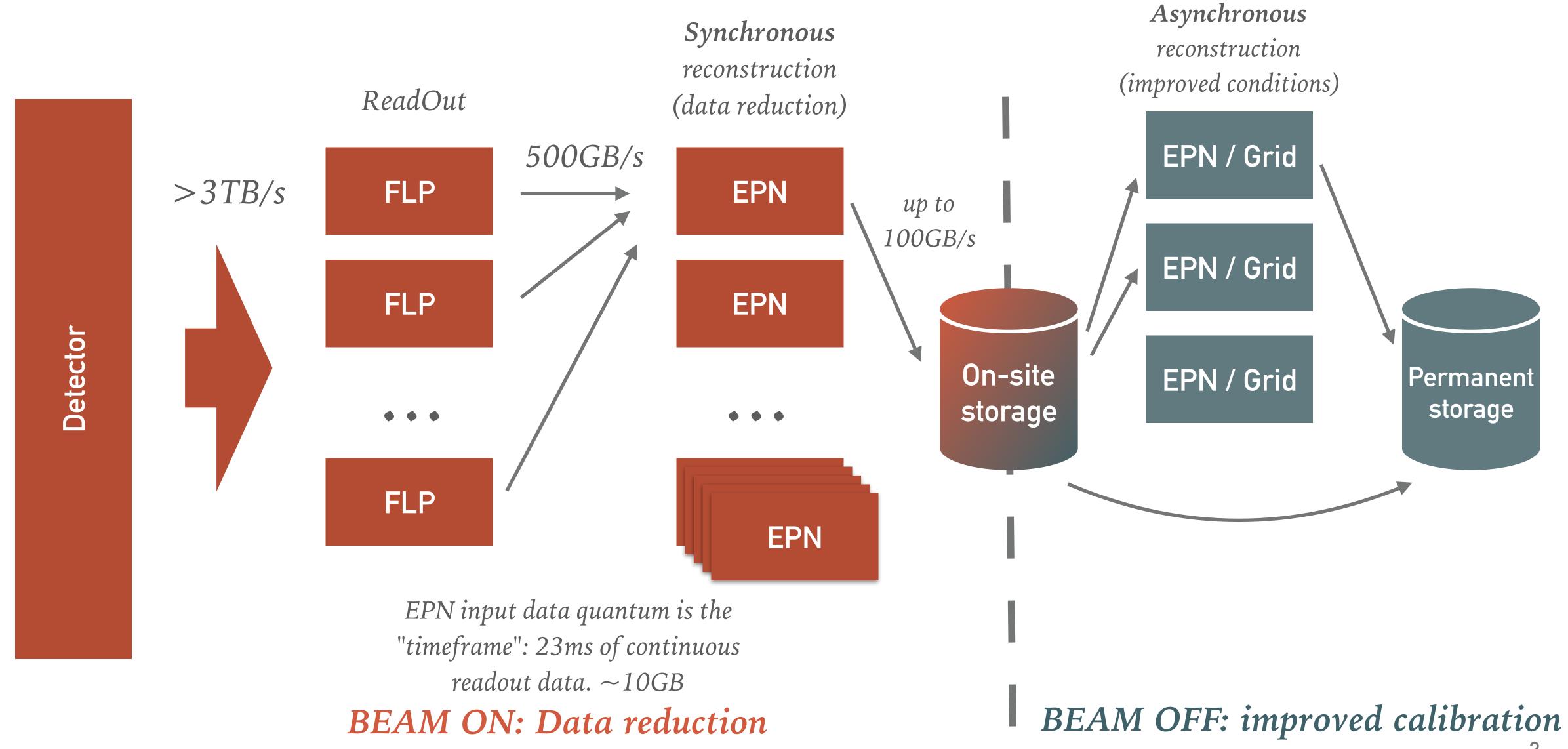
# Evolution of the ALICE Software Framework for LHC Run 3



Giulio Eulisse (CERN), for the ALICE Collaboration

# **ALICE IN RUN 3: POINT2**



#### ALICE 02 SOFTWARE FRAMEWORK IN ONE SLIDE

Transport Layer: ALFA / FairMQ1

- ➤ Standalone processes for deployment flexibility.
- ➤ Message passing as a parallelism paradigm.
- ➤ **Shared memory** *backend for reduced memory usage and improved performance.*

#### ALICE 02 SOFTWARE FRAMEWORK IN ONE SLIDE

Data Layer: 02 Data Model

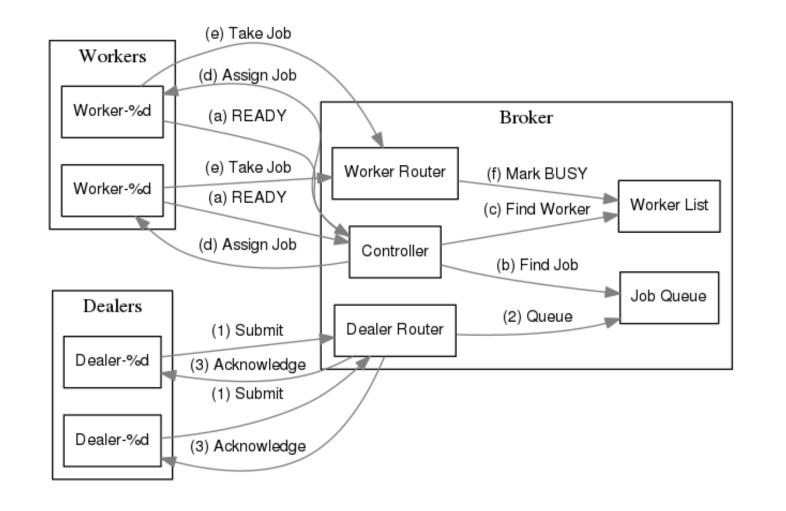
Message passing aware data model. Support for multiple backends:

- ➤ **Simplified, zero-copy** format optimised for performance and direct GPU usage. Useful e.g. for TPC reconstruction on the GPU.
- ➤ ROOT based serialisation. *Useful for QA and final results.*
- ➤ Apache Arrow based. Useful as backend of the analysis ntuples and for integration with with other tools.

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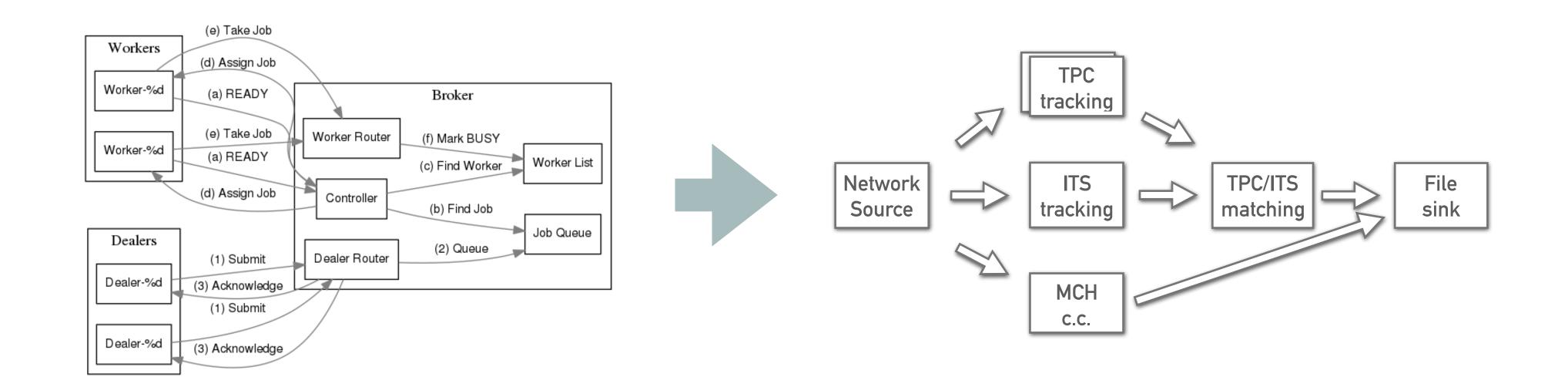
# DISTRIBUTED SYSTEMS ARE HARD



There are only two hard problems in distributed systems:

- 2. Exactly-once delivery
- 1. Guaranteed order of messages
- 2. Exactly-once delivery

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Since too many people did not get the joke, we started thinking how to simplify this for the user, as a result we decided to build a data flow engine (pipelines!) on top of our distributed system backend.

### ALICE 02 SOFTWARE FRAMEWORK IN ONE SLIDE

**Data Processing Layer** 

Data Layer: 02 Data Model

Transport Layer: FairMQ

Abstracts away the hiccups of a distributed system, presenting the user a familiar "Data Flow" system.

- ➤ Reactive-like design (push data, don't pull)
- $\triangleright$  **Declarative DSL** for topology configuration (C++17 based).
- ➤ *Integration* with the rest of the production system, e.g. Monitoring, Logging, Control.
- ➤ Laptop mode, including graphical debugging tools.

