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A New Tool For Measuring Detector Performance in ATLAS

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Abstract. The determination of the ATLAS detector performance with data is essential for all physics analyses and even more important to understand the detector during the first data taking period. Hence a common framework for the performance determination provides a useful and important tool for various applications. We report on the implementation of a performance tool with common software solutions for the corresponding data analyses. The tool provides a framework for gathering the input data, a common format of the output data, as well as methods to store the results in a collaboration wide accessible database. The aim is to implement an ATLAS standard that will be used for performance monitoring, physics analyses, and as realistic input to Monte Carlo event simulation. Deployment in every level of LHC data production centres, so-called Tier-1/2/3 centers, is supported. The overall concept of the performance tool, its realization and first experiences will be presented.

1. Introduction

The ATLAS [1] experiment is a multi-purpose physics detector at the Large Hadron Collider [2] (LHC) at CERN. The physics that shall be explored in proton-proton collisions at 14 TeV reaches from searches for new physics phenomena, like the Standard Model Higgs boson or super-symmetric particles, to measurements of Standard Model processes. Important for an accurate determination of the relevant cross-sections and physics parameters is the knowledge of the detector performance. The measurements of the detector response, like resolutions of energy, momenta and angles of triggered and reconstructed physics objects, the corresponding calibration scales, as well as trigger, reconstruction and identification efficiencies are input to practically all physics analyses.

The extraction of the performance parameters can be done either on the level of simulations of the ATLAS detector or directly from data, often referred to as *insitu* performance measurement. The latter method is essential for the first data taking periods to understand the behaviour of the ATLAS particle detection systems. It is also much preferred for later physics analyses because simulations, though already very accurate and advanced [3, 4, 5], are not able to describe all aspects of the detector behaviour. Especially, a performance determination based on collision data is able to monitor time-dependent changes and variations.

This article describes a new software framework [6] that will support the in-situ performance measurements by providing appropriate data structures, analysis tools and well-defined analysis steps. It is fully integrated into the ATLAS software environment ATHENA [7].

2. The Physics Scenario For A Performance Tool

A typical measurement of a proton-proton reaction at the LHC requires several event selection and reconstruction steps: triggering of interesting events, reconstruction of low-level physics objects, like particle tracks or energy clusters, of high-level objects, like electrons, muons, taus, photons and hadronic jets, and eventually the correct identification of the particles. In each step, the corresponding efficiency and resolutions need to be determined. The goal is to unfold the action of the detector and to deduce the underlying scattering reaction.

A commonly applied procedure is the so-called *tag & probe* method. It relies on the preparation of an unbiased sample of physics objects, the *probe* objects, which are used to calculate efficiencies and resolutions. The data sample is selected by means of an independent *tag* object or a *tag* selection. Here, one exploits the kinematics of well-known Standard Model processes, like Z boson production or top quark pair production.

As an example, the $Z \to \mu^+\mu^-$ process is used to determine the reconstruction efficiency of the ATLAS muon system. At nominal LHC beam energy and for an integrated luminosity of 100 pb^{-1}, about 50 thousand $Z \to \mu^+\mu^-$ events are expected to be detected. The *tag & probe* algorithm does not apply the nominal selection criteria, but asks for one triggered muon with high transverse momentum, p_T, reconstructed in the Inner Detector (ID) and Muon Spectrometer as a high quality track. The second muon is identified using only the Inner Detectors of ATLAS, the Pixel, SCT, and TRT detectors. The event topology is sketched in Figure 1. To efficiently reduce background, the two muons must have an invariant mass compatible with the precisely known, nominal Z boson mass [8] within a certain mass window. In addition, the identified tracks must be isolated from hadronic activity in the detector. The ID track represents the *probe*. One can now verify if the muon was also detected by the Muon Spectrometer by looking for reconstructed muons in a narrow cone around the ID track. Since for this track the Inner Detector and Muon Spectrometer measurements are independent, the muon reconstruction efficiency can be calculated as:

$$\epsilon = \frac{N_{\mathrm{muon-track}}}{N_{\mathrm{ID-track}}} , \qquad (1)$$

where $N_{\mathrm{ID-track}}$ is the number of ID *probe* tracks and $N_{\mathrm{muon-track}}$ the angular matched muon tracks. This formula assumes a background free selection, which is verified in Monte Carlo simulations to be about 0.2% [5]. With data the background contamination can be measured by a comparison of like-sign and opposite-sign muon pairs, which are from background and signal processes, respectively. In case of negligible background, it is sufficient to store only the *probe* track as an intermediate result, used later for the subsequent efficiency analysis.

