

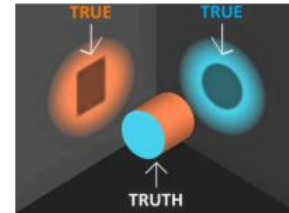
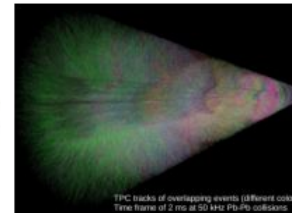
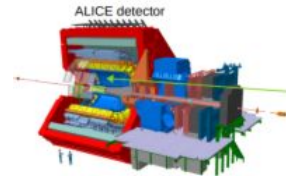
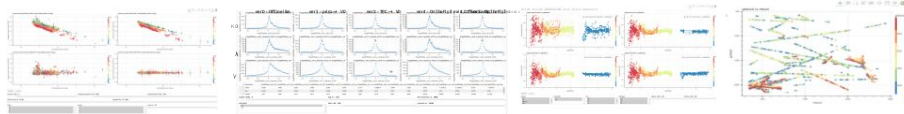


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RootInteractive expert tool for multidimensional statistical analysis, machine learning and analytical model validation.

Marian Ivanov (GSI Darmstadt), Marian Ivanov (UK Bratislava)
On behalf of ALICE collaboration



<https://github.com/miranov25/RootInteractive>

Alice Run 3 - goals and challenges

Record large pp and Pb-Pb minimum bias sample

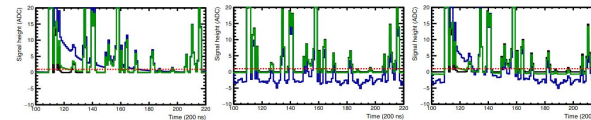
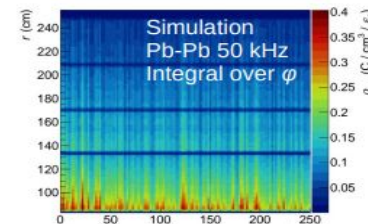
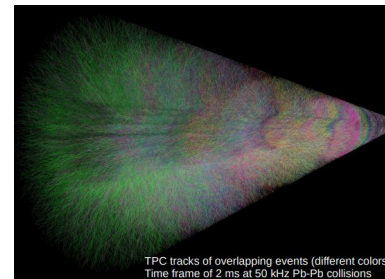
- Continuous readout at 50 kHz Pb-Pb collisions and 500kHz-1MHz pp collisions
- Unknown collision time
- Events overlapping in TPC \rightarrow substantial higher occupancy (~ 5 PbPb collisions, 100 pp collisions)

Tracking challenge: space charge in TPC detector distorting trajectories

- Non-uniform space-charge distorting E field
- Large space point distortions $O(5 \text{ cm})$ and Distortion fluctuations $O(5 \%) \sim 0.2 \text{ cm}$
- To be calibrated to $\sigma \sim 100 \mu\text{m}$ with space granularity $O(10^6)$ in space $O(1-5 \text{ ms})$ in time

PID challenge: Significant baseline bias and fluctuation

- Online digital signal processing to recover baseline (in FPGA)
- To be corrected below internal noise level



A high interaction rate environment, pile-up, distortions fluctuation, etc. ... necessitates the use of advanced methods of data analysis. Experts and highly customisable tools are needed

