fully async python backend
  - Using starlette & fastapi
  - Uses dask for ROOT file indexing work
- Dataset/columnset index
  - MongoDB
- Object store
  - Minio or other S3
  - Shared filesystem (yuck)
- ColumnClient
  - Python singleton client to:
    - REST API
    - xrootd federation (“FileCatalog”)
    - Object store
  - Liberal caching of responses



Nick Smith, “Coffea farm prototype”, Coffea Team meeting

Coffea Team https://github.com/CoffeaTeam/columnservice

Analysis Facility @ T2 Nebraska: next steps



Future items for UNL AF “coffea-casa”

We are looking for the volunteers (*other sites*) to try our developments!

- **Q4 2020 -** Invite first users to test “alpha” version of UNL AF (“coffea-casa”)
- **Q4 2020 -** Make “coffea-casa” products (Helm charts, modules) deployable in any other AF facility
    - Expected first test deployment of **FNAL AF** during 2021
- **Q4 2020 -** Finalize testing of ServiceX@UNL AF
- **Q1 2021 -** Deploy and test data delivery with Skyhook at UNL AF

Thank you for your attention!

Many thanks to the other teams (IRIS-HEP SSL, IRIS-HEP DOMA and Skyhook, Coffea Team) for materials

Backup slides

Analysis facilities: data analysis challenges

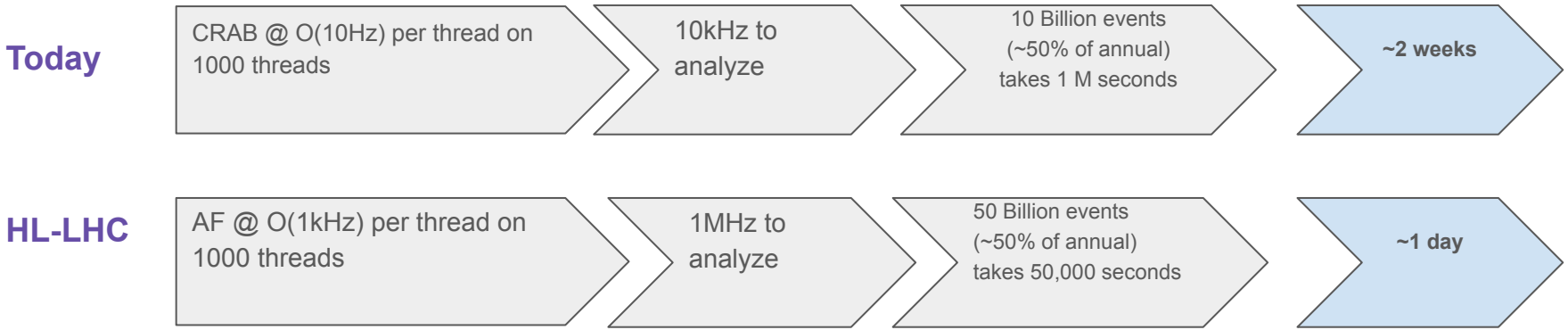
- Typical CMS analyses of MiniAOD in Run 2 reach rates **O(10)Hz**
- Columnar analysis of NanoAOD ~ **O(1kHz)** (both per hyperthread)

Analysis bottleneck in Run2 MiniAOD analyses is the creation of fast user ntuples

Expect 50% of analyses to use NanoAOD, most of the rest will use MiniAOD (from resource planning for HL-LHC)

The AF should help to assist with 90% of analyses using NanoAOD by merging parts or derived from MiniAOD into Nano (automatically, without the intervention of the end-user)

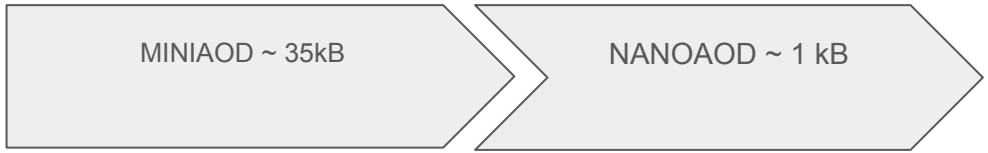
Analysis facilities: expected scaling



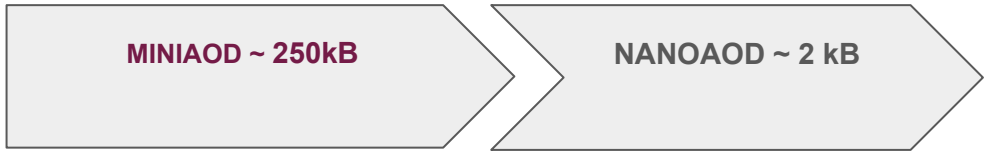
With the same resources, a much larger sample size can be supported for interactive analysis due to the inherent speed-ups in the technologies chosen