If the analysis does not rely on the muon isolation criteria to reject background or if the background level exceeds the Monte Carlo estimates, the simplified analysis described above is not applicable any more. In case of non-negligible background, the full Z decay spectrum is used. Figure 2 shows the signal mass peak above the QCD background. The mass distribution is fitted by a function which contains a signal and a background contribution, e.g. a combination of an exponential and a Breit-Wigner function. The area under the Breit-Wigner part can be interpreted as the number of signal events, i.e. events which result from a Z boson decay. The spectrum is reconstructed with two different selections. The first is using *tag* muons reconstructed in inner and muon detectors and *probe* muons identified as an ID track, but not necessarily reconstructed in the muon spectrometer. The second selects events where both muons of the Z decay fulfill the *tag* condition, i.e. are reconstructed in both muon and ID tracking systems. After subtraction of the background using the sidebands, the following numbers of selected events are expected for the two cases:

$$N_{\mathrm{2tags}} = \epsilon^2 N \qquad (2)$$

$$N_{\mathrm{1tag,1probe}} = \epsilon(1-\epsilon)N , \qquad (3)$$

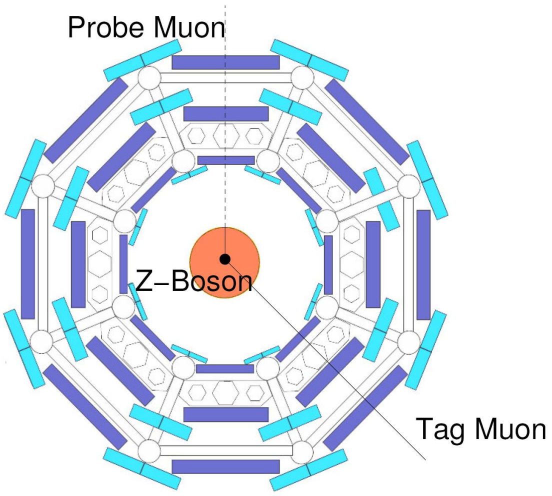

Figure 1. Schematic view of the ATLAS Muon Spectrometer with *tag* and *probe* muons. Their invariant mass must be compatible with the nominal Z boson mass.

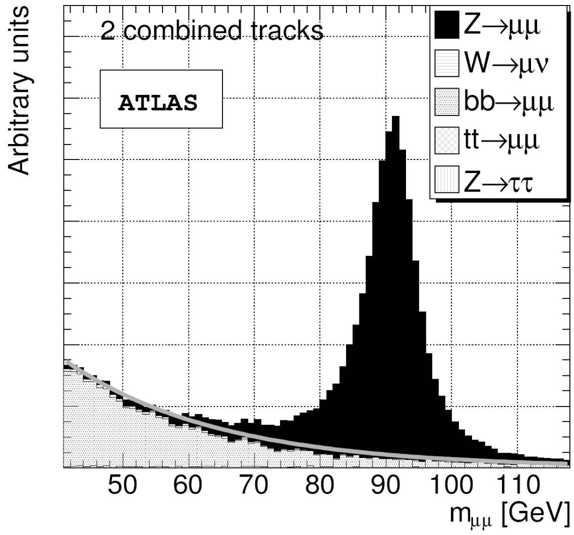

Figure 2. Reconstructed $Z \rightarrow \mu^+\mu^-$ spectrum with the signal peak and sidebands which are used to estimate the background level. The continuous grey curve shows the sideband parameterization. Here, the Z decays are selected using *tag* muons and *probe* muons reconstructed in both inner and muon detectors (combined tracks).

where N is the number of Z boson decays produced in the proton-proton collisions within the fiducial volume, and ϵ the reconstruction efficiency of the muon spectrometer. This efficiency can then be determined from the ratio of $N_{2\text{tags}}$ and $N_{1\text{tag},1\text{probe}}$. It is important to note that the efficiency test cannot be achieved on an event-by-event basis in this case. Moreover, the calculation of a binned efficiency, e.g. for different pseudo-rapidity regions of the detectors, requires at least two histograms for the two selections. This implies significantly larger data statistics than the first, more simple analysis case.