Message passing aware data model. Support for multiple backends:

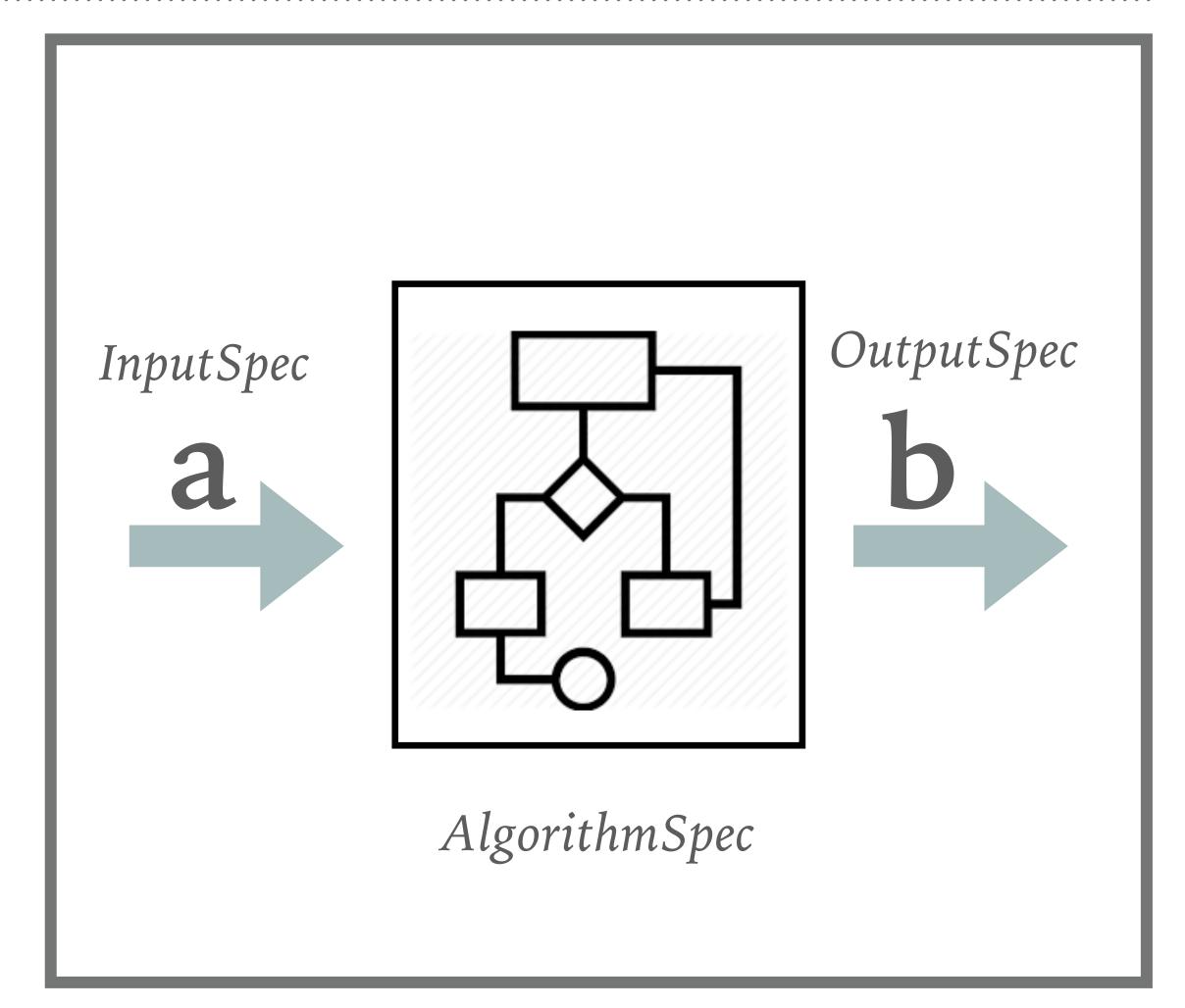
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- ➤ Message passing as a parallelism paradigm.
- > Shared memory backend for reduced memory usage and improved performance.

### DATA PROCESSING LAYER: BUILDING BLOCK

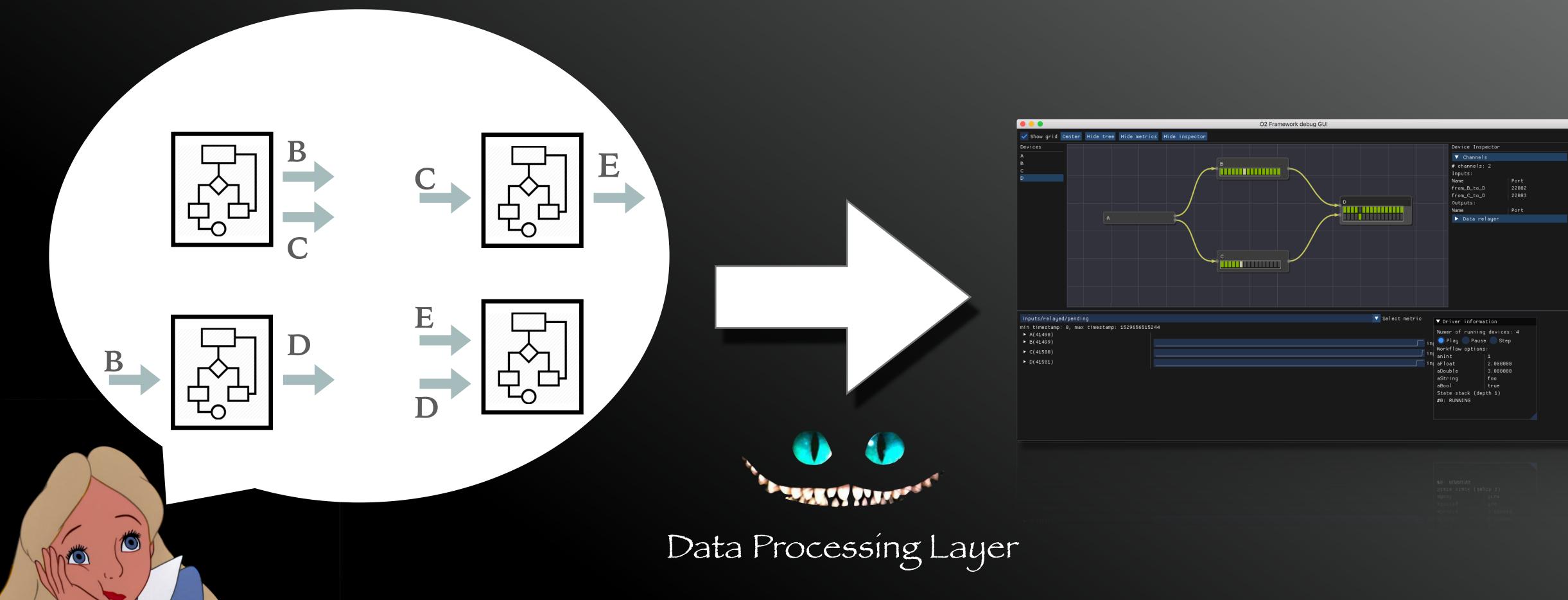
A DataProcessorSpec defines a pipeline stage as a building block.

- > Specifies inputs and outputs in terms of the O2 Data Model descriptors.
- ➤ Provide an implementation of how to act on the inputs to produce the output.
- Advanced user can express possible data or time parallelism opportunities.