Analysis facilities: expected scaling

Today (event size)



HL-LHC (event size)



If we can transition to use of NANO as primary driver then data volumes should be manageable

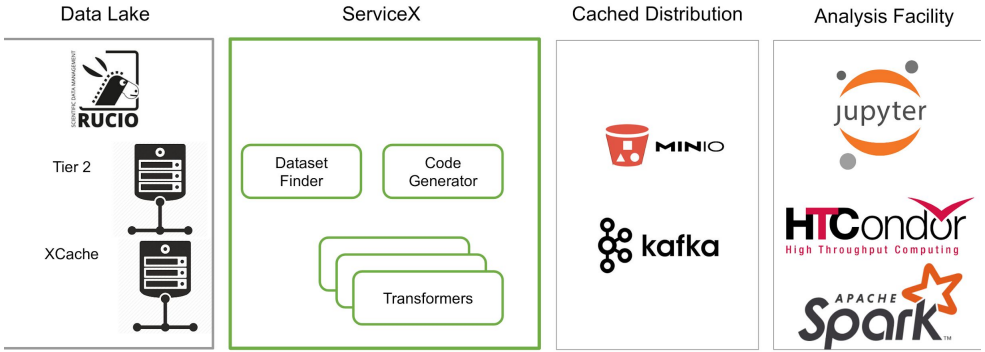
If we use a sample that is small enough to allow for interactive analysis in NANO (~ 50 Million events), it should be useable as driver for data delivery service to add objects from MINI overnight!

Analysis facilities: requirements

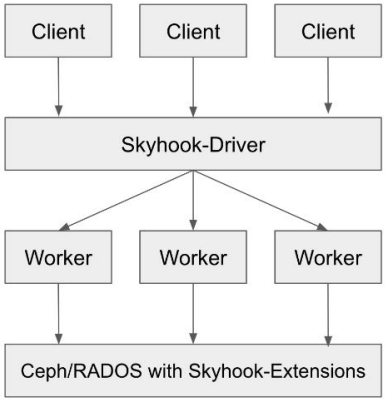
- **Interactivity:** AF needs to supports both interactive and batch mode
- **Low latency data access:** AF are expected to require low latency random access media to achieve best performance (via data access patterns)
  - Required as a part of uncertainties for WAN IO needs at Tier-2 centers hosting AF
  - A trade off investments in disk space in caching infrastructure against network bandwidth use
- **Reusability:** AF should support extraction of user defined data formats to migrate onto laptops, desktops, workstations at home institutions or at home
- **Easy Deployment:** AF services expected to be deployed with industry standard platforms like Kubernetes and etc. to facilitate easy deployment within a Tier-3s

Analysis facilities: object storages

- Column-based data delivery services such as *ServiceX, Coffea columnservice, or SkyHook* will require object stores such as Ceph or Minio to be provided by the facility