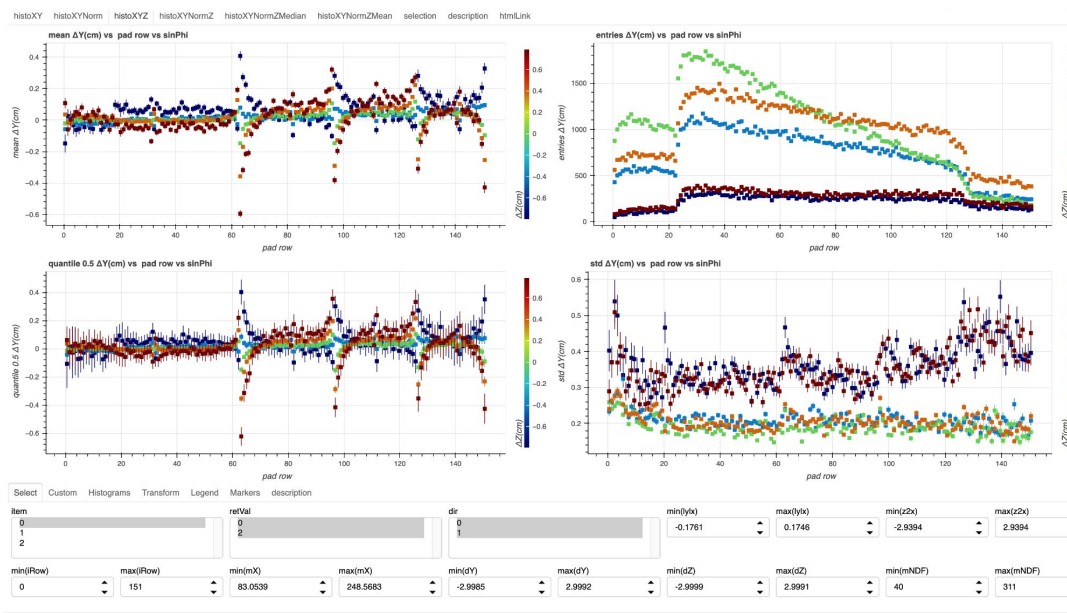
RootInteractive project

Seeing is believing

Querying/Iterative

Interacting/predicting is

understanding



Reconstruction/distortion monitoring example
 10^7 points x 50 attributes (space points, track, MC predictions)

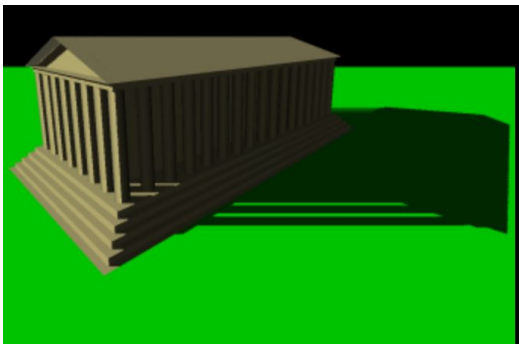
- <https://github.com/miranov25/RootInteractive#readme>

Multi-Dimensional interactive analysis - ML, fits, histogramming, data aggregation on server (Jupyter notebook, python scripts) and on clients $O(10^6-10^7$ rows, 10^8 entries rows x columns) (browser)

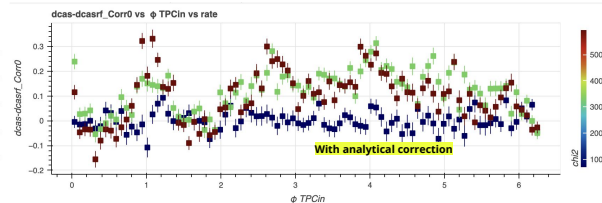
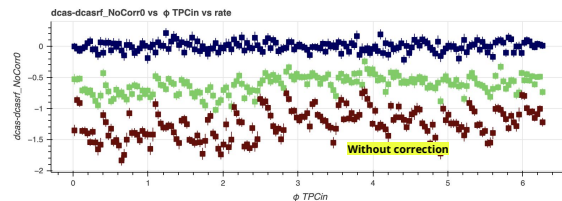
RootInteractive - current ALICE expert projects

- Run3 alignment & space point distortion calibration
 - Run3 digital signal processing
 - Run2, Run3 track reconstruction optimization, validation
 - MC/data mapping & TPC data volume studies
 - Run2, (Run3) expert differential QA/QC , performance parameterization, performance web pages
-
- Run3 (4D) reconstruction development - trackCombinator - V0, Cascade, Kink, cosmic finder
 - Fast simulation - fastMCKalman for detector and reconstruction optimization (Run3,Alice3)
 - Expert data representative sampling/skimming
 - PID calibration/validation and dEdx optimization
 - High dEdx,spallation tracking (collaboration with DUNE experiment)
 - Magnetic monopole reconstruction
-
- Particle production - MC generators parameter scan
 - Particle production as function of event properties

Multi-dimensional analysis vs shadow projections



Track DCA bias due space charge distortion contribution before and after correction
Reference-ML prediction at low rate without SC

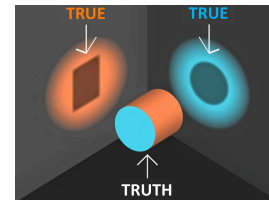


$$\sigma_{\vec{A} \ominus \vec{A}_{ref}} \leq \sigma_{\vec{A} (+)} \sigma_{\vec{A}_{ref}}$$

Object and reference objects (models/reference models, MC/Data, Data/ref. data), should be compared optimally in the full relevant multi-dimensional space.