DataProcessorSpec

# DATA PROCESSING LAYER: IMPLICIT TOPOLOGY

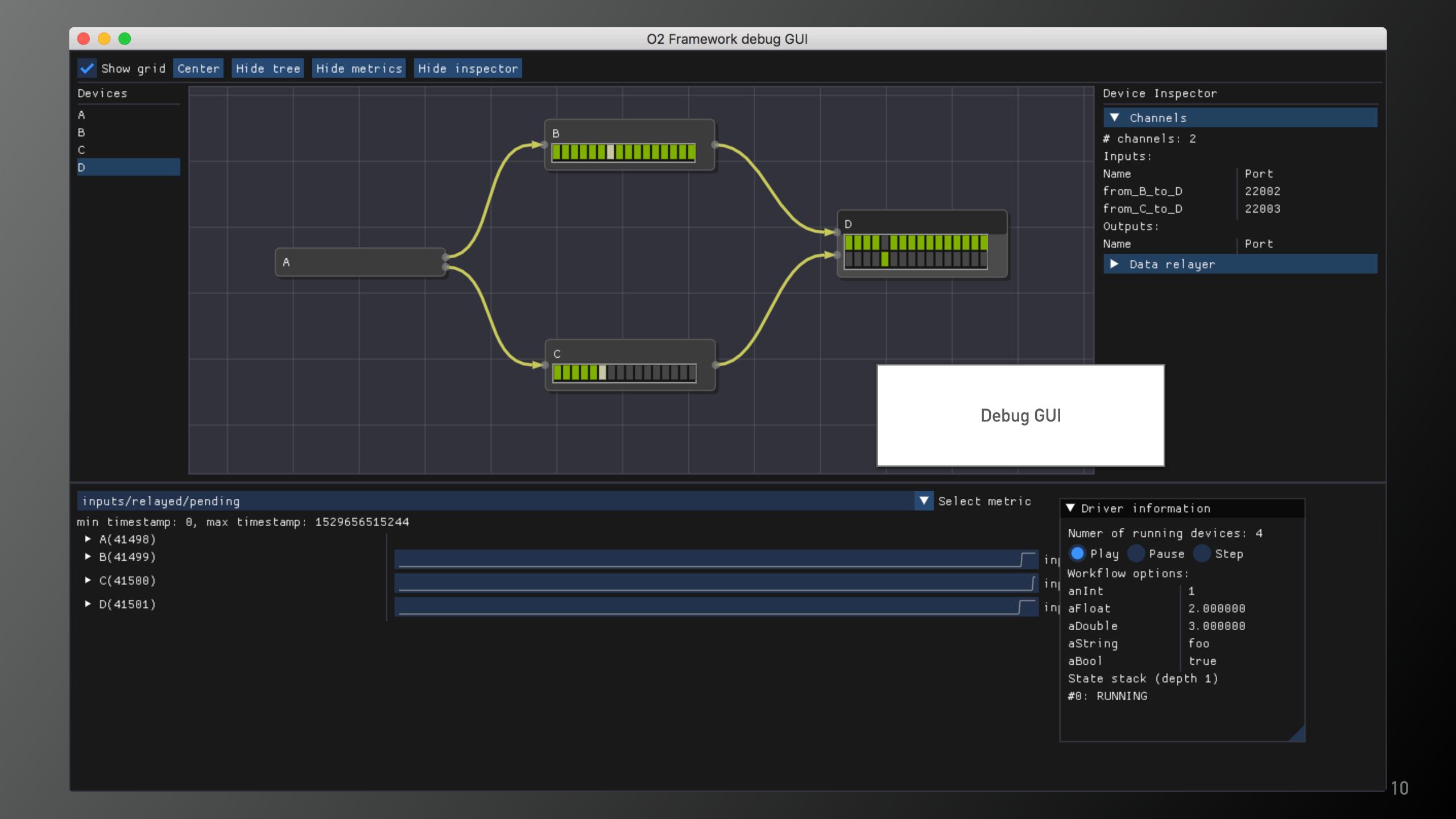


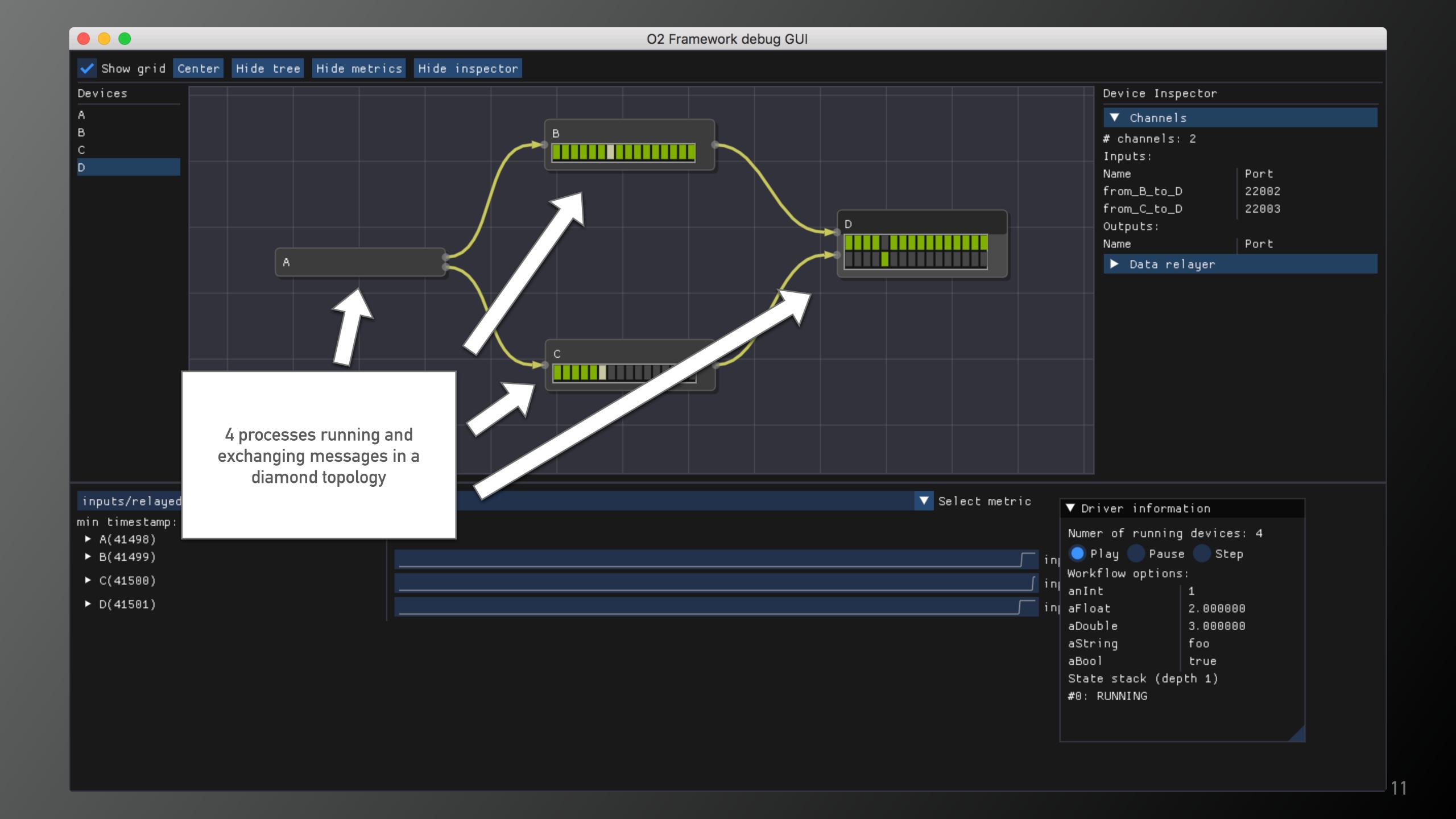
Topology is defined implicitly.

Topological sort ensures a viable dataflow is constructed (no cycles!).

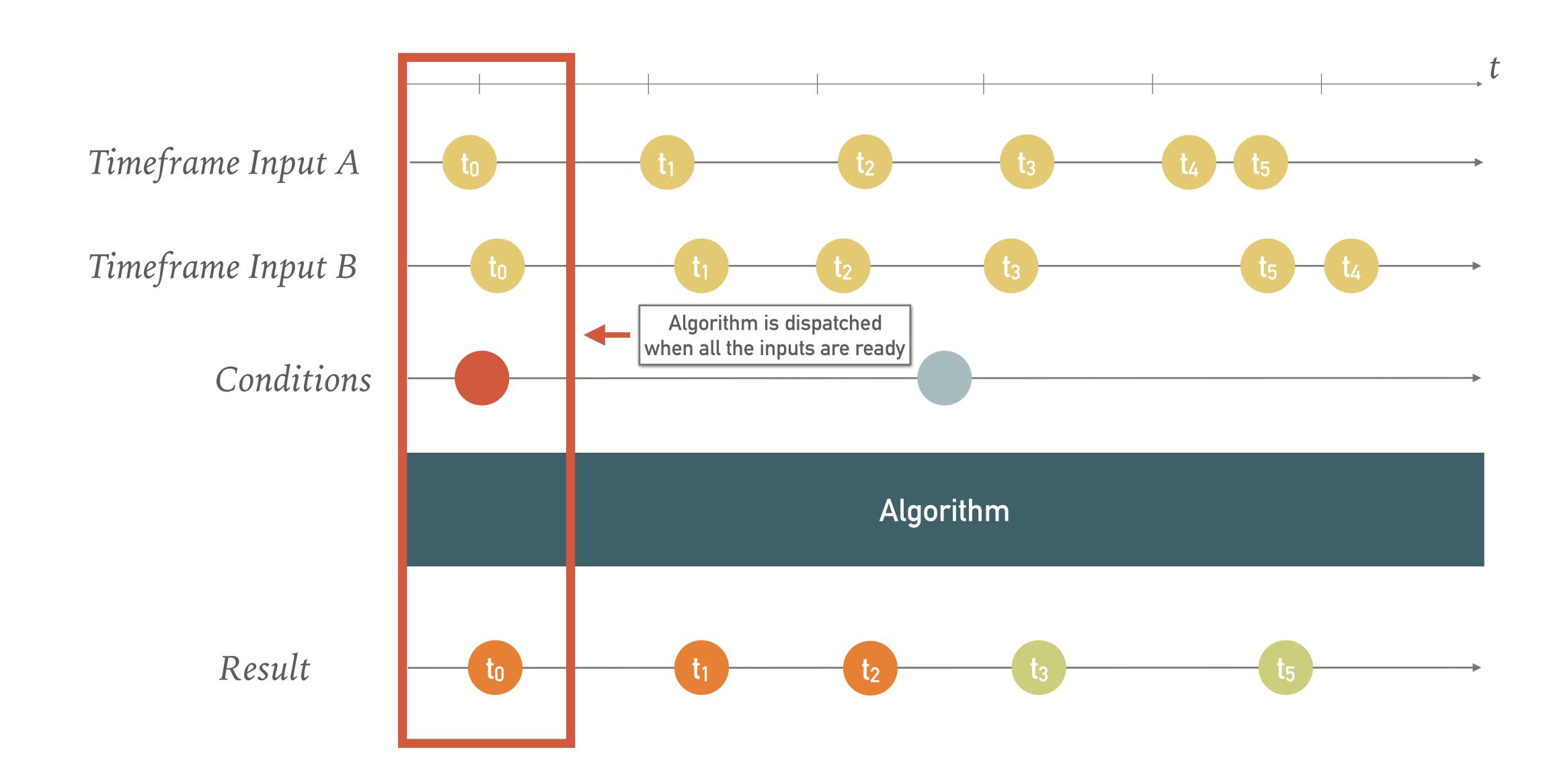
Laptop users gets immediate feedback through the debug GUI.