M. Weinberg, ServiceX: A columnar data delivery service for CMS



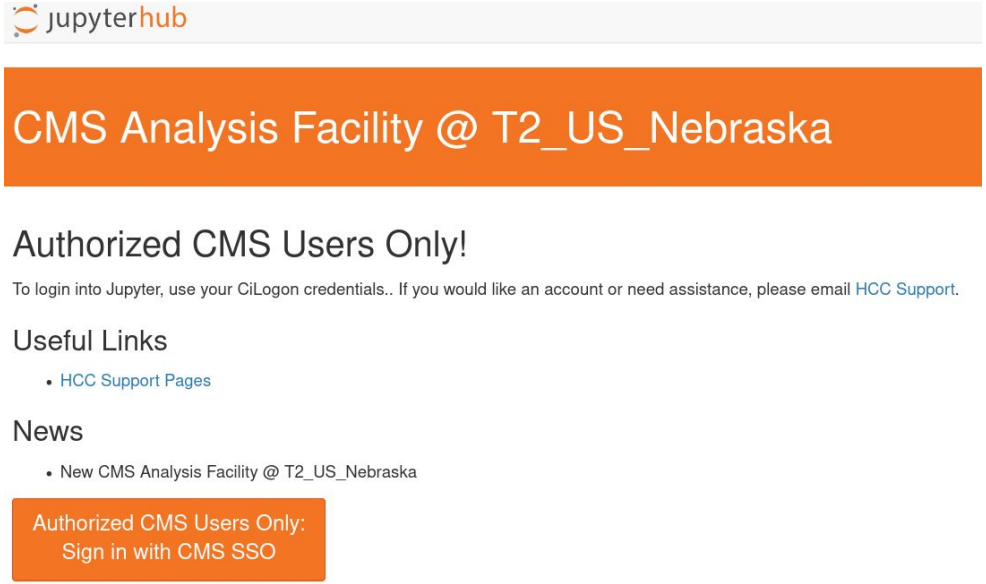
Arxiv 2007.01789

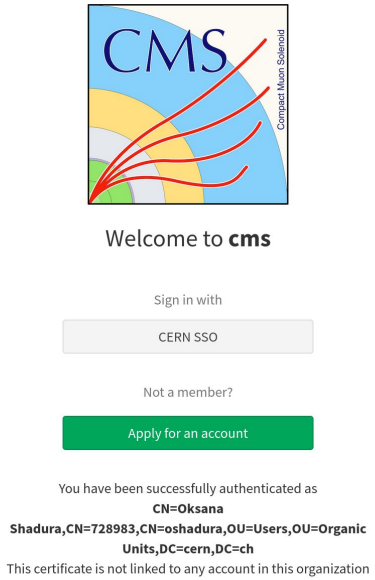
CMSAF @ UNL Setup

- JH setup: https://github.com/CoffeaTeam/jhub (except specific secrets)
- Docker images for Dask Scheduler and Worker: https://github.com/CoffeaTeam/coffea-casa
  - https://hub.docker.com/r/coffeateam/coffea-casa
  - https://hub.docker.com/r/coffeateam/coffea-casa-analysis
- Docker image for JupyterHub (to get macaroons in the launch env) https://github.com/clundst/jhubDocker
- Tutorials: https://github.com/CoffeaTeam/coffea-casa-tutorials

JupyterHub + JupyterLab + Dask setup @ UNL

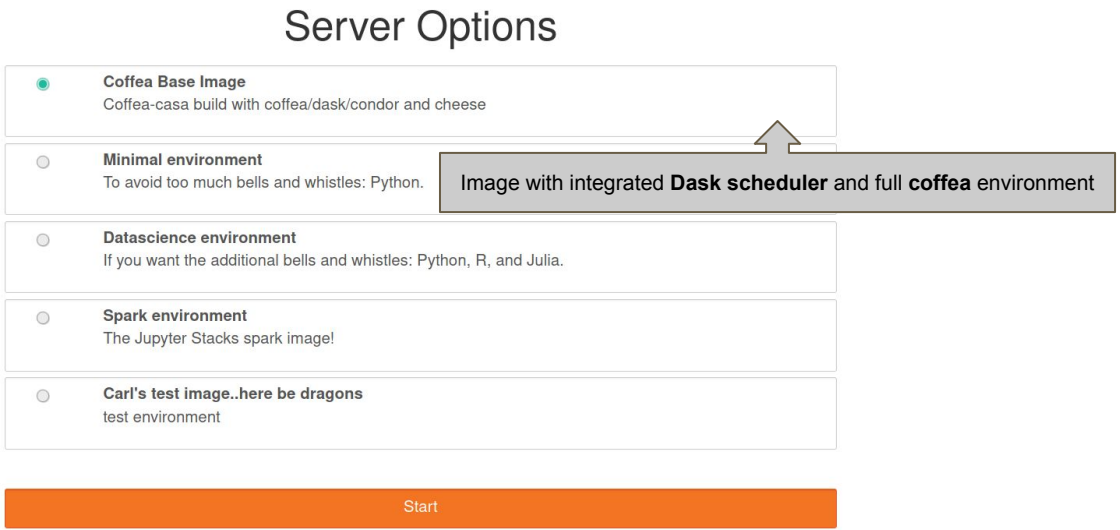
- JH is launched using Helm charts (together with users secrets)





CMSAF @ UNL Setup: Internals

- Docker image starting JupyterLab is integrated with HTCondor Dask Scheduler communicating with T3
  - Powered by Dask Labextention, which is integrated in the Docker image



CMSAF @ UNL Analysis: Demo

[1]:
```
import os
os.environ["OMP_NUM_THREADS"] = "1"
import numpy as np
%matplotlib inline
from coffea import hist
from coffea.analysis_objects import JaggedCandidateArray
import coffea.processor as processor
```