- Shadow projection → Assumptions, imagination and rhetorical art in describing data needed
- Comparison statements to be based on invariants or on normalized data - e.g. the difference between the object and the reference object
 - After projection impossible
- In many typical cases variance $\sigma_{\vec{A} \ominus \vec{A}_{ref}}$ is very often smaller by orders of magnitude
 - For example, the rms value of the difference between ionic currents and scaled average values can be used as an alarm criterion. We cannot use the ion current itself
- Differential approach - possibility to decompose and understand the data e.g. distortion due space charge, and alignment in figure above

Root Interactive general purpose tool for multi-dimensional statistical analysis



By oversimplifying in analysis level, the explanations tends to be more complex resp. wrong

Our goal to provide a tool to deal with multidimensional problem simplify data analysis in many dimensions :

- Fit and visualise N-dimensional functions including their uncertainties and biases
- **Easy to validate assumptions, numerically evaluate approximations, differentially compare models**
- Enable simple **functional composition** for (non-parametric, analytical/parametric) functions and error propagation
- Very fast feedback from day one - seconds instead of weeks, to allow interactive expert communication
- **Multidimensional parametric optimization**
- Easily configurable visualization of unbinned and binned data, interactive multidimensional histogramming/projection and derived **aggregate information extraction** on the server (Python/C++) and **client (Javascript)**
- **Client side application (standalone HTML document) without necessity to install additional software**

A detailed differential understanding of the detector system, MC and reconstruction/calibration performance is a prerequisite for the successful application of Machine learning in physical analysis

Consideration: symmetries, alarms and invariants

Aggregation/projections of normalized data e.g. (data-model), (MC-Data), (data-symmetry) in multiple dimensions :

- RMS spread is much smaller
- Alarms/Outlier tagging with statistical significance - e.g. (data-model) $> N \sigma$, or likelihood
- **Invariance/symmetries**
 - in-variance in time (using e.g. reference/average run), in-variance in space (e.g. rotation, mirror symmetry)
 - B field symmetry
 - data - non parametric/parametric analytical model
 - smoothness resp. local smoothness

In RootInteractive supported mostly comparing data with reference “symmetric regression” and “template support” automatic comparison to reference data

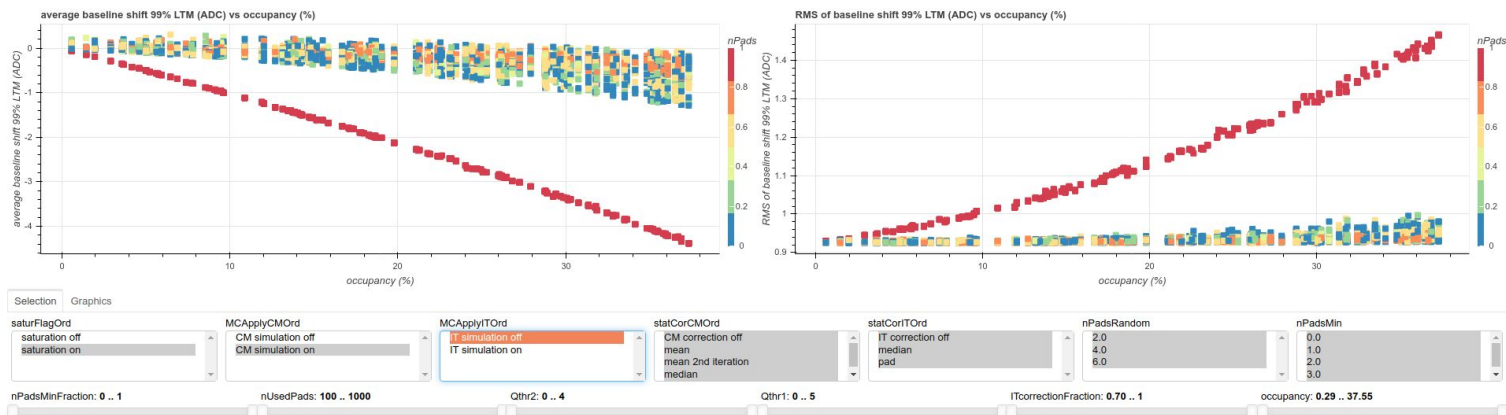
Multidimensional parameter optimization example - ALICE digital signal processing