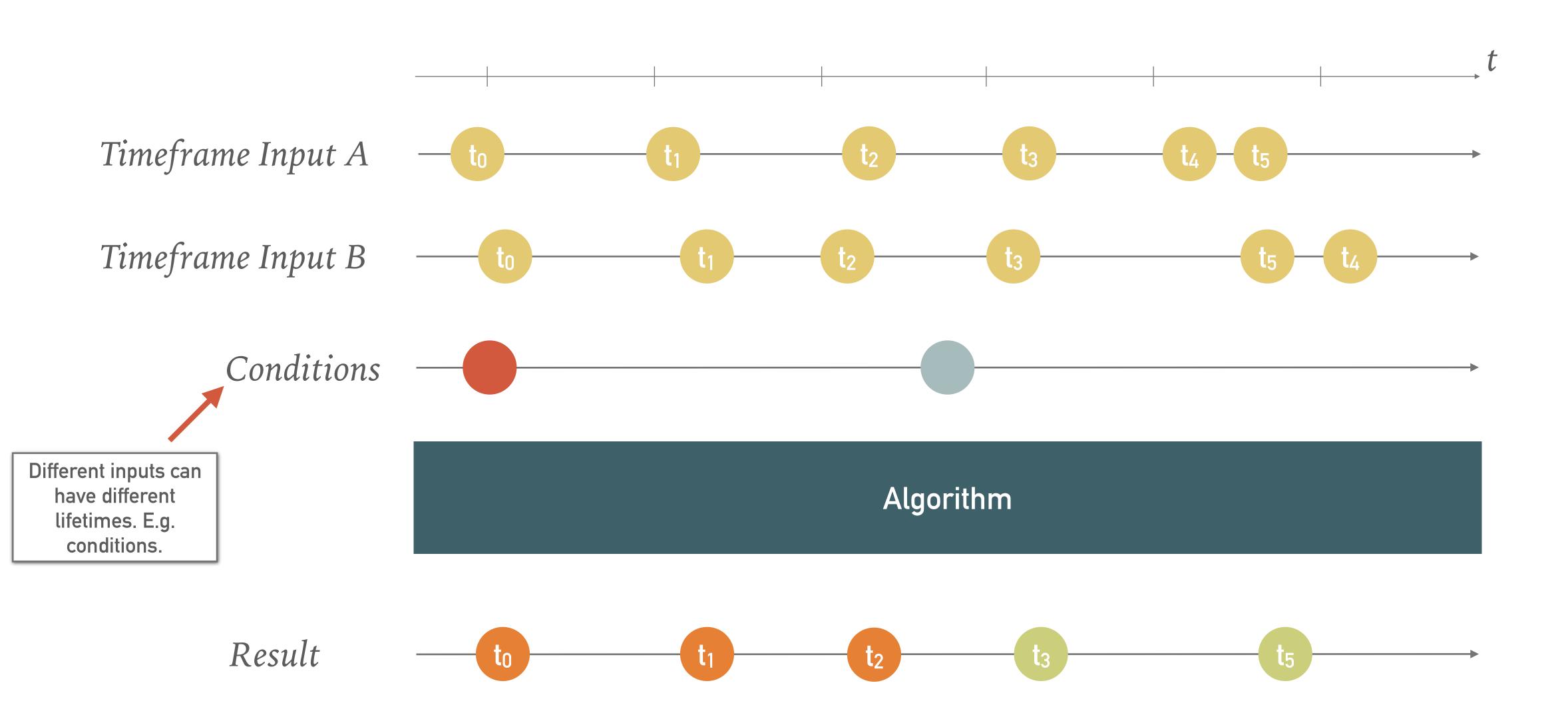
Service API allows integration with non data flow components (e.g. Control)

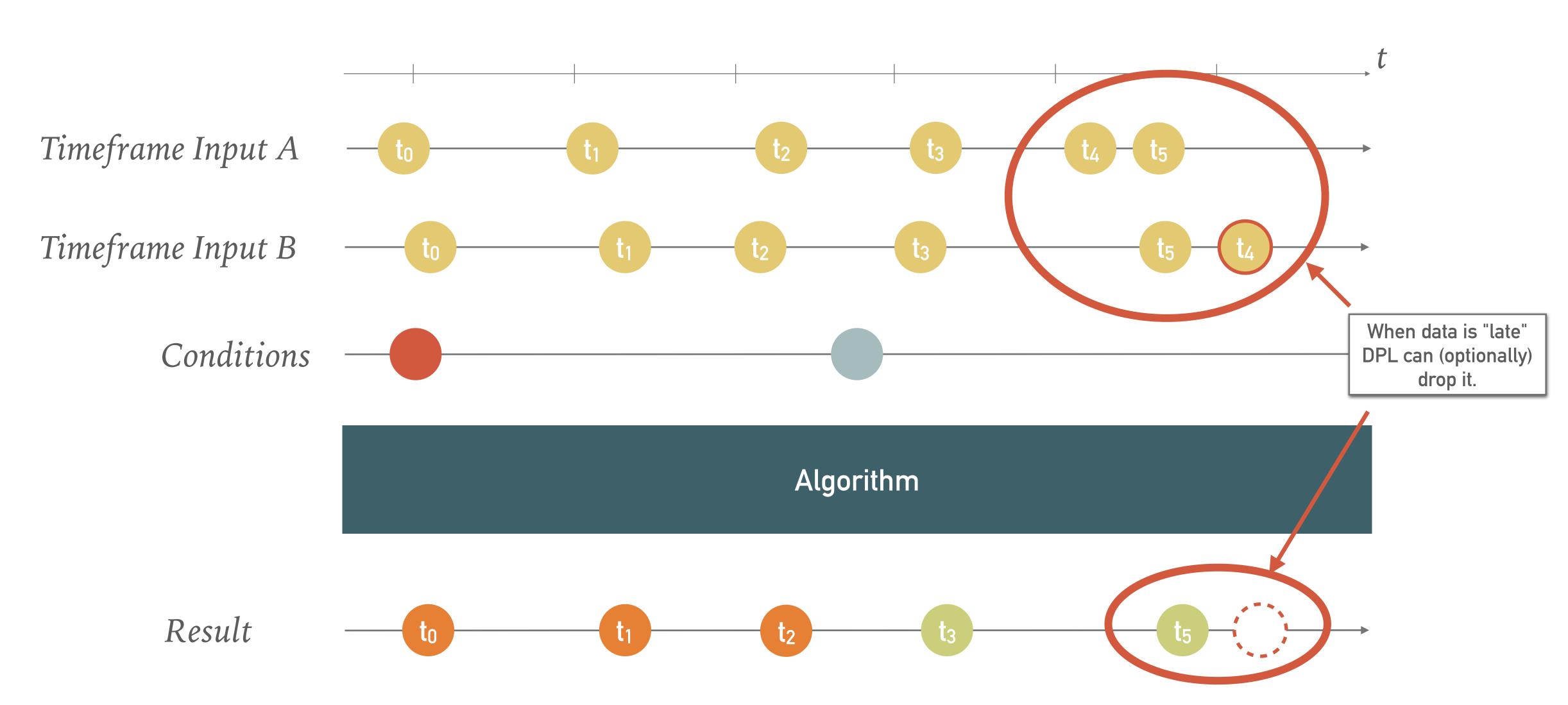


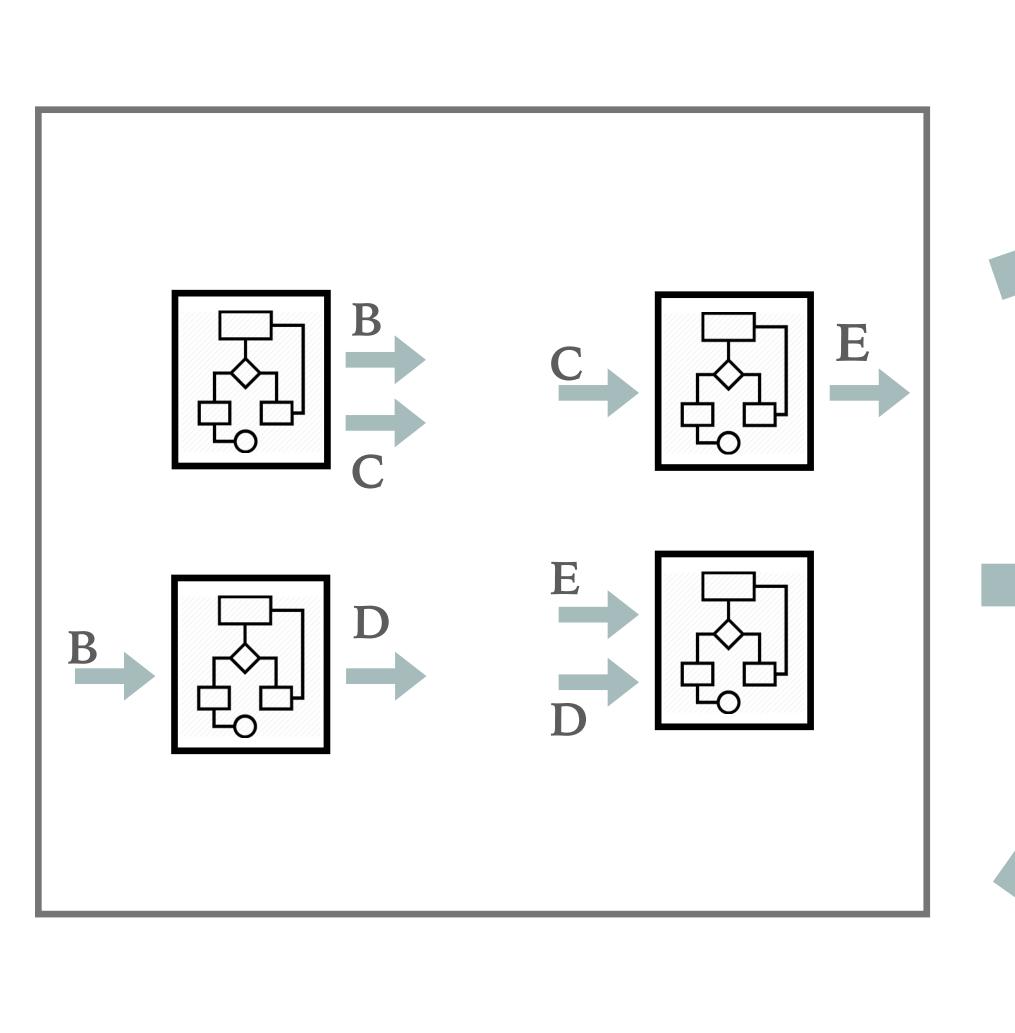


Data is described as pushed through the pipeline. Timeframe Input A Timeframe Input B Conditions Algorithm Result



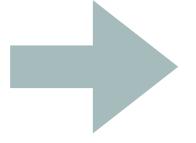






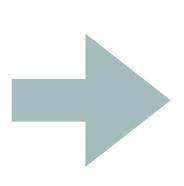
Compiles into a single executable for the laptop user















