From Static to Agile - Interactive Particle Physics Analysis in the SAP HANA DB

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Keywords: in-memory databases, scientific applications

Abstract: In order to confirm their theoretical assumptions, physicists employ Monte-Carlo generators to produce millions of simulated particle collision events and compare them with the results of the detector experiments. The traditional, static analysis workflow of physicists involves creating and compiling a C++ program for each study, and loading large data files for every run of their program. To make this process more interactive and agile, we created an application that loads the data into the relational in-memory column store DBMS SAP HANA, exposes raw particle data as database views and offers an interactive web interface to explore this data. We expressed common particle physics analysis algorithms using SQL queries to benefit from the inherent scalability and parallelization of the DBMS. In this paper we compare the two approaches, i.e. manual analysis with C++ programs and interactive analysis with SAP HANA. We demonstrate the tuning of the physical database schema and the SQL queries used for the application. Moreover, we show the web-based interface that allows for interactive analysis of the simulation data generated by the EPOS Monte-Carlo generator, which is developed in conjunction with the ALICE experiment at the Large Hadron Collider (LHC), CERN.

1 INTRODUCTION

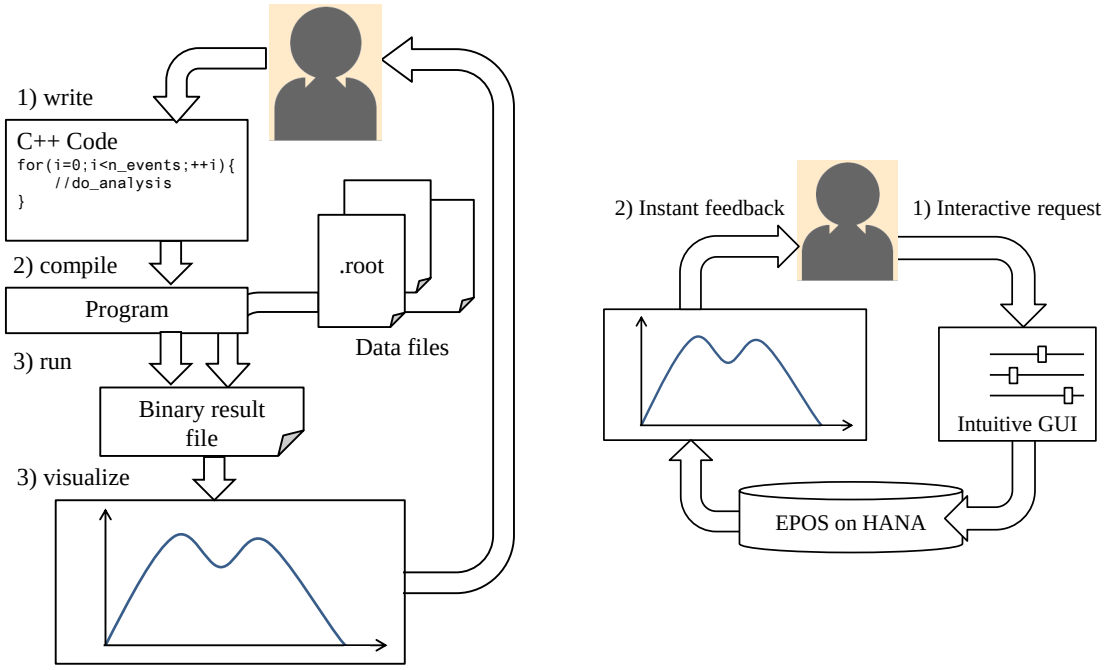
Researchers in the high energy particle physics community were one of the first who had to deal with the impact of massive data deluge because their experiments have produced petabytes of data per year since the mid-2000s. For example, the Large Hadron Collider (LHC) at the research center CERN in Geneva, Switzerland, produced data at a rate of 15 PB per year in 2009 (CERN, 2014). The sheer amount of raw data together with the requirement for efficient query processing techniques are among the reasons why this domain has recently gained attention in the database community (Ailamaki et al., 2010; Karpathiotakis et al., 2014; Stonebraker et al., 2009).

To evaluate their theoretic models, particle physicists compare the detector measurements with their expectations. Therefore, they use particle collision simulations, which consist of millions of particle events generated by Monte-Carlo-based algorithms. In a first step, the data produced by the event generators, such as EPOS (Drescher et al., 2001), are stored in large binary data files. In the following analysis step, the simulation data are filtered, joined with metadata and aggregated into distributions of certain physical observables. These distributions, which are commonly represented as 2D-histograms, are then compared with the actually observed distribution that is obtained from the actual detector measurements.

