Distributed Analysis in Production with RDataFrame

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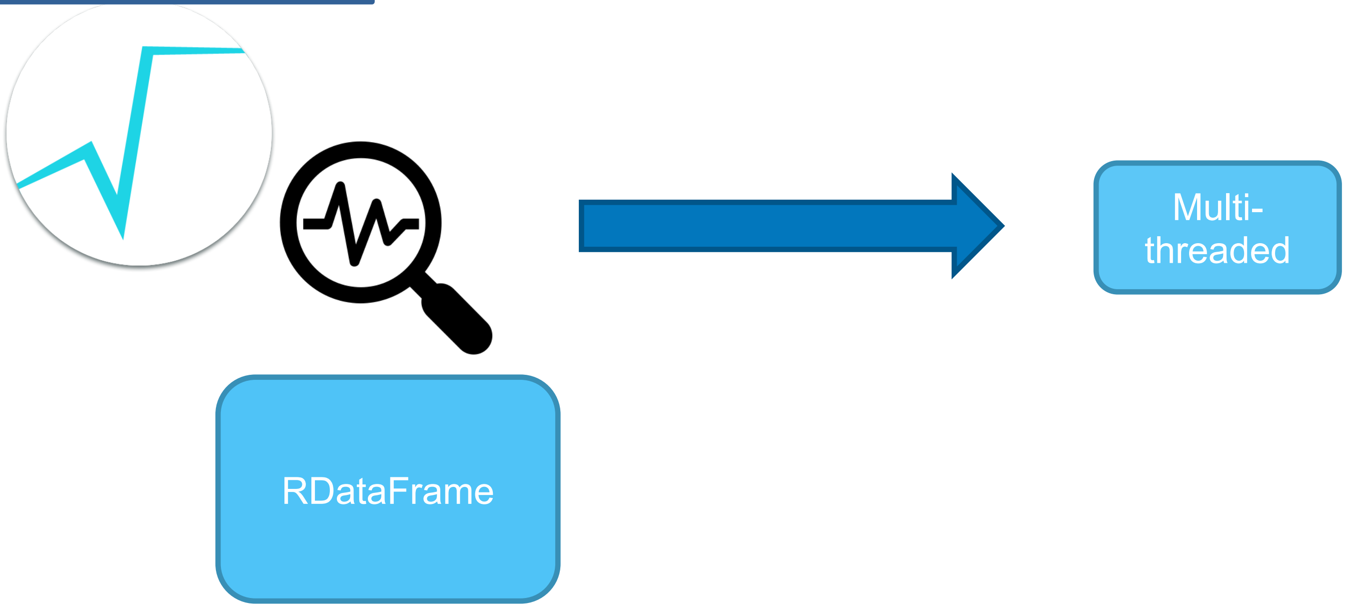
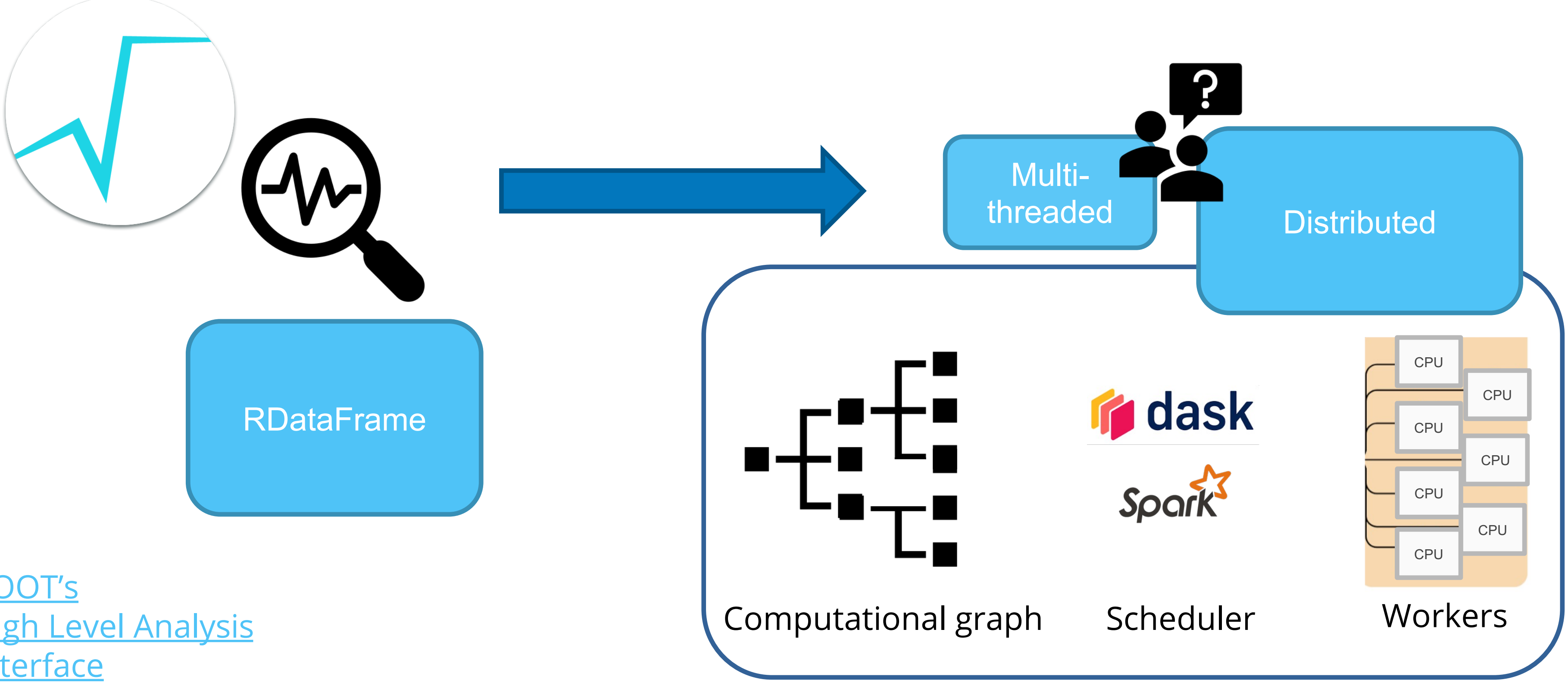
Introduction