As a last example, the determination of the energy scale and resolution for leptons shall be discussed. It is essential for many physics analyses, since it has a direct impact on the performance of the trigger and of kinematic selection cuts. For leptons in the energy range of 20 GeV to 60 GeV, one of the most common approaches to measure these quantities relies again on the Z boson decay spectrum. The energy resolution and energy scale of the leptons influence directly the measured width and the mass peak value, respectively. In order to determine the lepton momentum scale and resolution, the energy resolution functions predicted by Monte Carlo simulations are iteratively adjusted in width and scale until the modified simulation agrees with the measured Z peak. The additional smearing is then implemented by parameterized functions, which can be applied to the full ATLAS Monte Carlo simulation as well as fast simulation. A more detailed discussion can be found in [5].

The analysis examples seem to be different at first sight, but have a common underlying structure based on three steps. All methods start with a standard signal selection and the preparation of *probe* objects or the filling of data histograms. These are usually kept in an intermediate data storage for further analysis. In a second step, the corresponding performance quantity is calculated, either by fitting parameterized functions or by event and *probe* object

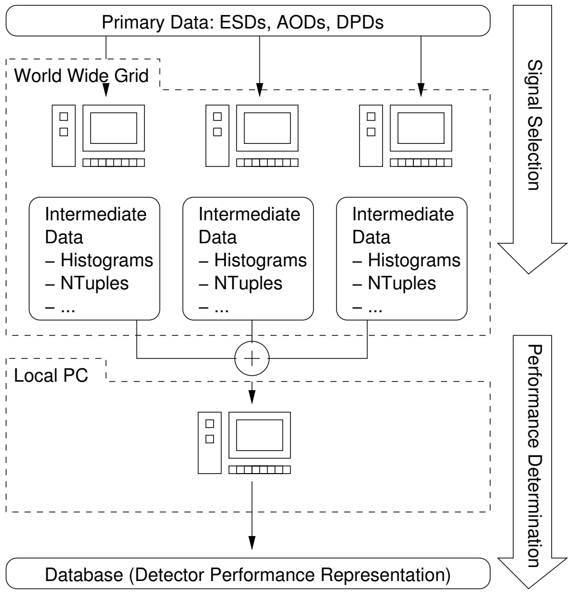

Figure 3. Computing model of the performance framework.

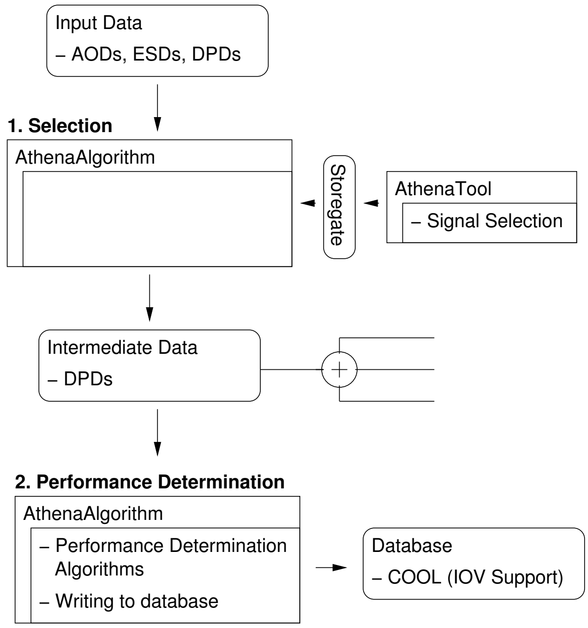

Figure 4. Performance package structure and analysis flow as it is implemented in the ATHENA software.

counting. The last step involves the representation of the performance measurement, which is typically a function of other parameters like pseudo-rapidity, η, azimuthal angle, ϕ, transverse momentum, p_T or other properties of the object under study. Eventually the result is stored in a data base.

3. Common Analysis Framework

The common framework of the performance tool is implemented in the ATLAS object oriented and C++ based software environment ATHENA [7]. It is subdivided into several software packages, which define the data structures, the analysis and user tools, the database structure and access, and provide a framework for the physics analysis step.