The usual analysis workflow of particle physicists involves writing C++ analysis scripts that are then compiled and run on many large data files (Karpathiotakis et al., 2014). These programs use the open source framework ROOT (Brun and Rademakers, 1997), which includes the data format to write and read particle data in binary files, and contains methods to calculate the physical observables, visualization tools, such as histograms, and statistical methods to quantify the accordance between simulation and measurement.

However, the requirement of rewriting and recompiling the C++ code, makes the common analysis a rather static workflow (Fig. 1(a)). For example, every time when a filter changes, the physicist usually has to modify the C++ program, compile it, and run again. Moreover, for each ad-hoc test on a smaller data subset, the corresponding data files have to be loaded again, in the worst case from hard disk.

A key requirement for an agile analysis is to get



(a) The common static workflow using C++ programs

(b) The agile workflow with "EPOS on HANA"

Figure 1: From static to agile workflows in particle physics analysis by using an in-memory RDBMS.

instant feedback, since the scientists might want to adjust the input parameters on the basis of the output histogram. Our idea is to achieve a dynamic workflow with immediate responses, without being penalized by long waiting times when parameters are altered (Fig. 1(b)). Being able to quickly adapt query parameters together with low response times is an important optimization goal in the context of online analytical processing (OLAP) in relational business database systems. Many of the typical particle analysis algorithms consist of a mix of expression evaluations, filters and aggregations – operations that are highly optimized in recent RDBMS. However, databases today still rely on simple heuristics to optimize expensive predicates or aggregates because optimal solutions or expensive to compute (Eich and Moerkotte, 2015; Neumann et al., 2005).

In this paper we present the efficient integration of state-of-the-art particle physics analysis algorithms on a large data set in SAP HANA DB (Färber et al., 2012), an in-memory column-store DBMS. We tackle the issue of optimizing complex queries with expensive expressions, predicates, aggregates and joins by explicitly modelling the crucial aspects of the query and leaving the easier optimization steps to the query optimizer. In particular, the contributions are:

1. We propose a natural mapping of particle data onto a relational snowflake schema and show how state-of-the-art particle physics analysis algorithms are expressed in SQL.
2. We describe the steps to tune our database schema and the relational queries to achieve interactive response times by using Analytical Views.
3. We compare the query response times of the static workflow based on C++ programs used today with the modelled approach followed in our system. By modelling the core parts of the queries exploiting domain knowledge we achieve more than an order of magnitude lower query response times. As a consequence users can interactively adapt parameters of the analysis which was not possible before.
4. We present an intuitive graphical user interface with a histogram display and easy-to-use filter bars.

2 DISMANTLING THE STATIC WORKFLOW

As part of the application, we first describe the analysis scenario, and second how a typical particle data analysis is implemented the conventional way using custom C++ programs.

2.1 Application Description

At the LHC protons and heavy ions are accelerated in a beam and steered to collide with each other at very high energies. This way the physicists get information about high energetic particle states and can validate their theories, such as the existence of the Higgs Boson. In collision experiments, physicists are generally interested in measures that are derived from the momenta $\vec{p} = (p_x, p_y, p_z)$ of the particles directly after the collision, since they give hints about resonating particle states.

In this work, we consider the analysis of two observables in high energy particle physics experiments that are of particular interest: the observables transverse (orthogonal to beam) momentum p_T and the pseudorapidity η, which describes the angle of a particle relative to the beam axis. Both observables are derived from the particle momentum components p_x,p_y, and p_z as follows:

1. Transverse Momentum:

$$p_T = \sqrt{p_x^2 + p_y^2} \tag{1}$$

2. Pseudorapidity:

$$\eta(p_x, p_y, p_z) = \frac{1}{2} \ln \frac{\sqrt{p_x^2 + p_y^2 + p_z^2} + p_z}{\sqrt{p_x^2 + p_y^2 + p_z^2} - p_z} \tag{2}$$

The distributions of the measured p_T and η observables are usually visualized with histograms that display the number of particles dN per bin dp_T or $d\eta$ for a configurable fine- or coarse-grained binning. The graph plotted in our graphical user interface (Fig. 3) gives an idea of the shape of the η distribution.

In addition, there are certain filter constraints of interest, such as *multiplicity classes* which narrow the amount of the considered data further down. However, we omit the details here and discuss them in section 4.2.