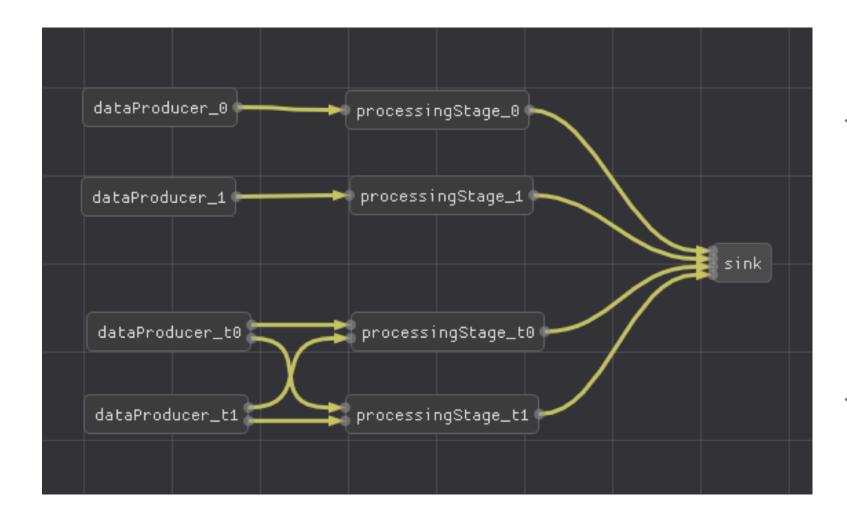
Integration with O2 Control system ongoing.\*

```
| #include "Framework/runDataProcessing.h"
                                                                          The previous example (GUI
 3 using namespace o2::framework;
                                                                                included) requires
 5 AlgorithmSpec simplePipe(std::string const &what) {
                                                                                 27 user's SLOC.
    return AlgorithmSpec{ [what](ProcessingContext& ctx) {
      auto bData = ctx.outputs().make<int>(OutputRef{what}, 1);
10
11 WorkflowSpec defineDataProcessing(ConfigContext const&specs) {
     return WorkflowSpec{
    { "A", Inputs{}, {OutputSpec{{"a1"}, "TST", "A1"}, OutputSpec{{"a2"}, "TST", "A2"}},
14
      AlgorithmSpec{
        [](ProcessingContext &ctx) {
16
         auto aData = ctx.outputs().make<int>(OutputRef{ "a1" }, 1);
         auto bData = ctx.outputs().make<int>(OutputRef{ "a2" }, 1);
18
19
20
      "B", {InputSpec{"x", "TST", "A1"}}, {OutputSpec{{"b1"}, "TST", "B1"}}, simplePipe("b1")},
     [ "C", {InputSpec{"x", "TST", "A2"}}, {OutputSpec{{"c1"}, "TST", "C1"}}, simplePipe("c1")},
22
      "D", {InputSpec{"b", "TST", "B1"}, InputSpec{"c", "TST", "C1"}}, Outputs{},
      AlgorithmSpec{[](ProcessingContext &ctx) {}}
24
2526
```

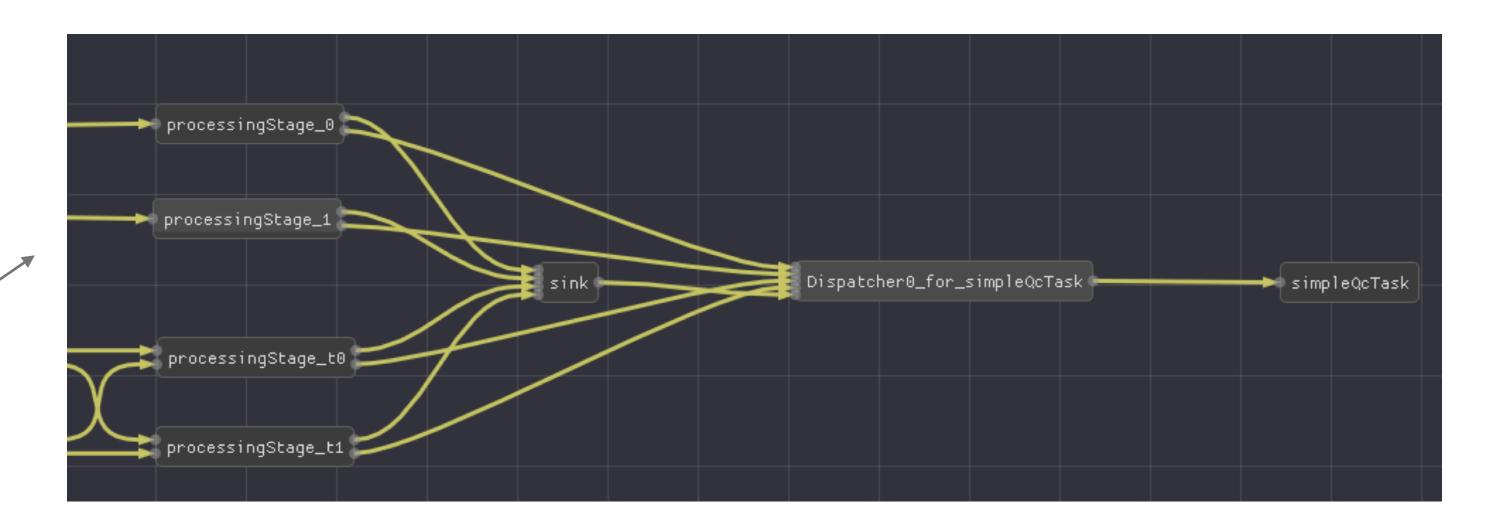
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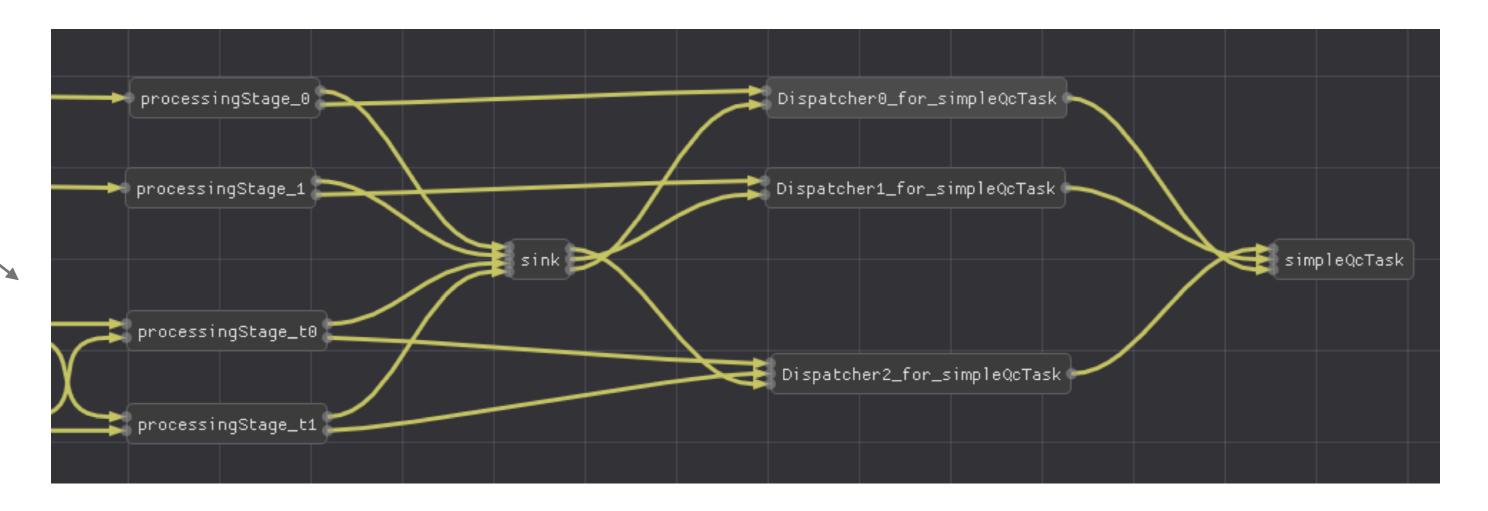
# A FEW EXAMPLES