The performance tool is designed to handle input from all official ATLAS data formats. In ATLAS, data is stored in different storage formats which are built from the detector raw data and contain higher level objects with an increasing concentration of information: event summary data (ESD), analysis object data (AOD), and derived physics data (DPD). This data is usually distributed world-wide to computing centers which are accessible through the data grid [9]. In the first step, the event selection and *tag* object identification is therefore performed on the grid. The output data, the *probe* collections, are written into DPD files and then transferred to a local analysis facility.

The final analysis step in which efficiencies and performance results are produced is run on a local computing cluster or even a local PC. The efficiency and performance information is eventually transferred to the ATLAS conditions database, called COOL [10]. The computing model of the performance framework is displayed in Figure 3.

The actual implementation of the analysis package in terms of ATHENA base classes is shown in Figure 4. Inside ATHENA, the access to event-by-event data is performed by an *Algorithm* which can execute *AlgTools*. In the performance package, the event selection and tagging algorithms are all implemented as *AlgTools*. For example, in case of the electron efficiency part of the performance package, tools for $Z \rightarrow e^+e^-$ selection, electron *probe* collection based on ID tracks and/or calorimeter clusters, and angular association of reconstructed electrons with trigger objects are available (among others). The intermediate *probe* collection is kept in the transient data store, called *StoreGate*. The final analysis step could run equally well on the transient data, but for processing of large data volumes the transient information is saved to DPD files.

The last analysis step is also an ATHENA *Algorithm*, which eventually uses database *AlgTools* to write into the COOL database. The final data format is a so-called POOL [11] file, which is an object-oriented storage format based on the ROOT [12] package. The POOL file can also be saved locally to allow checks of the analysis and an examination of the results before transmitting them to COOL. This option is also foreseen to be used in analyses performed by individual physicists which do not need to be distribute their results via COOL to all other collaborators.

4. Data Structure and Storage

The *probe* objects are usually reconstructed particle track, leptons, or jets. Only the parameters which are necessary for the subsequent analysis steps are stored in the intermediate DPD. The content of the DPD can be freely defined and string tags stored in the meta-data of the file are used to identify the data content using a C++ map. For example, the quantities stored for electrons are typically the reconstructed energy, reconstructed η and ϕ, the electron quality cut, trigger information, and the invariant mass of the *tag* and *probe* muon pair. In addition to the object information, also general event properties can be saved, like the p_T of the Z boson, the angular isolation of the *probe* to the next hadronic jet, the jet multiplicity, maximum and sum of the jet transverse momenta. For simulated events, properties of the matched generator level particle is important for verification of the performance algorithm. This results in relatively small DPD sizes, in the order of 0.33 kB per event, compared to the original input of 200 kB per event in an AOD file. The DPD is then passed to the final analysis.

Since the results of the performance algorithm depend in general on several parameters they are binned into a n-dimensional matrix, where n is the number of parameters which map the physics phase space. Typically n is in the order of 4, at most, because each matrix element should contain enough data statistics for meaningful calculations. Storage space can become another limitation although it is less important.

Variable size bins in each matrix dimension are supported. Matrix projection and slicing operations are implemented to eventually display the results in form of ROOT histograms or combine the result to a single average. The matrices are additive such that output produced on the grid, using many computing resources in parallel, can be easily combined. This puts also a requirement on the data format of the matrix entries which must support an additive operation. Otherwise the matrix content is only defined by the performance application.

For ordinary efficiency calculations, only the number of trials, N_{trial}, and successes, N_{success}, of the selection under study are stored. A support of weighted event counts is in preparation. Different efficiency formulae are implemented, the classical $\epsilon = N_{\mathrm{success}}/N_{\mathrm{trial}}$, together with the corresponding uncertainty, as well as the Bayesian $\epsilon = (N_{\mathrm{success}} + 1)/(N_{\mathrm{trial}} + 2)$, which assumes a flat prior. For more complicated algorithms, which rely on reconstructed mass spectra, for example, ROOT histograms and fit functions for signal and background parameterizations are filled into the matrix.