2.2 Conventional Static Analysis Workflow with Root

The conventional workflow of particle physics includes writing custom C++ analysis programs and working with binary files using the framework ROOT (Brun and Rademakers, 1997). These static analysis programs usually contain the following building blocks:

1. **Prerequisites:**
   Each program usually starts with commands to load one or multiple root data files. Moreover, data buffers are created which will be filled by the file interface for the data of interest. Depending on the number of analyzed data files, file checks and the number of addressed data attributes the prerequisites easily account for ten to hundred lines of C++ code. A snippet of our running example is shown below. In our full example this part requires 76 lines of code (LOC).

```
//open file and create event data buffers
TFile *f = TFile::Open(file);
float px[10000];
        ...
//set tree pointers to binary file
TTree *thead = (TTree*) f->Get("teposhead");
TTree *t = (TTree*) f->Get("teposevent");
t->SetBranchAddress("px", &px);
        ...
```

2. **Main analysis:**
   The main component is effectively a loop over the data of all particles, where each iteration may include the computation of physical observables and filter criteria, e.g., thresholds for high energetic particles.

```
//main loop over events (particle collisions)
for (int i = 0; i < nevents; i++) {
   t->GetEntry(i);  // sets all references
   //loop over particles in event
   for (int j = 0; j < np; j++) {
      //filter and calculate observables
        if(!filter(px,py,pz,...)) continue;
        buf = calculateObservable(px,py,pz);
      //write into buffer
        ...
   }
}
```

   The size of this code part heavily depends on the kind of analysis. It can be as few as ten or as much as hundred lines of code, depending on the analysis complexity (our – rather minimal – example took 18 LOC). Note that in our example of the pseudorapidity analysis, the inner event filter criterion is based on pre-aggregated multiplicity classes, which we discuss in section 4.2. Thus, the analysis program requires two loops on the whole dataset, which effectively bloats the script size further.

3. **Generate results and visualization:**
   Since the C++ programs are run on command line, there is no direct visualization of the computed results. Instead, the resulting plots are contained in histogram container class objects, which are again stored in binary result files. To visualize the result, the scientists can then either open the file using the graphical ROOT file browser, or print the histogram canvas directly from within the C++ analysis pro-

gram into a pdf- or png-file.

```
//postprocess and write into result file
...
TH1D* eta_hist = new TH1D(name, x_bins, y);
TFile result_file(''results.root'',''NEW'');
//write into binary root file
eta_hist.Write(''resulthist'');
```

In total, ROOT-based C++ analysis scripts consume usually from hundreds up to several thousands lines of code. Moreover, they contain a considerable amount of redundant code components, such as the file and reference handling, and the implementation of the binning and the custom aggregation. Also, the C++ programs have to be maintained by users, which are often not perfectly familiar with efficient C++ programming. In particular, the ROOT framework is implemented without multi-threading in mind. In particular, the library functions are not thread-safe. Hence, tuning complex analysis scripts is quite limited on modern multicore architectures. These limitations of the ROOT framework are one reason for the limited scalability observed in our experimental validation.

The turnaround time for an analysis[1] on a local system is constant for a given set of parameters. For every change of the parameters (in our example: the multiplicity class configuration) the analysis has to be run again, which includes parsing the data files repeatedly and also performing redundant computations.

3 EPOS ON HANA

For ad-hoc analysis, scientists want to adjust analysis parameters incrementally based on the previously obtained results in a dynamic feedback loop, as implied by Fig. 1(b). This is in contrast to the static analysis workflow outlined in section 2 which involves rewriting, recompiling and reloading data files. This motivated us to implement a web-based application – "EPOS on HANA" – which allows scientists to upload their experimental or simulation data for high energy physics and compare the results in histograms that are commonly used in the particle physics domain. While our application is extensible for other kinds of analysis tasks, we focused in this work on the η- and p_T-analysis. However, any other calculated measure that are derived from the raw data can be implemented.

As the core part, we now discuss the architecture of our application shown in Fig. 2 in detail. In the remainder of this paper, we show how the incremental workflow using our "EPOS on HANA" application can speed up the time for testing a different set of parameters by more than an order of magnitude compared to the static workflow using C++ programs and ROOT.

[1] In this paper, we only consider local analysis on local data subsets which are in the order of gigabytes. For large scale analysis with data sizes starting from several terabytes, the CERN-associated research groups usually employ a computing grid with turnover times of up to several days.

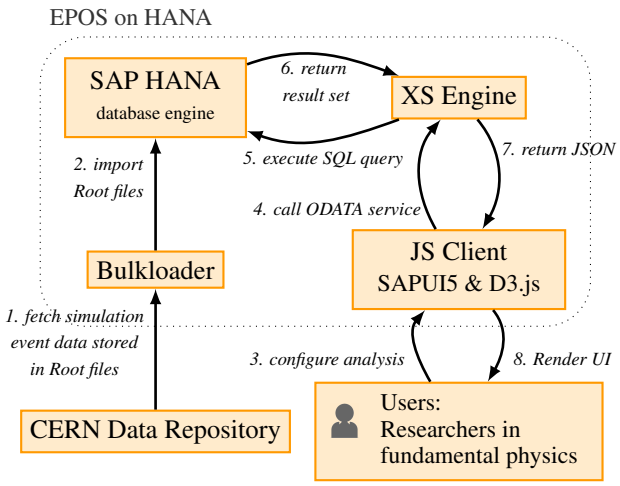


Figure 2: System Architecture of "EPOS on HANA"

3.1 System Architecture and Workflow

The general architecture of our application is sketched in Fig. 2. The graphical user interface is shown in Fig. 3. In this section we explain each component in detail. We also discuss each step that is performed when using "EPOS on HANA".