Digital signal processing (13 parameters in example) needed for particle identification and data volume optimization. **O(200000) parameter settings simulated/generated on server**

- parameters: effects (On/Off), algorithm (different version), parameters of individual algorithms

Simulation and visualization/aggregation (NDPipeline+RootInteractive) done by bachelor student, fully solving optimization problems of DSP (several attempts before failed)

- Dashboard to answer “all questions”, FEEDBACK time for follow up questions O(seconds)
- Standalone dashboards, others could reproduce result based on the instruction in presentation, movie instruction
- **Interactive expert use-case discussion within ONE meeting. DSP understand and solved. Project DONE.**



Presentation, notebook, interactive dashboard and movie in RootInteractive tutorial:

- https://indico.cern.ch/event/1135398/contributions/4764024/subcontributions/370740/attachments/2402507/4114272/CMITSimuGEMTPC_RootInteractiveTutorial10032022.pdf
- https://indico.cern.ch/alice-lhc-offline/alice-lhc-notes/-/blob/master/JIRA/ATO_459/parameterScan.ipynb
- https://indico.cern.ch/event/1073883/contributions/4588170/attachments/2334149/3886420/simulScan_02112021.html
- <https://indico.cern.ch/event/1135398/contributions/4764024/subcontributions/370740/attachments/2402507/4109039/CMITSimulationsGEMTPC.mps>

Machine learning in RootInteractive - differential validation of MC/data and ML models

Using external models:

- E.g comparing the U-Net for the distortion correction with simple data driven Machine learning using Random Forest
- Parameter optimization in respect to different cost functions

RootInteractive extensions wrappers to scikit-learn and xgboost

- Fast approximation of functions and local PDFs

Interactive validation in RootInteractive on client $O(10^6-10^7)$ points

- Unbinned predict
- Aggregated information for further postaggragation
 - Local mean, median, STD - unbinned predict
 - Local kernel regression parameters -aggregated information on the mesh
 - Usually statistical properties of predict- value, resp. Mash of 1D histograms
- Generalized kernel linear regression on client (ND groupby+rolling+kernel)
- Predict on client (wasm+ONNX) in queue

Generalized linear (kernel) regression in RootInteractive - client side

Example, declaring generalized linear kernel regression

```
regressionArray=[  
  {"name": "regre1", "varX": ["x1", "x2" ..., "xn"], "varY": "y1", "weights": "w"}  
  {"name": "regreAgg1", "varX": ["x1", "x2" ..., "xn"], "varY": "y1", "weights": "w"}  
  {"name": "varAgg": ["xagg1", "xagg2" ..., "xaggn"], "nbinsAgg": [...], "rollingAgg": [...]}  
]
```

● Scikit-learn like user interface

- https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html
- Using fit and predict
- Regression predict new data source can be used as an alias function

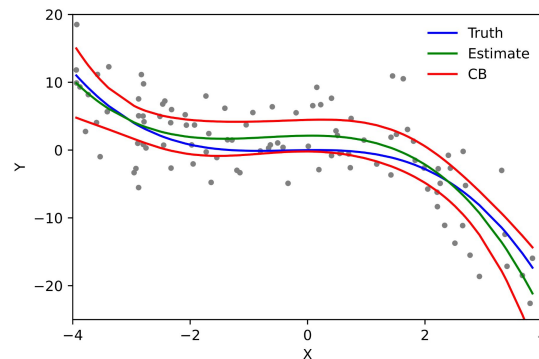
● Pol0 group-by regression, mean, median, quantiles, RMS

● Pandas groupby + ND-rolling/sliding kernel + Linear regression

- Interface as in the C++ code in original ND pipeline
- Using fit and predict on the grid
- Prediction of values and derived variables (using local fit parameters, e.g local derivatives)
- Predict is new data source
- **Work in progress**

- https://en.wikipedia.org/wiki/Linear_regression
- https://en.wikipedia.org/wiki/Kernel_regression

Linear regression is a **linear** approach for modelling the relationship between a **scalar** response and one or more explanatory variables



Example of a cubic polynomial regression, which is a type of linear regression. Although *polynomial regression* fits a nonlinear model to the data, as a **statistical estimation** problem it is linear, in the sense that the regression function $E(y | x)$ is linear in the unknown **parameters** that are estimated from the **data**. For this reason, polynomial regression is considered to be a special case of **multiple linear regression**.