Detector response functions are derived from comparing simulations to measured mass spectra with data, e.g. from leptonic Z boson or J/ψ decays, as described above. The resolution and scale parameters therefore need to be obtained first for the transition from the ideal particle on Monte Carlo generator level to the simulated detector level. And in a second step the difference from the simulated detector level to real data must be described. Both can be done in terms of

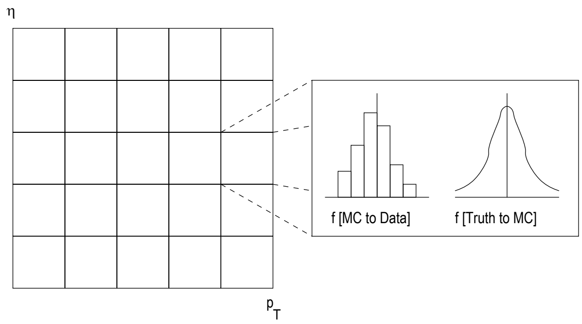

Figure 5. Schematic representation of a 2-dimensional performance matrix with η and p_T as parameters and resolution PDFs or histograms as entries.

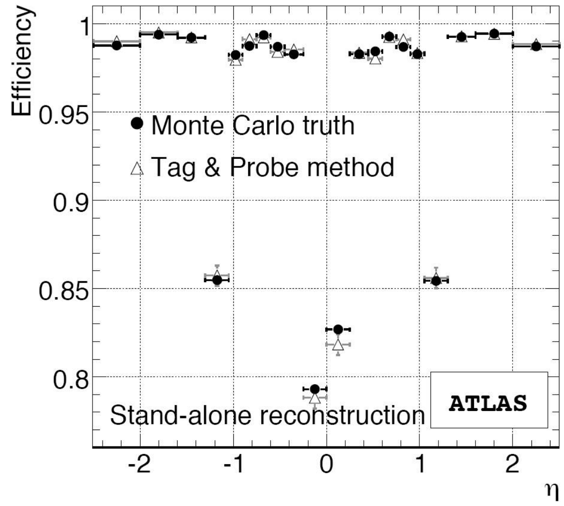

Figure 6. Muon reconstruction efficiency determined from simulated $Z \rightarrow \mu^+\mu^-$ events and the corresponding background in 100 pb^{-1} of ATLAS data. The result from the *tag & probe* method compares very well with the expectation directly derived from Monte Carlo information. The inefficiencies at $|\eta| \approx 0$ and $|\eta| \approx 1.2$ are due to the small gap between two muon barrel systems and the barrel-endcap transition region. This graphic is output of one of the first applications of the performance tool in ATLAS.

continuous probability density functions (PDF) or histograms, which then become entries in the matrix. This is schematically shown in Figure 5. In a future version, the combined information is concentrated into a so-called *RooWorkspace* which is part of the RooFit [13] package available in ROOT. Thus the functionalities of RooFit, which especially supports PDF calculations like folding operations etc., will become directly available to the end user of the performance tool. The general concept is however that the user interface should hide the internal complexity of the calculations.

Before the result matrices are written to POOL files and eventually to the COOL database, the data content is passed through a converter routine. The converter transforms the content and the matrix definitions, like the binning, in a unique way into vectors of integer and floating point numbers. The converter is integral part of the matrix C++ class and is used for both packing and un-packing the data. The correct transformation is guaranteed by identification tags added to the data. The ROOT I/O object streaming is used to eventually convert simple and complex objects of the matrix data, like integer and floating point vectors as well as *RooWorkspaces* containing PDF functions, into POOL format [11].

When data is transferred to COOL a unique identifier is attached to the data. This identifier contains information about the *probe* object, the performance parameter that was measured, the physics channel, the author or producer of the result, the software version of the package, and finally an interval of validity (IOV). The identifier structure is shown in Table 1. The IOV tag

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gives precise information for which data taking period or for which Monte Carlo set the stored matrix can be used.

Table 1. Database information which is used to uniquely identify the performance result in the COOL database. Some examples for possible identifier values are shown in the right-most column.