Data Generation. In a first step, the Monte-Carlo generated event data and the corresponding metadata are stored in ROOT files. This is done by domain-specific programs as discussed in Section 2 and not part of our application. At the moment, generated and experimental data are provided from a global CERN data repository. However, part of our future considerations is to integrate the Monte-Carlo data generation to the database system.

Data Loading. Next, this simulated event data is loaded into column store tables of the SAP HANA DB using a customized parallel bulk-loading tool. The bulk-loader parses a set of Root files and performs batched inserts into the database using the HANA ODBC interface. This data usually remains unchanged for subsequent analysis tasks in various studies, so the data has to be loaded only once for multiple analyses.

Moreover, the UI offers the option to upload experimental data, i.e., data that has been measured with

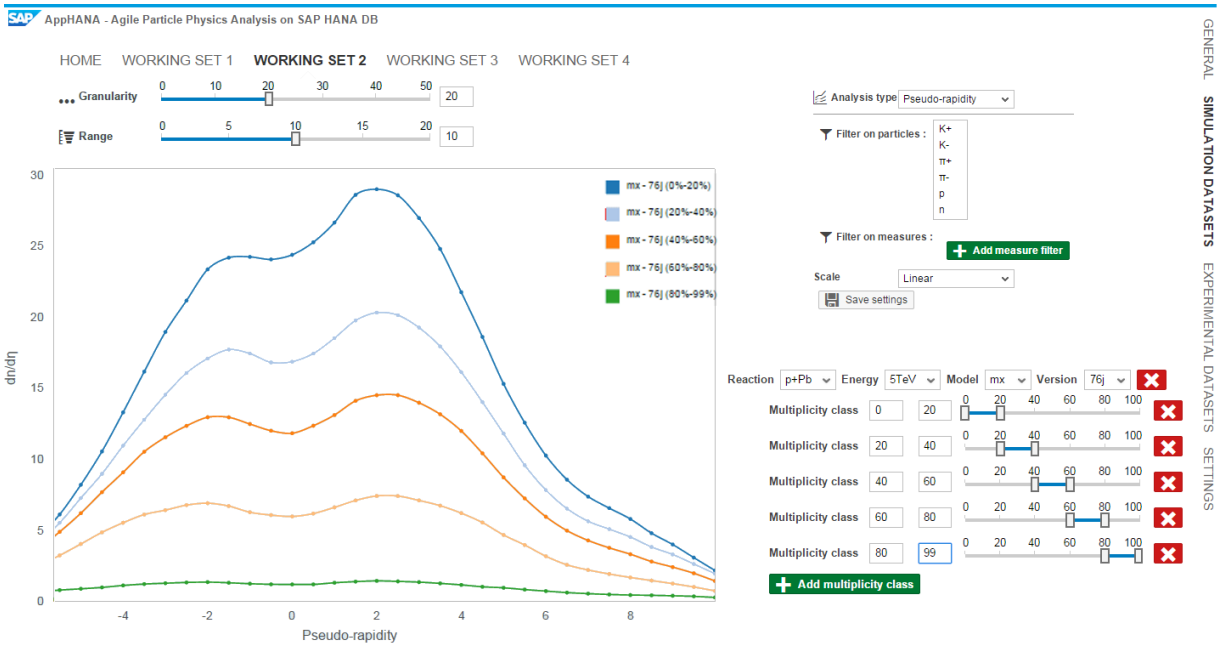


Figure 3: The EPOS on HANA GUI showing the pseudorapidity (η) curves for different multiplicity classes

the detectors at CERN and are publicity available as a CSV-file, for example from the Durham HepData Project (Durham University, 2014). The corresponding experimental data curve can be displayed together with the lines in the chart, providing a convenient way of comparing the experiments with the Monte-Carlo simulation. Theoretical physicists are eager to develop the best simulation model for real high-energy physics experiments. A central tool like "EPOS on HANA" is expected to be very useful to be able to share simulation and experimental data in a central platform and to compare the quality of simulations to other simulations or experimental data.

Interactive Querying. In the third step a physicist enters the web-based user interface of the "EPOS on HANA" application, which is shown in Fig. 3, and configures the analysis task. This includes choosing simulation or experimental data sets used for the physical analysis. The interactive querying capability is the main feature of our application. In the configuration part, the scientists can define the general settings, such as the analysis type (pseudorapidity η, or transverse momentum p_T), and/or global filters on any physical measure in the data set. Then, arbitrary multiplicity classes $[\alpha_i, \beta_i]$ can be added to the panel. Each multiplicity class corresponds to a line in the chart. The display part on the left-hand side of Fig. 3 shows the histogram, which is implemented with the D3.js[2] framework. Two control bars enable the user to dynamically change the granularity and the range of the histogram.