Data preparation - RDataFrame <-> awkward (new interface)

Defining RDataFrame

```
ROOT::RDataFrame df(nTracks);
auto rdf = df.Define("qVector", "getQVector(160)")
               .Define("LogqVector", "ROOT::VecOps::Log(qVector)")
               .Define("qStd", "StdDev(qVector)")
               .Define("qMean", "Mean(qVector)")
               .Define("qLStd", "StdDev(LogqVector)")
               .Define("qLMean", "Mean(LogqVector)")
               .Define("qMedian", "TMath::Median(qVector.size(), qVector.data())")
               .Define("qLMedian", "TMath::Median(qVector.size(), LogqVector.data())")
               .Define("qTrunc", "truncate(qVector);")
               .Define("LogqTrunc", "ROOT::VecOps::Log(qTrunc);");
```

Loading awkward array

```
In [7]: 1 %%time
        2 array = ak.from_rdataframe(
        3         rdf,
        4         columns=(
        5             "LogqTrunc",
        6             "LogqVector",
        7             "qMean",
        8             "qMedian",
        9             "qStd",
        10            "qTrunc",
        11            # "qVector",
        12            "qLMean",
        13            "qLMedian",
        14            "qLStd",
        15            ),
        16 )
```

CPU times: user 1min 44s, sys: 884 ms, total: 1min 45s
Wall time: 10.2 s

dEdx optimization example

- Defining the data and derived function (C++) with native data representation
- loading the data → awkward array
- Execution scaling with number of cores (32 used in example)
- ML training/prediction → RDataFrame ()

Significant performance increase with parallel "RDataFrame ↔ awkward" in respect to previously used direct Tree queries interface. Used extensively, e.g. in fastMCKalman (distortion simulation/correction) and in trackCombinator (V0, cascade, cosmic, loop finder) prototyping use case studies

RootInteractive/Multi-Interactive project preparation and presentation

Expert data preparation

- Agreement on data to collect and aggregate
- Data sources
- Variables to import - asking questions
- Symmetries, invariances and possible alarms
- Pre-aggregation
- Data sampling
- Machine learning models
- Underlying Analytical models if exist
- Re-iteration

Data presentation:

- **Agenda: presentation, notebook, dashboard+ (optional)movie)**
- Goal
- **Data preparation explained**
- **Variables description**
- Observation highlights with snapshot from dashboard
- Domain experts, participants in the meeting should be able to participate in decisions, resp. be able to interact with dashboard data based on description in presentation

The data is presented in a multidimensional way. The aim is to answer all questions within one meeting/session. If the information is not sufficient, new data sources to be agreed on.

RootInteractive pad map dashboard declarations

User defined RootInteractive properties are required to get the html output (explained in next slides)

- **Alias array for derived variable/function definition - e.g defining status bitmask**
 - `aliasArray=["IDC0_OK","(0x2*(abs(IDC0_MeanRF0_LRatio)<sigmaRFCut0))|(0x4*(abs(IDC0_MeanRFL_LRatio)<sigmaRFCutL))",...]`
- **Variable array**
- **Parameter array - to control parameterized functions, selection and variable selection for ND histograms**
- **Widget descriptionArray**
- **Widget layout dictionary**
- **Histogram array**
- **Figure array**
- **Figure layout dictionary**

`aliasArray, variables, parameterArray, widgetParams, widgetLayoutDesc, histoArray, figureArray, figureLayoutDesc = getDefaultVarsDiff()`

*Simplification of using interface using set of predefined parameterizable templates to define standard layouts, extending only user defined widget control.
Templates focussed mostly on comparison of data and reference data, resp comparison of their distributions for user defined selection*