Database ID	Description	Examples
Object	Physics object stored in the database	Muon, Electron, Tau, Jet
Container	Name of AOD/ESD container	StacoMuonCollection, TriggerMu20
Type	Description of Performance Parameter	Efficiency, Scale/Resolution, Fake-Rate
Channel	Physics channel used in analysis	$Z \to \mu^+\mu^-$, $J/\psi \to \mathrm{e^+e^-}$, $\mathrm{t\bar{t}}$
Author	Author or Producer	MuonPerformanceGroup, JohnDoe
RecoSWV	Software Version used for reconstruction	14.0.21
IOV	Data: run number interval(s)	1432 - 1438
	Monte Carlo: Simulation Software Release	13.0.1

5. Present and Future Applications

The performance tool is currently used by the ATLAS E/γ and Muon working groups, and the Tau and Jet/Missing-Energy working groups plan to make use of the tool. An example of a physics study is shown in Figure 6. Other analyses are being implemented, like electron reconstruction efficiencies from $Z \to \mathrm{e^+e^-}$ and $J/\psi \to \mathrm{e^+e^-}$ events, electron trigger efficiencies, muon resolutions, tau fake rates from $Z \to \mathrm{e^+e^-} + \mathrm{jets}$.

The short-term goal is to apply it to first ATLAS data which are expected in 2009. In the first low-luminosity phase, data samples covering larger time and run intervals will be analyzed. Later, when the instantaneous luminosity reaches the design value, the performance tool shall be used for run-by-run feedback of the detector performance. For high statistics monitoring processes it may also be possible to establish efficiency and performance data that properly include time variations. This will not only be important for precision physics, like W or top quark mass determination, but also for searches, where non-functioning or inefficient sub-detectors may create fake physics signals, e.g. missing energy signatures.

An ideal client for the performance tool is the fast Monte Carlo simulation, called ATLFAST [14]. The fast simulation takes 4-vectors of particles on generator level and applies a tracking through the magnetic field and creates energy deposits in the calorimeters, both in a simplified way. Eventually, a smearing of the angles, momenta and energies, as well as detection efficiencies are applied to the reconstructed physics objects to resemble the full Monte Carlo simulation of ATLAS with the GEANT4 package. The ATLFAST procedure does not take fine details of the detector functionality into account, but applies averaged corrections. The resulting particle distributions agree well with the GEANT4 simulation, which is documented in Reference [14]. The gain of this approximation procedure is in processing time per event which is drastically reduced from about 2000 s to about 0.1 s, for a typical $\mathrm{t\bar{t}}$ event. Thus, for high rate processes like QCD jet or top-pair production, ATLFAST is the way to produce large statistics Monte Carlo samples. According to the ATLAS Computing model [9], about 80% of the ATLAS Monte Carlo event production will be done using a fast simulation, since the necessary computing power for a complete full simulation will not be available, even if grid resources are used.

The particle resolutions, even in case of the full simulation, are however not expected to describe the real detector in all details. The correct detector modelling is not a trivial task, since, e.g., material distributions have to be known precisely to simulate energy loss and multiple scattering of particles correctly. The AOD output of ATLFAST can therefore be passed through a second correction phase, which applies resolution and efficiencies as measured with data. Here, the performance tool is foreseen to be linked to the ATLFAST production. A mechanism that maps analysis object data (AOD) after detector correction directly to files of the same AOD format is already in place. The necessary information about the detector perfomance is currently taken from individually produced, local data files. It is therefore planned to replace those by a direct access to the performance information stored in the COOL database. In this way, the fast simulation can be adjusted to properly describe the detector performance as measured by the performance tool. The 2-phase production has the advantage that a reasonable Monte Carlo simulation is already available after the original ATLFAST production, and final performance parameters can be updated and refined. The correction mechanism on AOD level would also be a way to include time-dependent detector behaviour.

Another application of the performance tool is the study of systematic uncertainties on detector performance and efficiencies. This is important for all physics analyses and measurements. Currently only statistical uncertainties on the parameters determined are provided in the performance data. However, new data structures are being developed to include systematic effects. Multiple data matrices with systematic variations of parameters is a possible solution and different use-cases are currently being studied.

6. Summary and Outlook

The performance tool provides useful and standardized service to the ATLAS collaboration, and performance data can be distributed via the ATLAS central database. The interesting use-cases are: benchmark studies of the ATLAS performance groups, realistic fast Monte Carlo simulation, and the individual physics analyses. Fully working examples are implemented and in use.

Integration of the performance tool into the data processing at the Tier-0 computing centre is foreseen. The functionality will be continuously extended, for example to include treatment of systematic uncertainties, and corresponding data structures are being designed. The goal is a wide deployment of the tool and its applications within ATLAS to facilitate the analysis of ATLAS data.

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