The web-based interface is realized as a JavaScript client-side application that uses the SAP UI5 library (May et al., 2014) for the basic widgets and D3.js for the histograms.

Internal Update Request. In the fourth step, after the parameters for a diagram have been modified, the JavaScript client requests the updated data from the server-side JavaScript application. This server-side logic is delivered by the Extended Scripting (XS) engine of the SAP HANA data platform. The data can be accessed via an ODATA interface defined for the main view used for this particular analysis.

Efficient SQL Execution. The ODATA services implemented in the XS engine transforms the ODATA request into the corresponding SQL query. The SQL query is executed by the high-performance in-memory columnar engine of SAP HANA (Färber et al., 2012). The main memory DBMS offers highly optimized execution by using parallelized database operators for aggregations, filters, joins, and others. Moreover, we have tuned the physical schema of the database to

[2] A JavaScript library for manipulating documents based on data. `http://d3js.org`

achieve interactive response times, even when accessing data for billions of particles. The tuning steps will be described in more detail in the following section.

Return Feedback. In step six, the query result is returned to the ODATA service in the XS engine. This service generates the corresponding JSON-response which is sent back to the client-side JavaScript front end. In the final step the client renders the diagrams based on the received data.

As a result, any changes to either the multiplicity classes or the general filters lead to a realtime recalculation and redrawing of the corresponding curves. Just like physicists would do, the demonstration allows users to dynamically adjust the data curves via the intuitive control bars, and experience immediate feedback for their parameter configuration. This has not been possible with the static workflow using C++ code.

Extensibility. Although we are only presenting the pseudorapidity/p_T-analysis in this application paper, the framework can easily be extended by further analysis types. To add an additional analysis type, an analysis reference SQL query has to be implemented *once* and linked to the ODATA request in the JavaScript client source code, which is editable by the application administrator. In the same way, existing analysis queries can be manipulated until they suit the requirements of the scientists.

4 RELATIONAL IMPLEMENTATION AND TUNING STEPS

In this section, we describe step-by-step the relational implementation of the analysis described in section 2. The complete pseudorapidity analysis can be covered by standard SQL commands provided in SAP HANA. According to our notion, SQL is general enough to express many typical queries of particle physics analysis. However, if special functionality is required that can not be expressed by the means of SQL, it could potentially be integrated into user defined functions, which however, is out of the scope of this paper.

Although an initial naive SQL implementation of the pseudorapidity analysis according to the architecture in Fig. 2 already reduced the response times by a factor of about 4x, we applied additional tuning steps to achieve a greater performance. Hence, the second part of this paper is about the different variants of the queries used in our performance evaluation. Below, we first present the relational mapping, followed by an incremental description of the steps we have taken to improve performance by more than a factor of 40x.

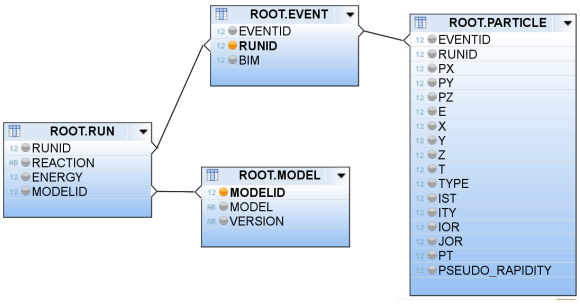


Figure 4: Table Schemes and the Join Paths of the `Multiplicity` View.

4.1 Relational Particle Schema

Fig. 4 shows the relational schema used to represent the particle data structure for the simulation data.

At the highest level, experiments and simulations can be separated into *runs*. In the context of the Monte-Carlo generated data, each simulation run is labeled with the reaction type, the center-of-mass energy of the particle collision, and the theoretical model that was used in the simulation. Runs are inserted into the `run` table. The simulation meta information, which includes the Monte-Carlo generator model and version used for the corresponding run, are stored in the separate table `model`.

Runs are made of ten-thousands of *events* which form the next level in the hierarchy. An event represents a particle collision, each consisting of around 1000 tracked particles in our data set. Each event can be assigned an impact parameter *BIM* which defines how central the beams have collided. The events are stored in the `event` table.

The last table in our hierarchy, the `particle` table, stores the actual physical information of the measurement. Each row refers to one particle which has attributes that refer to its position (x,y,z) or its momentum (p_x,p_y,p_z), as well as further attributes that describe its type, and others.

In terms of a data warehouse, the `particle` table is the fact table, and the other tables are dimension tables of a very simple snowflake schema.