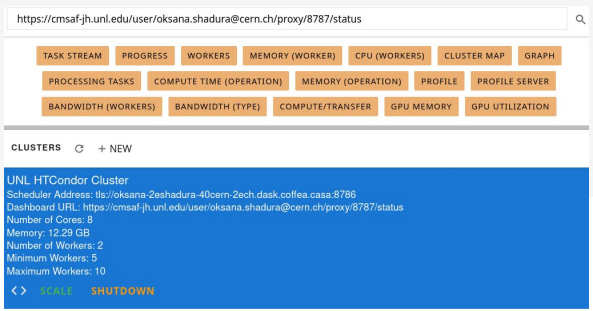
[2]:
```
# This program plots an event-level variable (in this case, MET, but switching it is as easy as a dict-key change). It also demonstrates an easy use of the book-keeping cutflow tool, to keep track of the number of events processed.

# The processor class bundles our data analysis together while giving us some helpful tools.  It also leaves looping and chunks to the framework instead of us.
class Processor(processor.ProcessorABC):
    def __init__(self):
        # Bins and categories for the histogram are defined here. For format, see https://coffeateam.github.io/coffea/stubs/coffea.hist.hist_tools.Hist.html && https://coffeateam.github.io/coffea/stubs/coffea.hist.hist_tools.Bin.html
        dataset_axis = hist.Cat("dataset", "")
        MET_axis = hist.Bin("MET", "MET [GeV]", 50, 0, 100)

        # The accumulator keeps our data chunks together for histogramming. It also gives us cutflow, which can be used to keep track of data.
        self._accumulator = processor.dict_accumulator({
            'MET': hist.Hist("Counts", dataset_axis, MET_axis),
            'cutflow': processor.defaultdict_accumulator(int)
        })

    @property
    def accumulator(self):
        return self._accumulator

    def process(self, events):
        output = self.accumulator.identity()

        # This is where we do our actual analysis. The dataset has columns similar to the TTree's; events.columns can tell you them, or events.[object].columns for deeper depth.
        dataset = events.metadata["dataset"]
        MET = events.MET.pt

        # We can define a new key for cutflow (in this case 'all events'). Then we can put values into it. We need += because it's per-chunk (demonstrated belo
        output['cutflow']['all events'] += MET.size
        output['cutflow']['number of chunks'] += 1

        # This fills our histogram once our data is collected. The hist key ('MET=') will be defined in the bin in __init__.
        output['MET'].fill(dataset=dataset, MET=MET.flatten())
        return output

    def postprocess(self, accumulator):
        return accumulator
```

[3]:
```
fileset = {'SingleMu' : ["root://eospublic.cern.ch//eos/root-eos/benchmark/Run2012B_SingleMu.root"]}

from dask.distributed import Client
from coffea_casa import CoffeaCasaCluster

from dask.distributed import Client

client = Client("tls://oksana-2eshadura-40cern-2ech.dask.coffea.casa:8786")

output = processor.run_uproot_job(fileset=fileset,
                        treename="Events",
                        processor_instance=Processor(),
                        executor=processor.dask_executor,
                        executor_args={'client': client, 'nano': True},
                        chunksize=250000)
```

```
[########################################] | 100% Completed |  1min 20.9s
```

Starting client and scheduler

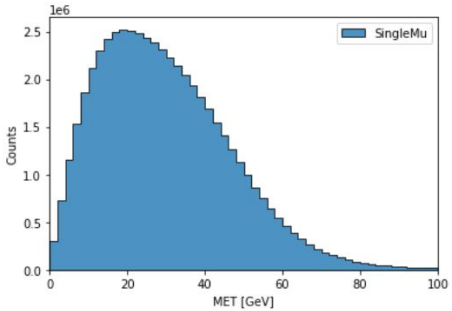
Custom method *CoffeaCasaCluster hidden in Dask Labextention* (on top of dask_jobqueue.HTCondorCluster) to deploy Dask on common HTCondor job queue with possibility to specify Dask worker image and other parameters)



CMSAF @ UNL Analysis: Demo

[4]:
```
# Generates a 1D histogram from the data output to the 'MET' key. fill_opts are optional, to fill the graph (default is a line).
hist.plot1d(output['MET'], overlay='dataset', fill_opts={'edgecolor': (0,0,0,0.3), 'alpha': 0.8})
```

[4]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd945413b50>
```



[5]:
```
# Easy way to print all cutflow dict values. Can just do print(output['cutflow']["KEY_NAME"]) for one.
for key, value in output['cutflow'].items():
    print(key, value)
```

```
all events 53446198
number of chunks 214
```

CMSAF @ UNL Analysis: Demo