Since ROOT 6.14 (2018)



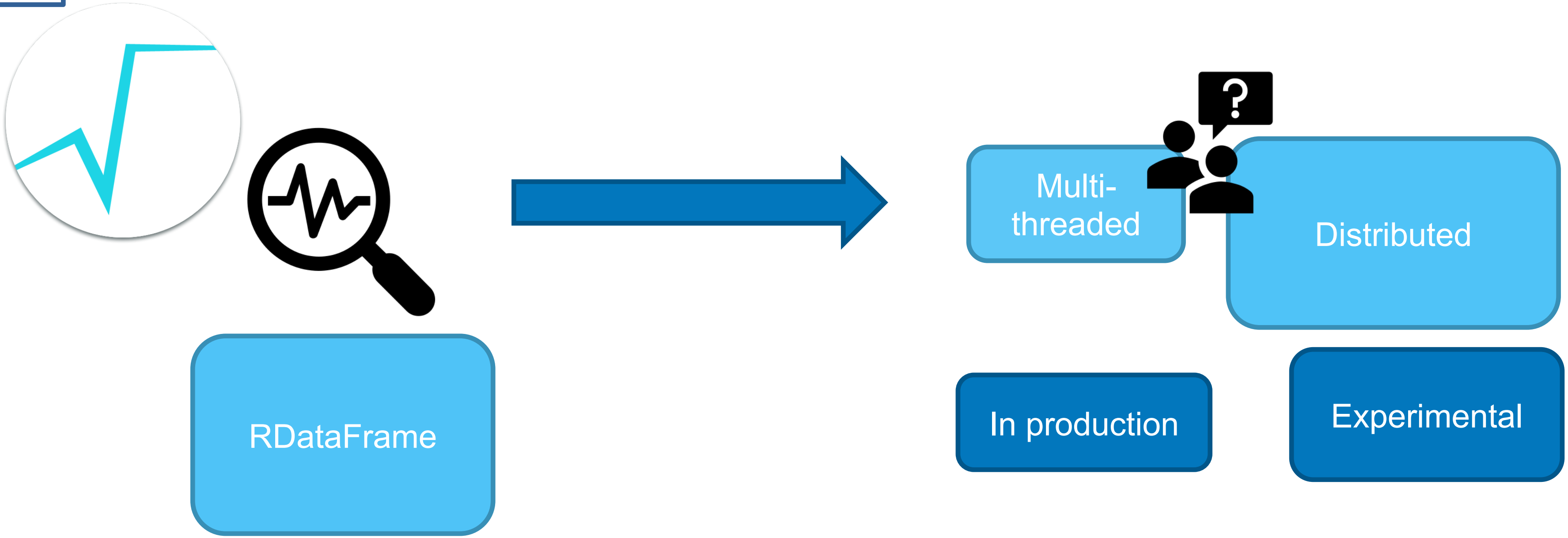
[ROOT's
High Level Analysis
Interface]