Functions on client - derived variables and functional composition

Predefined parametric javascript function

```
# here we can define derived variables - to define some invariances eg abs(XX_Mean/XXXMedain)<
aliasArray=[
#   ("", "dNprimdx*padLength"),      # ionization over pad
  ("Unit", "1+roc*0"),
  ("phi", "arctan2(gy, gx)"),
  ("QMax_Clusters_OK", "(0x1*(NClusters_Clusters_Mean>minEntries))|(0x2*(abs(QMax_Clusters_MeanRF0_LRatio)<sigmaRFCut0))|(0x4*(abs(QMax_Clusters_MeanRFL_LRatio)<sigmaRFCutL))"),
  ("QMax_Digits_OK", "(0x1*(NClusters_Digits_Mean>minEntries))|(0x2*(abs(QMax_Digits_MeanRF0_LRatio)<sigmaRFCut0))|(0x4*(abs(QMax_Digits_MeanRFL_LRatio)<sigmaRFCutL))"),
  ("SAC0_OK", "(0x2*(abs(SAC0_MeanRF0_LRatio)<sigmaRFCut0))|(0x4*(abs(SAC0_MeanRFL_LRatio)<sigmaRFCutL))"),
  ("IDC0_OK", "(0x2*(abs(IDC0_MeanRF0_LRatio)<sigmaRFCut0))|(0x4*(abs(IDC0_MeanRFL_LRatio)<sigmaRFCutL))"),
  ("IDC0_OK", "1+(abs(IDC0_RMS/IDC0_Mean)<0.5)"),
  ("IDC0_MeanOK", "0x1*(IDC0_RMS<5) [0x2*(IDC0_MeanLxCut)"]
]
```

Anonymous function (used for example in ND histograms as weights or variable)

varX	varY	varYNorm	varZ	varZNorm
gx	gy	Unit	QMax_Digits_Mean	QMax_Clusters_Mean

```
{
  "name": "histoXYNormZData",
  "variables": ["varX", "varY/varYNorm", "varZ"],
  "nbins": ["nbinsX", "nbinsY", "nbinsZ"], "axis": [1,2], "quantiles": [0.35,0.5], "unbinned_projections": True,
},
{
  "name": "histoXYZNormData",
  "variables": ["varX", "varY", "varZ/varZNorm"],
  "nbins": ["nbinsX", "nbinsY", "nbinsZ"], "axis": [1,2], "quantiles": [0.35,0.5], "unbinned_projections": True,
},
}
```

Figure axis transformation

xAxisTransform	yAxisTransform
lambda x: log(1+x)	lambda x,y: y/x

Custom javascript function (javascript function as a text)

```
# defining custom java script function to query (used later in variable list)
aliasArray+=[{
  "name": "funCustom0",
  "variables": [i for i in variables if "ustom" not in i ],
  "func": "funCustomForm0",
},
{
  "name": "funCustom1",
  "variables": [i for i in variables if "ustom" not in i],
  "func": "funCustomForm1",
},
{
  "name": "funCustom2",
  "variables": [i for i in variables if "ustom" not in i],
  "func": "funCustomForm2",
}
]
```

padrow

Select Custom Histograms Transform Legend Markers

return IDC0_RMS<2

funCustomForm0

return IDC0_RMS/IDC0_Mean

Many different ways to define derived variables and functional composition.
Dependency trees to resolve functional and data source dependencies.

Histogram declaration - calibration QA browser

Set of the 2D, 3D (ND) histograms declared ()

```

histoArray=[
{
  "name": "histoXYData",
  "variables": ["varX","varY"],
  "nbins":["nbinsX","nbinsY"],
  "axis":[1],"quantiles": [0.35,0.5],"unbinned_projections":True,
},
{
  "name": "histoXYNormData",
  "variables": ["varX","varY/varYNorm"],
  "nbins":["nbinsX","nbinsY"],
  "axis":[1],"quantiles": [0.35,0.5],"unbinned_projections":True,
},
{
  "name": "histoXYZData",
  "variables": ["varX","varY","varZ"],
  "nbins":["nbinsX","nbinsY","nbinsZ"],
  "axis":[1,2],"quantiles": [0.35,0.5],"unbinned_projections":True,
},
{
  "name": "histoXYZNormData",
  "variables": ["varX","varY/varYNorm","varZ"],
  "nbins":["nbinsX","nbinsY","nbinsZ"],
  "axis":[1,2],"quantiles": [0.35,0.5],"unbinned_projections":True,
},
{
  "name": "histoXYZNormData",
  "variables": ["varX","varY","varZ/varZNorm"],
  "nbins":["nbinsX","nbinsY","nbinsZ"],
  "axis":[1,2],"quantiles": [0.35,0.5],"unbinned_projections":True,
},
},

