WP14: Activities and Plans

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Introduction

Challenge and Solutions (Andreas @ ALICE Week, 03.2019)

- Challenge: Cope with 100x larger number of collisions to analyze
- Solutions
  - Only AOD for analysis
  - Reduce time spend in I/0
    - fast storage access ➜ dedicated Analysis Facilities
    - deserialisation overhead from complex nested data structures ➜ flat tables
  - Exploit parallelism
    - multiple data processing devices and multiple analysis tasks
    - task parallelism (multiprocessing and shared memory with DPL)
    - columnar data format ➜ vectorisation (RDataFrame)
    - declarative analysis providing automatic automatisation in the background
  - Exploit common data skimming and filtering

Analysis data format: requirements

Dario @ CHEP2018

New data format should reduce as much as possible the cost of deserialization: some generality will be lost for the sake of improved speed

- **Simple, flat**: numbers only (no classes), use tables, cross-reference via numeric indices
- **Columnar**: SoA in-memory structure for better growing/shrinking and vectorization
- **Extensible**: base format is immutable, but easily extensible because it's SoA
- **Chunked**: a single timeframe can be divided in smaller units processable in parallel
- **Zero size for null objects**: filtered-out fields do not use RAM memory
- **Recompute, don't store**: do not store everything because recomputing may be cheaper
- **No data restructuring**: disk → memory → network should use similar representations

Task: Design and implementation of prototype data layout

Period: 07.2019 – 02.2019

- Define minimal universal data set (AOD) for all analyses: Ruben @ WP1, 01.11.2018
- Extract flat Root tree containing the minimal data set and representing the time frame AOD: prototype is ready + analysis task
- Convert the Root representation to Apache Arrow tables and test the functionality: prototype is ready, see later
- Convert the Root representation to SOAContainer data and test the functionality: in progress, expected in 05.2019
- Convert the Root representation to Libflatarray data and test the functionality: not started, for the moment is optional

The Analysis Object Data (AOD) format

Goal:

- minimize the information kept on AOD to save disk space
- **maximize performances with light simple flat data-objects instead of heavier C++ objects**

Current idea is to have flat data tables, initial implementation based on "Ruben's table".

- **Barrel track table = standard helix parameters of each track**
- **Covariance table for barrel tracks**
- **Extra barrel track table = more detailed info like track chi2, number of clusters, PID signal ..**
- **Muon track table**
- **Calorimeter track table**
- **"Vertex" table = info about the collision vertex**
- **Other “small” tables: FIT, ZDC**

Associating objects (e.g. tracks) to vertices

In each timeframe:

- 22 ms of data-taking
- ~1000 PbPb collisions
- ~Millions of tracks per dataframes

→

In AOD tables, each candidate is associated to a given vertex in the vertex table

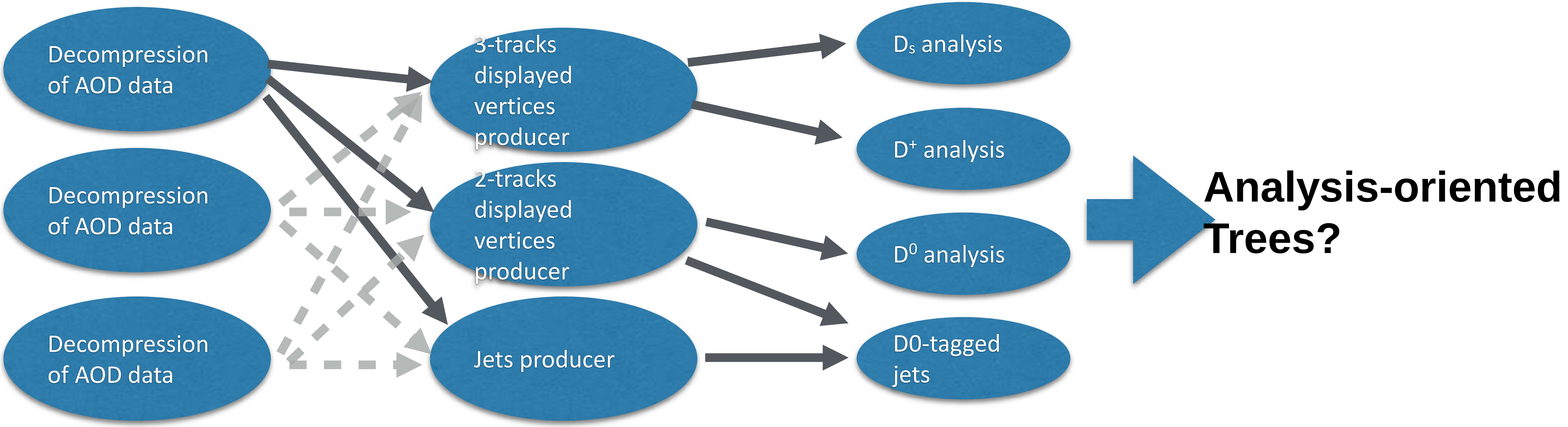
- done in the reconstruction level
- same track can be re-associated to more vertices!