Since ROOT 6.24 (2021)



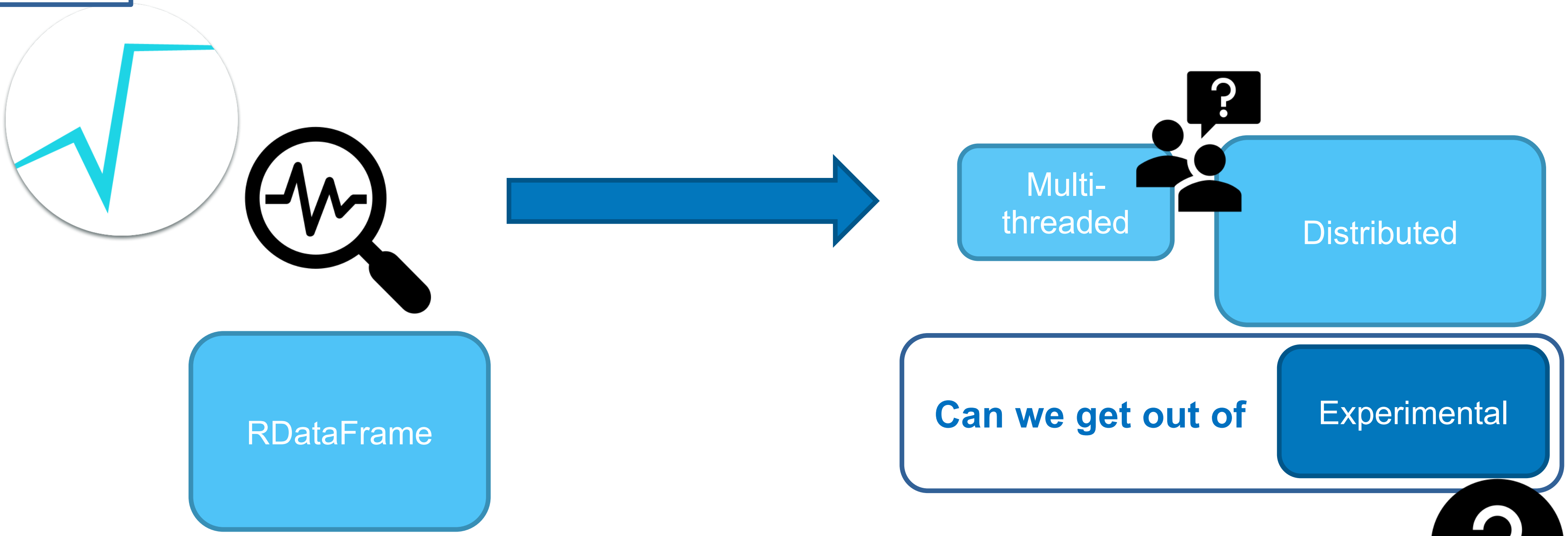
[ROOT's
High Level Analysis
Interface]

Today



[ROOT's
High Level Analysis
Interface]

Tomorrow



- What is the **user interface** like?
- Which **data input sources** are supported?
- What about the **Pythonisations**?
- Does DistRDF perform well with various **Analysis Facilities**?