Calculated Attributes. Calculating the derived physical observables, e.g. p_T (Equation 1) or η (Equation 2), with each query is usually expensive. In particular, the data is loaded once in batches, and after

that never changed again. However, the event data is typically queried many times, and this motivates the first tuning step: By creating p_T and η as a *calculated attributes*, the database system materializes η and p_T at insertion time. Thereby, we trade additional memory consumption for the redundant data for faster query response times because expensive expression evaluation is avoided when retrieving the rows of the `particle` table. Moreover, we turn expensive expressions into cheap ones which simplifies the task of the query optimizer (Neumann et al., 2005).

4.2 The Analysis as SQL Query

The textual description for a single η (p_T) analysis query is as follows:

For each η (p_T) bin of the histogram, return the normalized number $\bar{N}$ of the particles that have the corresponding η (p_T) value and were produced in events of a certain multiplicity class $[\alpha, \beta]$.

Additionally, there can be multiple filter constrains on the observables, such as a minimum value thresholds on p_T or a range filter on η (centrality filter).

The *multiplicity* refers to the number of particles that were produced in one event, which is non-constant and depends on the particular interactions that occurred in the corresponding collision. As mentioned in section 2, the physicists often want to narrow the distributions down by separating the collision events into several multiplicity *classes* to get insights on a more fine-granular level. This part of the query is of particular interest for the SQL implementation, since it has a major influence on the execution runtime. In general, a single pass over the data is required to determine the multiplicity classes, before a second pass can perform the actual aggregation of the calculated measures.

We use the range $[\alpha, \beta]$, $0 \leq \alpha \leq \beta \leq 1$ to denote all events that are part of a certain multiplicity class. To be more precise, assume the data set has a total of N events. Then, a multiplicity class with $[\alpha, \beta]$ refers to all events that have a multiplicity that is higher than the $N_L = \alpha N$ events with the lowest multiplicity, but lower than the $N_H = \beta N$ events with the highest multiplicity.

The SQL query in Listing 1 implements the analysis; outer parameters are denoted by the "?"-symbol. The expression contains two nested queries: The first nested query determines which events are conforming to the filter constraints on the reaction type and the definition of the used Monte-Carlo model. Moreover, it selects only events that belong to the given multiplicity class $[\alpha, \beta]$ – by applying the `limit <ncount> offset <nmin>` command on the ordered result list of event multiplicities. The corresponding parameters are derived from the multiplicity class delimiters as follows: $\texttt{ncount} = (\beta - \alpha)N$ and $\texttt{nmin} = \alpha N$, where N denotes the number of events, which is pre-calculated using the `event` table.

Listing 1: The η-analysis as SQL query

```
select bin, sum(event_count.c) AS hist01
from
( select eventid, count(*) as c
  from particle, run, model
  where reaction = ? and energy = ?
    and model = ? and version = ?
    and run.modelid = model.modelid
    and particle.runid = run.runid
    and particle.pseudo_rapidity > ?
    and particle.pseudo_rapidity < ?
  group by eventid
  order by c desc limit ? offset ?
) as multiplicity,  -- NESTED MULTIPLICITY
(select runid, eventid, round(pseudorapidity)
        as bin, count(*) as c from particle
  where ( px != 0 or py != 0 )
  group by runid, eventid, round(pseudorapidity)
) as event_count   -- NESTED EVENT_COUNT
where abs (bin) < 20
  and multiplicity.eventid = event_count.eventid
group by bin order by bin
```

The resulting events (identified by `eventid`) are then joined with the second nested query which performs the histogram binning by aggregating the large `particle` table per bin and per event. The condition `px != 0 or py != 0` is required to avoid division by zero in Eqn. 2. Finally, the top-level aggregation sums up the events in all bins to create the result histogram. Note that as pointed out in section 2, it is impossible to perform the whole query with a single pass over the data.

Nevertheless, the prepared SQL statement in Listing 1 is yet simplified, since it only contains a single histogram query. For multiple histograms (i.e., multiple lines in Fig. 3) we construct a composite query using unions of the two nested queries with parameters specific for the diagram line. Moreover, we used the calculated attribute `pseudorapidity`, instead of calculating η by means of SQL expressions. We will use this query – but with the explicit computation of the pseudorapidity attribute – as the base line for the naive SQL-based approach in our evaluation.

4.3 Analytical Views

HANA offers a number of modeling capabilities to tune the execution of complex queries like the one presented in Listing 1. In a business context, this allows application developers to precisely define business semantics of queries, for example by encapsulating logical query units into views. However, these capabilities can also be used to tune the execution of complex queries, and this will be the focus in the remainder of this section. Analytic views are used in a conventional business warehouse environment to model OLAP data that includes measures. For example, a transactional fact table representing the sales order history would include measures for the quantity and the price. In our scenario, the measures are the calculated columns η and p_T, respectively. We use two analytical views to model the η analysis query in a calculation scenario (Große et al., 2011), which are related to the two nested queries as indicated by the comments in Listing 1.