```

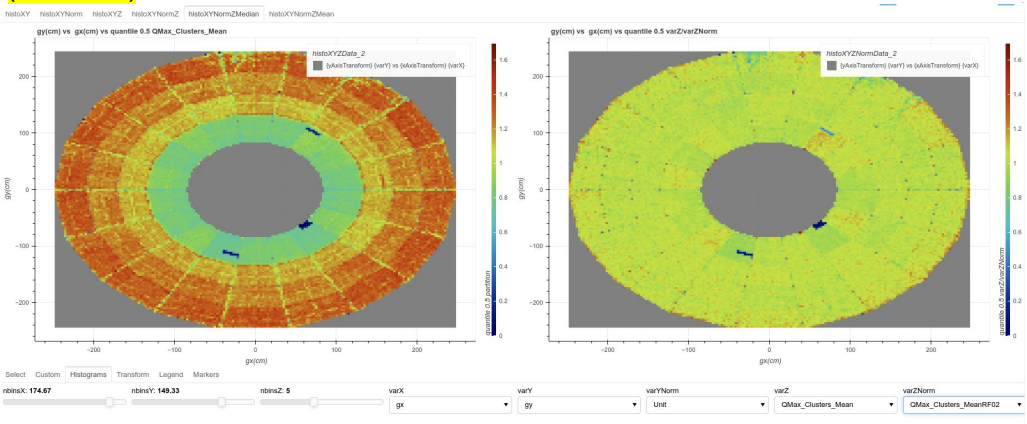
Anonymous function (used for example in ND histograms as weights or variables)

The interface shows a control panel with dropdown menus for variable selection and sliders for binning. The variables selected are varX: gx, varY: gy, varYNorm: Unit, varZ: QMax_Digits_Mean, and varZNorm: QMax_Clusters_Mean. Below these are sliders for nbinsX: 30, nbinsY: 30, and nbinsZ: 5.

Parameterized histograms:

- Variables and weights could be any variable from data source (column, derived functions, anonymous function)
 - In the QA/calibration browser variables defined by user selecting (varX,varY, varZ)
 - Binning controlled by parameters (nbinsX, ...)
- Derived aggregated data exported as new data source
 - Declaring quantiles and projections
 - Projection could be binned (fast) and unbinned

QA example mean charge: left - raw values(varZ), right-normalized to "expectation" (varZNorm)



Customizable Ndimensional histograms and projection. Example:

- X,y median profile of cluster charge map (left) and normalized to phi symmetric RF prediction

Webasm interface - under development

New functions/transformations/data sources using wasm:

- Fast Fourier transform
- Convolution, deconvolution
 - Numpy like interface (binned data)
 - Functional interface (unbinned kernel function)
- ONNX interface
- Based on benchmark transformation of the older javascript numerical code to wasm

<https://webassembly.org/>

RootInteractive - conclusion

RootInteractive is used extensively and successfully in many ALICE use cases for multidimensional analysis