Detailed presentation of Giulio and Gian Michele during EP-AIP meeting, 11.03.2019

A draft of structure for Run3 analysis

Need to develop and optimize a analysis structure that fully exploit the characteristics of the new Framework:

- maximal "sharing" of common processes and optimal use of shared memory



IMPORTANT: should we have an extra analysis layer on skimmed Trees?

- e.g. skimmed Dataframe analysis-oriented (e.g. HF Tables, Jet …) that can be processed in HPC clusters could dramatically reduce the analysis-cycle
- Need to study an effective compressed format, estimate size and develop optimised analysis software
- Develop a bookkeeping system for storage/skimming

Work in this direction with 2018 data is being carried out on a 32-core server with GPU that ALICE CERN group recently bought with Torino and Utrecht

Multiple possibilities being investigated

Fully declarative

RDataFrame Based solution

A mix of all the previous ones

Traditional analysis

Python Pandas

Vectorised "skin" based solution

Traditional event loop on proxy objects

Traditional way of doing things will always be possible

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Traditional analysis

What follows is a elaboration on how to map the analysis on RDataFrame, following discussions from the presentation of [Danilo Piparo @ AIP meeting].

Single loop with RDataFrame (New! Nested loops also supported now!

Get an RDataFrame iterating on candidates obtained via O2

```
auto candidates = o2::analysis::doSingleLoopOn(input);
```

Select Good candidates

```
auto filtered = candidates.Filter("cand_type & 1");
```

Fill an histogram

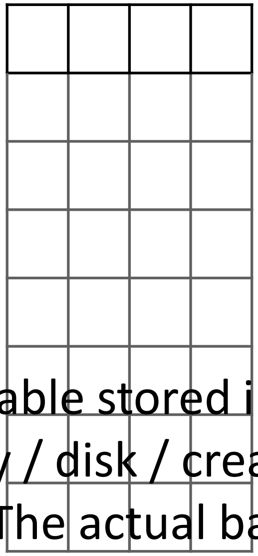
```
auto h1 = filtered.Histo1D("inv_mass");
```

Draw it

```
h1->Draw();
```

← Event loop actually runs here.

RDataFrame internals



Actual table stored in memory / disk / created on the fly. The actual backend will depend on the context.

RDataSource

RDataSource abstracts from the user the act of fetching row from a table. Different implementations depending on the backend.

RDataFrame

RDataFrame abstracts from the user how to iterate on a set of rows and how actions are performed on them.

Role of the analysis framework: provide helpers to construct useful views on the data, using the above building blocks.

Only one of the possibilities...

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Quick preview of a python based solution in the presentation of Giulio

Ongoing Framework level Efforts

Performance optimisation (*mostly ROOT team with our contributions*):

- *Bulk reads (us & ROOT team)*
- *Vectorisation (ROOT team)*
- *GPU support (ROOT team)*
- *Fast path in RCombinedDS for common analysis cases (us)*
- *Profiling of the RDataFrame solutions w.r.t. the other ones.*

Helpers for analysis (us)