Listing 2: The η-analysis using analytical views

```
select bin, sum(event_count.c) as hist01
from   CV_EVENT_COUNT,
     ( select eventid, count(*) as c
       from   CV_MULTIPLICITY
       limit ? offset ?
     ) as multiplicity
where abs(bin) < 20
  and multiplicity.eventid =
                        CV_EVENT_COUNT.eventid
group by bin order by bin
```

The `CV_MULTIPLICITY` is used to obtain an ordered list of the event multiplicities, ordered by the event ID (`eventid`). It joins the `particle` table with the dimensional attributes (Fig. 4) and counts all particles that conform the optional filter constraints on η and/or p_T.

The `CV_EVENT_COUNT event_count` view contains the first stage of the histogram aggregation that counts the particles grouped by the bins of the physical observables *and* the event IDs.

The resulting analysis query, shown in Listing 2, selects the matching event IDs from the `CV_MULTIPLICITY` view according to the parameters for the multiplicity range $[\alpha, \beta]$, by using again the `limit` and `offset` commands as described before. The event IDs are then joined with the `CV_EVENT_COUNT` view, followed by the final aggregation, which creates the histogram by grouping the normalized number by the observable of interest, η or p_T.

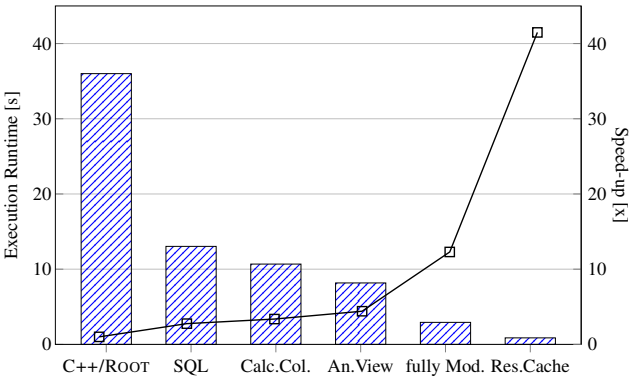


Figure 5: Execution runtime (bars) and speed-up gain (curve) due to our different tuning steps of the particle physics analysis in HANA.

Modeller. We modelled the final query execution plan using the graphical plan analysis tool available for the SAP HANA database. The modeller allows the application developer to exploit domain-specific knowledge, and thus it is possible to realize optimizations that cannot be derived by query optimizers today, e.g. deriving common sub-expressions or utilizing specific database operators. This part of "EPOS ON HANA" is of practical interest beyond our application, since some of the techniques used by us are also employed in other web-based applications on the SAP HANA DB (SAP Fiori, 2014).

Result Cache. Since some of the filters, such as the global p_T threshold, do usually not change during the analysis, it is not necessary to recalculate intermediate results all the time. In particular, this applies to the analytical views described above. Therefore, SAP HANA DB uses a result cache for analytical views. If the respective view query is time consuming, and the view size is comparatively small, the result cache buffers the view and enables a fast execution of the adjacent queries.

5 EVALUATION

In our evaluation, we show how our performance tuning described in the previous sections step-by-step improved the overall query runtime. As test system, we used a 32-core server with Intel Xeon X7560 CPUs @2.27 GHz and 500 GB of main memory.

In particular, we compare (from left to right in Fig. 5):

1. The conventional execution, performed on files using a C++ program and the ROOT framework.

2. A naive SQL execution in SAP HANA DB using our schema of Fig. 4.
3. The SQL execution using the calculated columns instead of expression evaluation as in Listing 1.
4. The SQL execution using the `multiplicity` analytical view.
5. A fully modeled SQL execution using the views `multiplicity` and `event_count` as in Listing 2.
6. Same as 5.) but with enabled view result cache.

Figure 5 shows that already the naive SQL-based approach taken by our web-based application is faster than the C++-based implementation. The reasoning behind this performance boost is two-fold: first, the data is kept in main memory and hence, there are no expensive file reads, which are slower even though the files are cached in the file system. Second, operations like aggregations, filters, and joins that are implicitly done in the hand-written C++ Code are implemented more efficiently in the database system.

In our experience, the computation of the complex expressions and the complex grouping logic were dominating factors of the query execution time. Hence, the utilization of the materialized calculated columns further improved the query performance by about 25%.

When using the first analytical view, the `multiplicity` view, we achieve another 25% speedup. With the fully modelled query using both the `multiplicity` and `event_count` views the execution runtime is reduced to below 3 seconds, and a total speedup of 13x, showing the potential of HANA's internal optimizer when using the modelling infrastructure and analytical views discussed in Section 4.