[ROOT's High Level Analysis Interface]

Code Stability

User Interface

Multi-threaded, non-distributed RDF

```python
ROOT.EnableImplicitMT()

RDataFrame = ROOT.RDataFrame

df = RDataFrame(treeName, fileName)
```

Distributed RDF

dask

```python
RDataFrame = ROOT.RDF.Experimental.Distributed.Dask.RDataFrame

df = RDataFrame(treeName, fileName, daskclient=daskclient)
```

Spark

```python
RDataFrame = ROOT.RDF.Experimental.Distributed.Spark.RDataFrame

df = RDataFrame(treeName, fileName, sparkcontext=sparkcontext)
```

Continue with Analysis – no code differences

```python
myAnalysis = df.Define(...).Filter(...).Histo1D(...)
```

dask Spark

Feature parity between MT RDF and DistRDF conserved where applicable

- Recently added a few new RDF query functions, for example:

```python
GetColumnNames(), GetColumnType("columnName")
```

User Interface – Constructor Unification

Multi-threaded, non-distributed RDF

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Spark

```python
RDataFrame = ROOT.RDF.Experimental.Distributed.Spark.RDataFrame

df = RDataFrame(treeName, fileName, sparkcontext=sparkcontext)
```

Unify the three RDataFrame constructors based on the 3rd input argument specifying the executor

```python
RDataFrame = ROOT.RDataFrame(treeName, fileName, executor=SupportedExector)
```

executor=
- None → Multi-threaded, non-distributed RDF
- daskclient → dask
- sparkcontext → Spark

User Interface – Functional Unification

Some functional calls for Distributed and MT versions differed

```python
if type(df).__module__ == "DistRDF.DataFrame":
    variationsfor_func = ROOT.RDF.Experimental.Distributed.VariationsFor
else:
    variationsfor_func = ROOT.RDF.Experimental.VariationsFor
```

Now → unified version for both cases

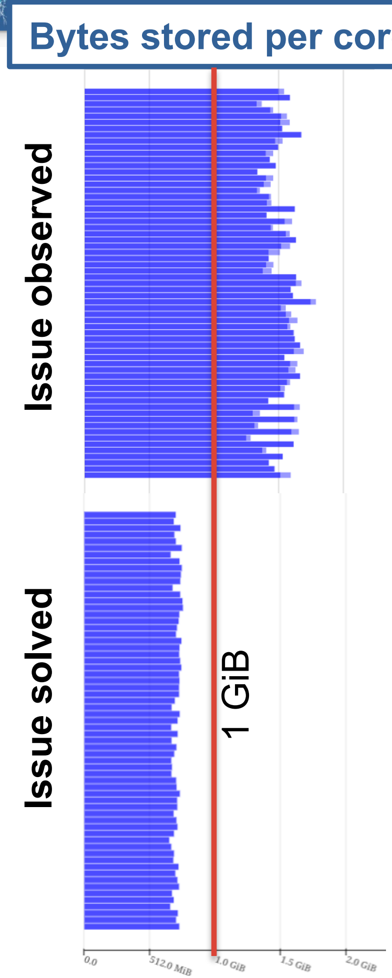
```python
ROOT.RDF.Experimental.VariationsFor
```

Also:

```python
ROOT.RDF.RunGraphs
```

True **zero code change** for the user between MT and distributed RDF

Memory Usage



Issue observed: in some computationally heavy workflows, memory of the HTCondor Workers was increased to the level that the application was unusable

```
Worker tcp://127.0.0.1:36501 (pid=11453) exceeded 95% memory budget. Restarting...
Worker tcp://127.0.0.1:44505 (pid=11521) exceeded 95% memory budget. Restarting...
Worker tcp://127.0.0.1:38437 (pid=11474) exceeded 95% memory budget. Restarting...
Worker tcp://127.0.0.1:34547 (pid=11497) exceeded 95% memory budget. Restarting...
```

Issue solved: artifacts of the cached computation graphs on distributed workers are now better managed

New Features

User Interface – C++ Code Inclusion

- Distributed RDF is fully Pythonic
- What if I have some C++ **functions in a header file?**

dask

Before

```python
def load_header():
    """Load C++ helper functions. Works for both local and distributed execution."""
    try:
        # when using distributed RDataFrame 'my_header.h' is copied to the
        # local_directory of every worker (via `distribute_unique_paths`)
        localdir = get_worker().local_directory
        cpp_header = Path(localdir) / "my_header.h"
    except ValueError:
        # include the local execution as well
        cpp_header = "my_header.h"

    ROOT.gInterpreter.Declare(f'#include "{str(cpp_header)}"')


ROOT.RDF.Experimental.Distributed.initialize(load_header)
```

dask Spark

Now

```python
ROOT.Distributed.DistributeHeaders("my_header.h")
```

User Interface – C++ Code Inclusion

- What if I **I want to declare some C++ code?**

dask Spark

```
ROOT.Distributed.DeclareCppCode("""
        bool check_number_less_than_five(int num){
            return num < 5;
        }
        """)

df = ROOT.RDataFrame(treeName, fileName, executor=SupportedExecutor)
df_filtered = df.Filter("check_number_less_than_five(rdfentry_)")
```