# COMPOSABLE WORKFLOWS

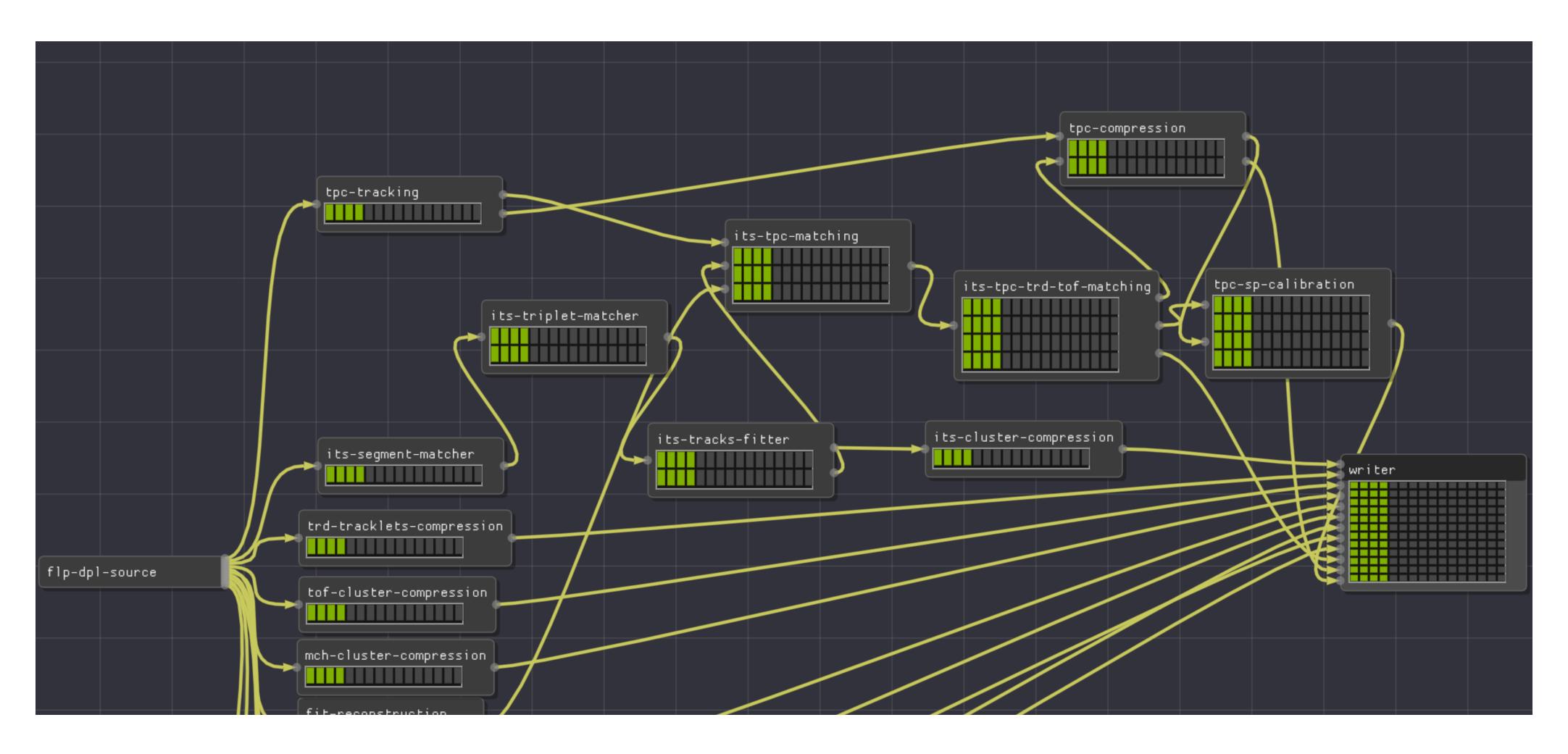


Declarative configuration allows for easy customisation: e.g. adding a (one or more) dispatchers for QA.



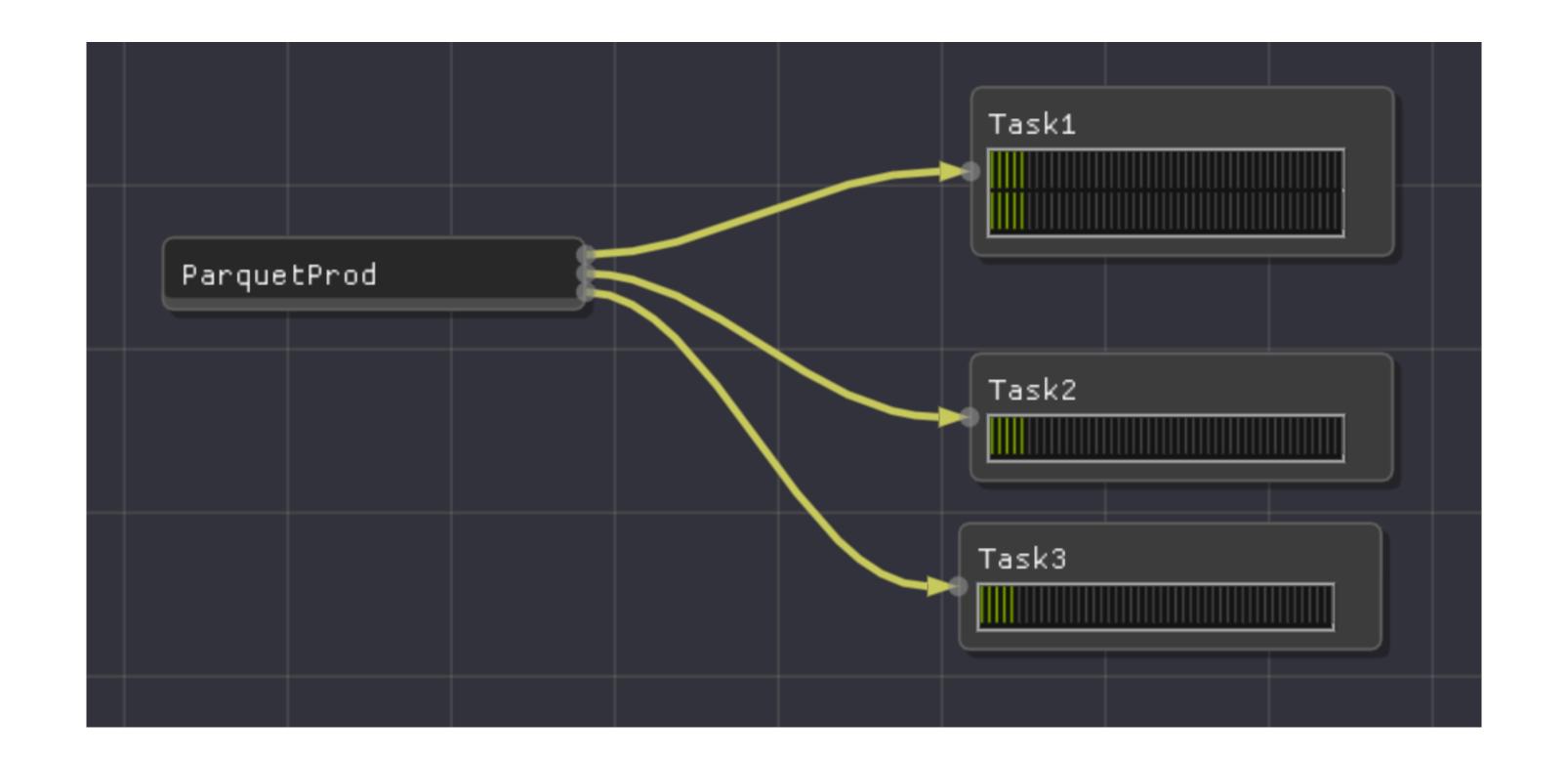


# RECONSTRUCTION & GENERAL DATAFLOW



# DPL AND ANALYSIS

We are investigating about using the Data Processing Layer also for Analysis.



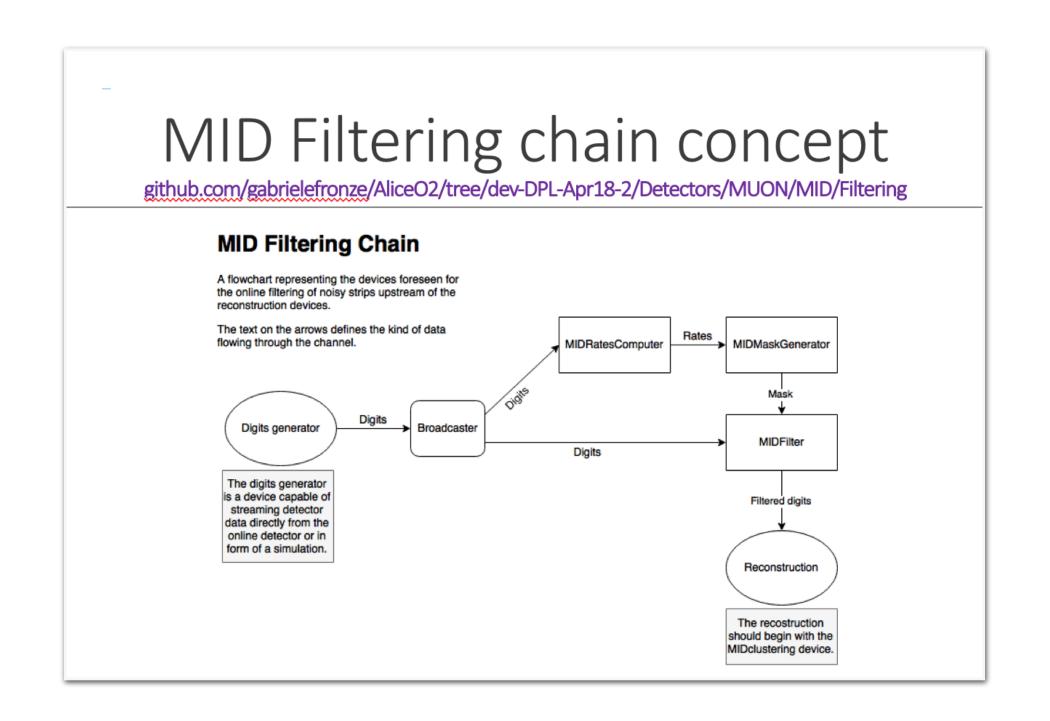
# PARALLEL DIGITIZATION

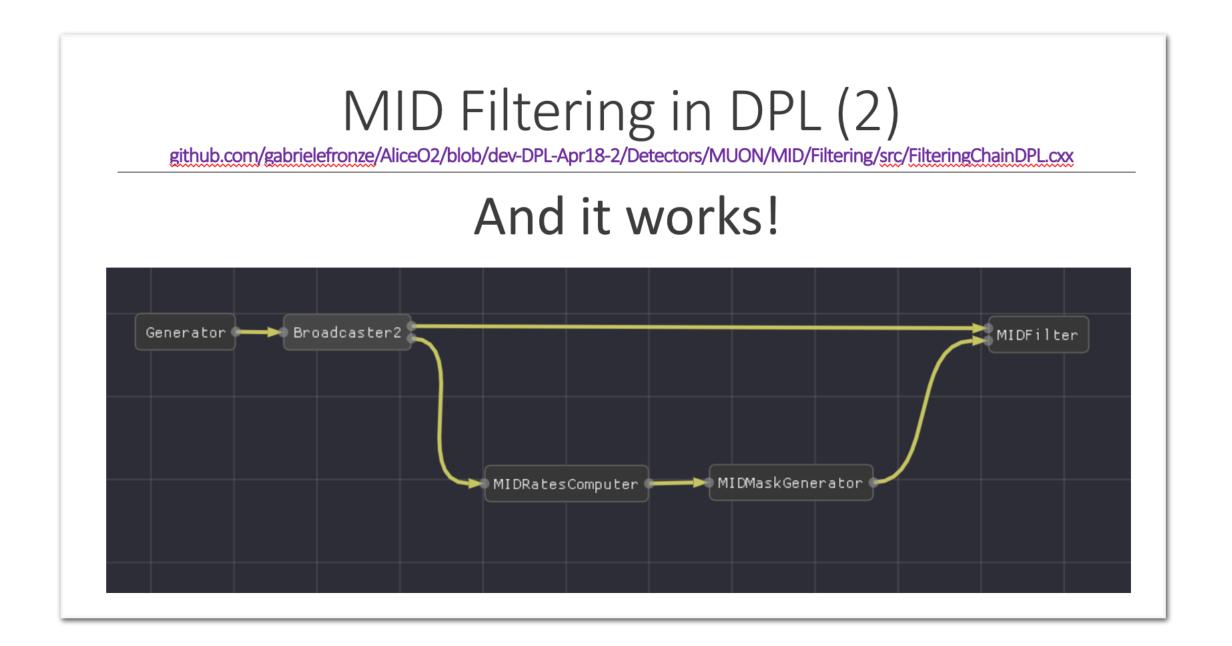
TPCDigitizer0 TPCDigitizer1 TPCDigitizer2 TPCDigitizer3 TPCDigitizer4 TPCDigitizer5 TPCDigitizer6 TPCDigitizer7 