The result cache enables the caching of smaller intermediate results, for example the `event_count` view, which does not change throughout the analysis. Thus, it helps to reduce the execution runtime down to about a third compared to step 5.

As a result, we achieve an overall performance improvement of more than a factor 40 compared to the hand-crafted C++ code using the ROOT framework. Of course hand-tuned C++-code should outperform our system, but as discussed the usage of frameworks like ROOT inhibits common optimizations, e.g push-down of expressions and filters.

Not only is this interface more easy to use, it now also allows for truly interactive and incremental analysis of the simulation and experimental data. As future work we intend to compare our approach with the direct access to the RAW Root-files as presented in (Karpathiotakis et al., 2014), e.g. using the Smart Data Access framework available in SAP HANA.

6 RELATED WORK

The increase in data size and demand for scalable data processing of several scientific domains has led to an increased attention for scientific data processing in the database community (Ailamaki et al., 2010). In that context, some specialized database systems with scientific focus have emerged and advanced in the recent decade.

Array DBMS. In many scientific domains, for example astronomical image processing, data is usually stored in structured representations, such as multidimensional arrays. Since the relational data model of conventional DBMS did not match the requirements for scientific data processing, which is often based on arrays to achieve data locality, systems like RasDaMan (Baumann et al., 1998) or SciDB (Stonebraker et al., 2009) emerged. However, particle physics data does not have an array-like structure that requires element locality, but are rather a huge set of many independent measurements, hence, our analysis would not benefit from using an array-based DBMS. Although the authors of a related project come to a similar conclusion (Malon et al., 2011), there have been efforts to utilize SciDB for the ATLAS Tag Database (Malon et al., 2012).

Particle Physics and Database Systems. The ATLAS Tag Database (Cranshaw et al., 2008; Malon et al., 2011; Malon et al., 2012) stores event-level metadata in a relational database system, so that scientists can preselect events according to their analysis criteria by relational means. Based on the preselection, the analysis is then run conventionally using C++ programs on ROOT files, but only using the selected raw data files rather than on the whole set. This approach deviates significantly from our work, since in EPOS on HANA the complete analysis is performed in the DBMS, and selection criteria are a part of the main analysis.

The idea of combining customized in-situ processing on raw data files with the advantages of the columnar data processing capabilities of a modern DBMS has already been mentioned in (Malon et al., 2011). A similar – "NoDB" – approach was implemented in the work of Karpathiotakis et. al. (Karpathiotakis et al., 2014), which addresses another workflow from high energy physics (Higgs Boson Search). In their work, the authors propose an adaptive strategy, which utilizes Just-In-Time (JIT) access paths and column shreds for query processing.

We agree with the authors that it would be infeasible to store as much as 140 PB of raw data generated

at CERN in a database system, in particular when regarding main-memory DBMS. However, the query of the Higgs Boson search considered in (Karpathiotakis et al., 2014) resembles a highly selective exhaustive search on the vast amount of all raw data files. In contrast, our EPOS on HANA application is rather geared towards an incremental analysis of medium-size data sets, in the range of up to several terabytes, which are typical sizes for Monte-Carlo simulation data. We argue that the column-oriented data layout and efficient data processing capabilities of modern in-memory DBMS enable to shift the actual computation into the database engine. Together with the JavaScript-based SAPUI5 framework that allows flexibility and extensibility of the analysis application, our system offers the infrastructure to host the complete analysis workflow in the database, making commercial systems like SAP HANA more interesting for the high energy physics community in the future.

7 CONCLUSIONS

In this paper, we showed how an interesting application from the challenging and data intensive domain of particle physics, can be accelerated using a high-end column-store RDBMS. We mapped the static particle physics analysis workflow based on custom C++ code and the ROOT framework (Brun and Rademakers, 1997) efficiently onto SQL queries on relational tables. This opens the door for physicists to benefit from the parallelized join and aggregation operators of the in-memory DB SAP HANA. Moreover, by carefully utilizing analytical views and result caching we achieve instant result feedback on intermediate data sizes, and an overall speedup of more than an order of magnitude. In contrast to the static conventional approach, we turned the static into an agile workflow, and enabled the user to adjust parameter settings just in time. Besides the extensibility and capability of our framework to serve more than just the presented analysis requests, we believe that this approach shows is a right step into speeding up traditional science workflows.

ACKNOWLEDGMENTS

We thank the group of Prof. Werner from the Unversité de Nantes and the SUBATECH research laboratory for providing us insights into their domain-specific problem setting and provided data from the EPOS Monte-Carlo generator. We also thank Julien Marchand and Arne Schwarz for developing the initial version of the tool and helping to improve it. Moreover, we express our gratitude to our fellow colleagues in Walldorf for fruitful discussions and support.

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