- What if I **I want to use shared libraries?**

dask Spark

```
ROOT.Distributed.DistributeHeaders("my_header.h")
ROOT.Distributed.DistributeSharedLibs("lib_my_header.so")
```

Input Data Sources

- Before ROOT 6.32: TTree or empty data source
- In 6.32: Introduction of **RNTuple** – see [ACAT 2024]() talk
- New addition: **RDatasetSpec**

```
meta = ROOT.RDF.Experimental.RMetaData()
meta.Add("meta_key", "meta_value")
```

```
mySample = ROOT.RDF.Experimental.RSample("mySampleName", treeName, fileName, meta)

spec = ROOT.RDF.Experimental.RDatasetSpec()
spec.AddSample(mySample)

df = ROOT.RDataFrame(spec, executor=daskclient)
```

- **In progress:** implement [FromSpec]() functionality for DistRDF
  - Create an RDataFrame from a JSON specification file

```
df = ROOT.RDF.Experimental.FromSpec("my_spec.json", executor=daskclient)
```

Use of Pythonisations

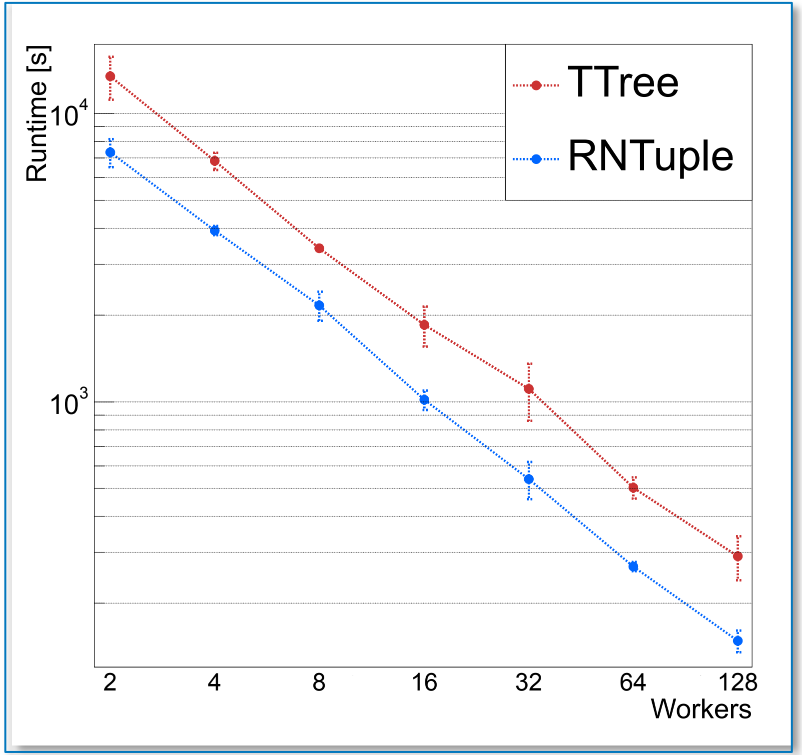
- More Pythonic ROOT → distributed RDF analysis much easier
- For example, **background estimation using Boosted Decision Trees (BDT)** in Analysis Grand Challenge → pre-trained XGBoost model files
  - How to easily use those in RDF?
  - **Before**: external C++ class needed
  - **Now**: easily save XGBoost models into ROOT files and use those further with TMVA's RBDT, see ROOT AGC repository for more details

```
from xgboost import XGBClassifier

myBdt = XGBClassifier()
myBdt.load_model(f"myModel.json")
ROOT.TMVA.Experimental.SaveXGBoost(myBdt, "myBdt", "myModel.root", num_inputs=num_inputs)
```