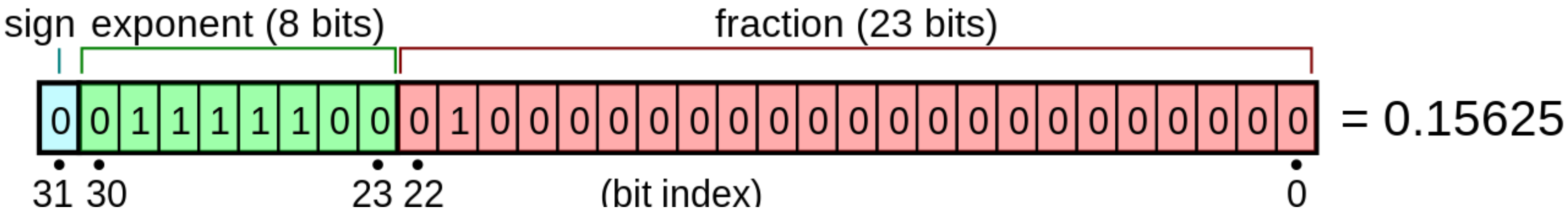
- *Filtered collections*
- *Triple / nth-ple loops*
- *Ability to plug current analysis tasks at the end of RDataFrame processing*

Run2 ESD to Run3 converter: first v ersion done, see the presentation of Giulio

- *No need for intermediate files*
- *Support O2/DPL*
- *Support Python Pandas & Tensorflow*

Storage with reduced precision (truncated fraction)

Used by CMS (discovered by Giulio)



107 PbPb events from 2015, no trigger selection

Type	Size	Truncation	Zip	Fraction, %
Ru1/2 ESD	510222529	no	yes	100.0
O2 AOD	50089236	no	yes	9.8
O2 AOD	47382919	4 bits	yes	9.3
O2 AOD	42018412	8 bits	yes	8.2
O2 AOD	37870154	12 bits	yes	7.4
O2 AOD	30360347	16 bits	yes	6.0

Task: Develop interfaces to access the flat data representations

Period: 02.2019 – 05.2019

- Data manager and reader for Run1/Run2 backward compatibility
- “Skins” for the Apache Arrow data access
- SOAContainer “skins”
- “Skins” for libflatarray
- On-the-fly calculation of derived quantities (primary and secondary vertex positions and covariance matrices, etc.)
- All these tasks probably will be completed with some delay

Task: Define and reimplement set of reference analyses for benchmarking

Period: 11.2018 – 06.2019

Several candidates are identified:

- Minijet analysis in small systems
- Investigation of longitudinal and azimuthal structure of the near side jet peak in Pb-Pb collisions
- Particle flow analysis
- Open charm analysis
- The conversion depends partially on the previous task

Task: Investigation of RDataFrame-based analysis

Period: 03.2018 – 07.2019

- RDataFrame for skimming and slimming: partially done
- RDataFrame with cartesian product of tables (for nested loops): done, pull request to be merged in Root6
- RDataFrame reimplementation of the analysis examples from the previous task: ongoing
- Performance studies and conclusion on the suitability of RDataFrame for Run3 analysis: not started

Task: Reimplementation of analysis tasks using DPL – analysis devices

Period: 03.2018 – 09.2019

- Prototype of multiple IO devices, multiple analysis devices and data sync to store the results: prototype presented @ CHEP2018
- Reimplementation of the reference analyses from p.3: ongoing
- Reimplementation of simple analysis train: not started
- Performance measurements of DPL-based trains on analysis prototype facility: not started

Task: Development of the Lego train system for Run3

Period: 09.2018 – 05.2020

- Adapt the system to the analysis devices from p.5: not started
- Redesign of the Web interface and data base backend: initial proposal prepared by Markus
- Continuous integration and automatic train testing: not started
- R&D on dynamic reconfiguration of the Lego trains: not started

Task: Development related to the future usage of Machine Learning

Period: 11.2018 – 12.2019

- Direct Python integration: done in Root6, ALICE prototype presented by Gian Michele
- Data exchange via Apache Arrow tables: prototype presented by Giulio
- R&D on using Apache Spark and Pandas for ML analysis: ongoing,
- Many other MKL activities, see the presentation of Gian Michele

Task: Development of additional GRID analysis features

Period: 07.2019 – 12.2019

- Efficient use of multicore job queues with analysis devices: not started
- Performance measurements and benchmarking: initial data provided by Costin

Task: Analysis data challenge

Period: 01.2020 – 03.2020

- Large scale tests of the functionality in local, analysis facility and GRID modes
- Performance measurements and benchmarking
- Recommendations for the usage of different resources

Task: Final design and implementation of analysis facilities

Period: 04.2020 – 10.2020

- This task depends on the outcome of the analysis data challenge and the general policy wrt the analysis facilities