See talk from Sandro: "A scalable and asynchronous detector simulation system based on ALFA" (https://indico.cern.ch/event/587955/contributions/2937621/)

# DPL USAGE: MID FILTERING CHAIN

Nice demonstrator by Gabriele Fronzè for MID filtering.





#### **SUMMARY**

- ➤ The challenges posed by Run 3 imposed to rethink ALICE Computing Architecture, blending the traditional Online and Offline roles.
- ➤ The message passing ALFA Framework is the foundation of ALICE O2 Software Framework.
- ➤ We built a message passing / shared memory friendly data model which minimises copy and (de-)serialisation.
- ➤ Taking advantage of the O2 Data Model we build a **data flow engine on top of ALFA** to reduce user code and abstract away common hiccups of distributed systems.

# BACKUP

# **TIMEFRAME**

Data quantum will not be the event, but the "Timeframe".

- > ~23ms worth of data taking in continuous readout. Equivalent to 1000 collisions. Atomic unit.
- ➤ ~10GB after readout. Vast majority in TPC clusters.
- ➤ Compressed to ~2GB after asynchronous reconstruction, mostly thanks to track-model-compression.
- $\triangleright$  100x the number of collisions of RUN2.
- > All MinBias. We need to (lossly) compress information, not filter it.

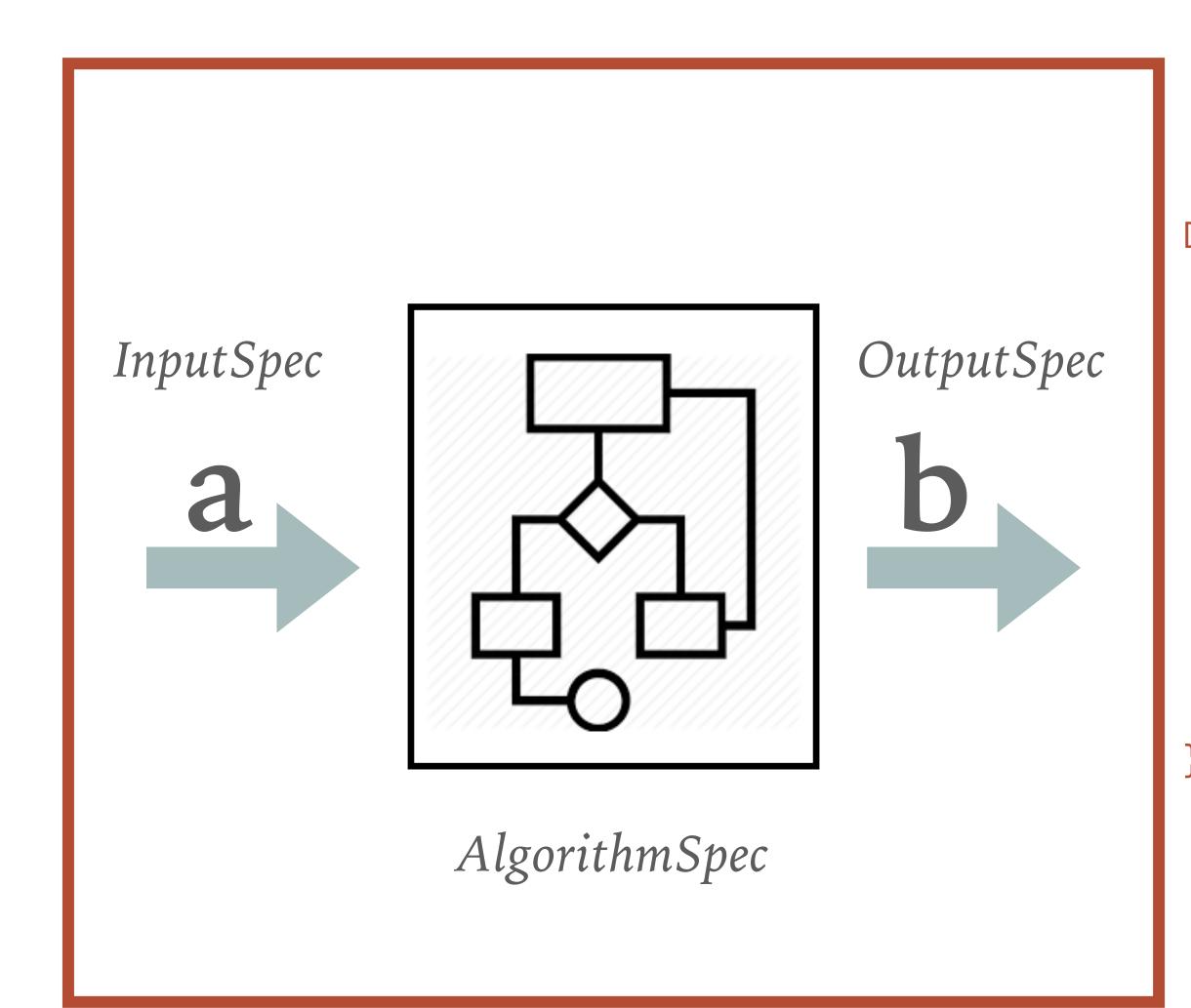
# 02 DATA MODEL

A timeframe is a collection of (header, payload) pairs. Headers defines the type of data. Different header types can be stacked to store extra metadata (mimicking a Type hierarchy structure). Both header and payloads should be usable in a message passing environment.

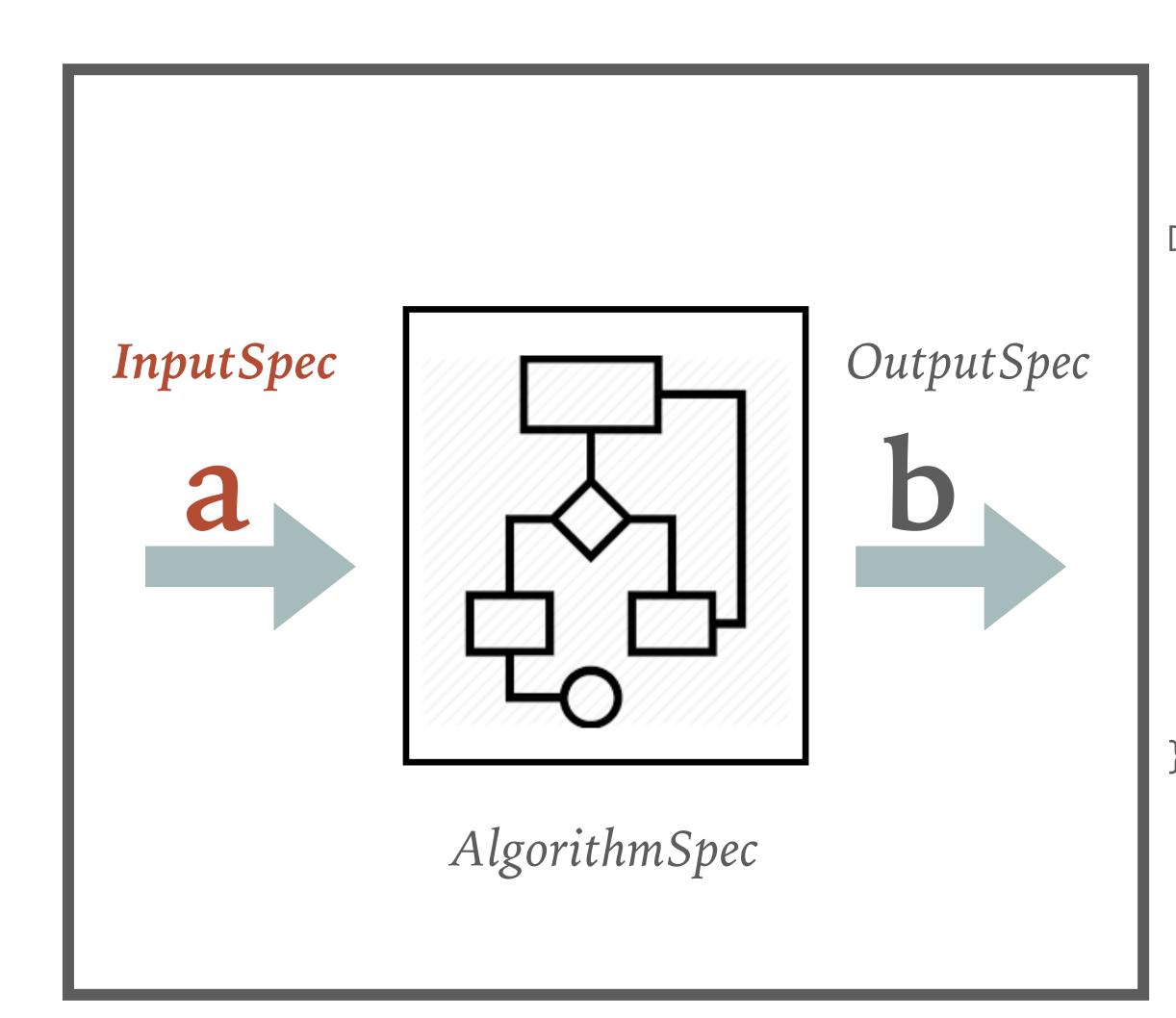


Different payloads might have different serialisation strategies. E.g.:

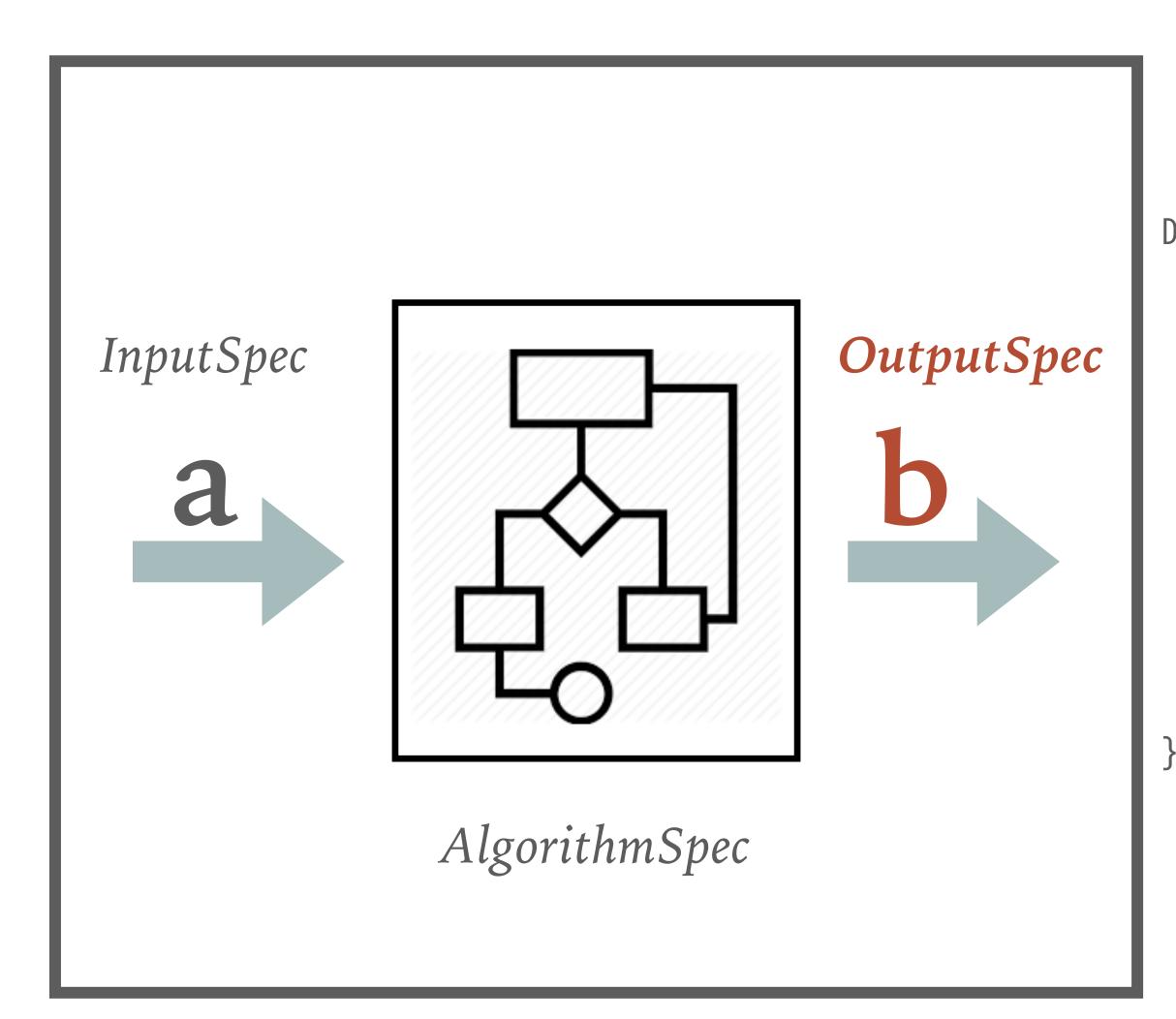
- > TPC clusters / tracks: flat POD data with relative indexes, well suitable for GPU processing.
- > QA histograms: serialised ROOT histograms.
- > AOD: some columnar data format. Multiple solutions being investigated.



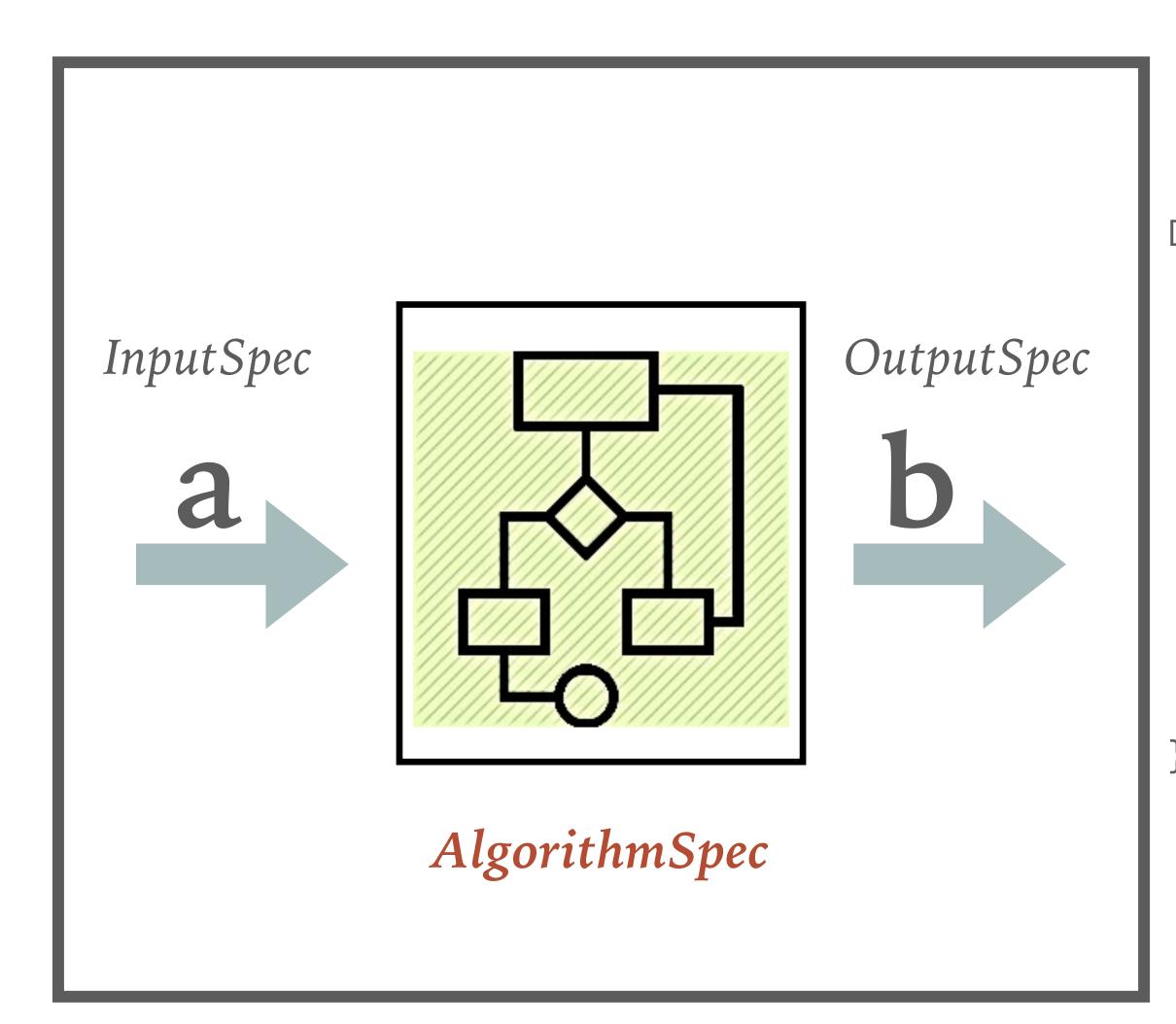
```
DataProcessorSpec{
   "A",
   Inputs{
      InputSpec{"a", "TPC", "CLUSTERS"}
   },
   Outputs{
      OutputSpec{{"b"}, "TPC", "TRACKS"}
   },
   AlgorithmSpec{
      [](ProcessingContext &ctx) {
        auto track = ctx.outputs().make<Track>(OutputRef{ "b" }, 1);
      }
   }
}
```



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   }
}
```

## HOW DO YOU LIMIT CONTEXT SWITCH COSTS?

We will have a number of **running** processes which is ≤ the number of cores.

Our tasks take long on a CPU scale (seconds) thanks to the fact we treat one timeframe at the time (~1000 collisions). User code runs lock free.

By describing our computation in terms of **composable pipeline stages** we keep door open for (eventually dynamic) NxM mapping between data processors and actual processes.

We are willing to pay an extra price for the sake of:

- ➤ Ease of deployment (microservices!)
- ➤ Crash resilience (data taking!)
- ➤ Ability to distribute over multiple nodes (HPC!)
- ➤ Flexibility (run GEANT3 + GEANT4 + FLUKA)

Limiting factor is in any case the GPU for TPC tracking (at least for the synchronous phase).