Analysis Facilities

- AGC with the BDT inference
- **Leverage all mentioned improvements of distributed RDF**



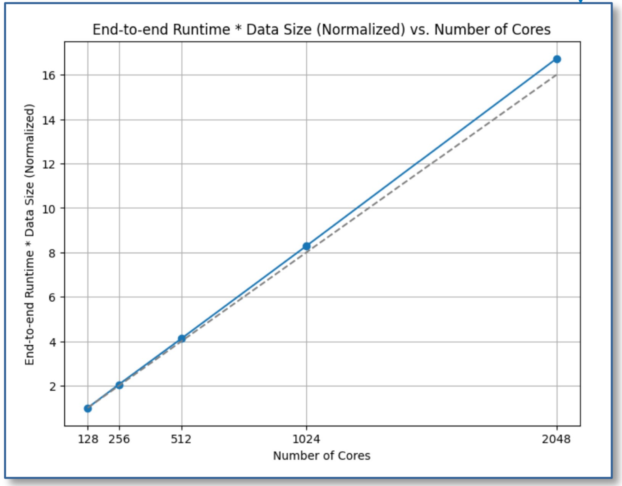
More details in this talk

- Ideal scaling for both
- RNTuple: **1.5 – 2x** faster than TTree → with zero code change for the user

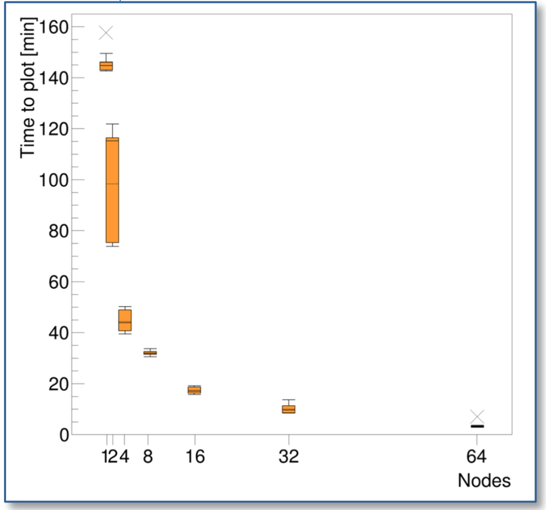
Other Analysis Facilities

Over the years

Jülich HPC, CERN HPC, also check: AWS, INFN



Boulis J.

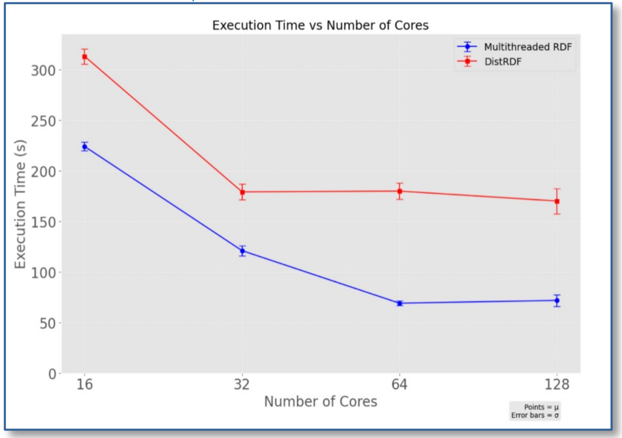


Padulano V.E. et al.

Performed many different benchmarks on various AFs

Recently

LUMI HPC, also check: ALPS HPC



Mehrabi A.

More results at: plenary talk on RNTuple

Next Steps and Conclusion

Next Steps

- **Optimize RNTuple processing** post first RNTuple production release
- Generalize **RDatasetSpec** to accommodate complex workflows

Inputs and collaboration suggestions from users
(e.g. testing DistRDF in your AF)
are always very welcome!

Conclusion

Can we get out of Experimental **?**

- User interface: **stabilised** and **unified**, with **easy inclusion of C++ code**
- Data input sources include **TTree, RNTuple** and **RDatasetSpec**
- The more **Pythonisations** in ROOT, the better the distributed RDF
- Distributed RDF is performant in many different **Analysis Facilities**

Conclusion

Can we get out of Experimental **?**

YES!

Watch out for the next ROOT releases