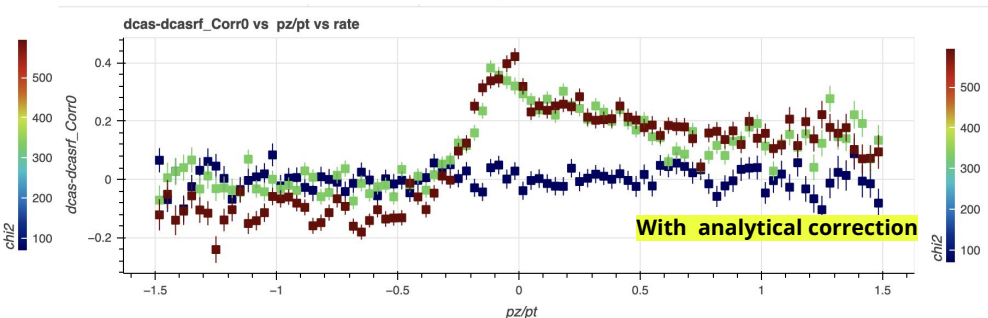
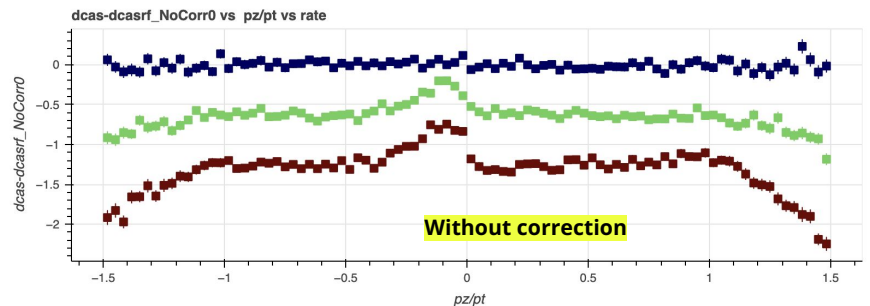
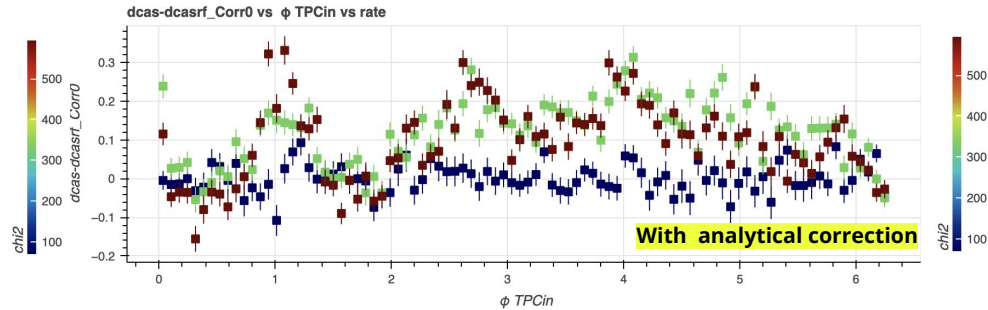
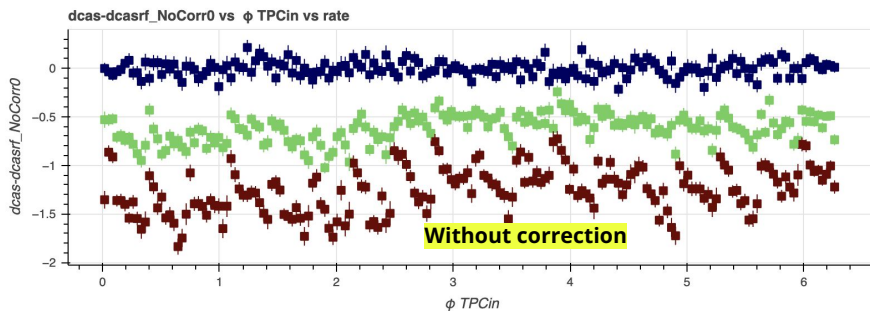
- Most important expert tools for the many use cases - .e.g. distortion calibration, reconstruction and dEdx optimisation, preparation of a new reconstruction algorithm (trackCombiantor)

Current use cases, now mainly related to detector(calibration, simulation, QA) and global reconstruction (RUN3, RUN2 as reference, Alice 3)

Pilot N-dimensional physical analysis with sampled/skimmed data is in the queue

Backup

DCA-DCA0 bias - rate evolution (4,330 kHz, 660 kHz)



DCA bias in phi direction strongly eliminated - residuals O(2 mm) **comparable with intrinsic resolution** of the tracks in vertex O(0.2 cm). New analytical fits - fitting also density profile

DCA bias in theta direction strongly eliminated. Remaining bias due charge up on C side - to add up in the analytical fit version (IFC and OFC fit). Charging up rate and time dependent (see Run1, Run2 studies)

RootInteractive usage in ALICE

in following slides code snippet with user code declaration shown for illustration without further discussion

Machine learning - derived variables - RF regression - per channel QA example

```
statDictionary={"mean":None,"median":None,"std":None}
```

```
varListG=["Ix","Iy","GainMap","A_Side"]
```

```
varListLocal=["Ix","Iy","GainMap","roc"]
```

```
vars=[
```

```
  "NClusters_Clusters_Mean","NClusters_Digits_Mean",
```

```
  'QMax_Clusters_Mean','QMax_Digits_Mean',
```

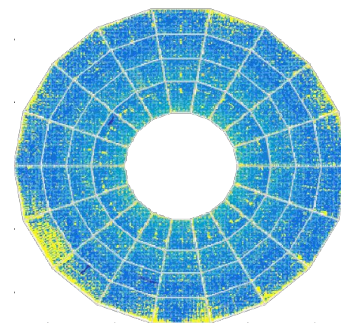
```
  'IDCO_Mean','SACO_Mean'
```

```
]
```

```
statOut=miErrPDF.predictStat(dfK0[variableX],statDictionary)
```

Per channel QA and example derived QA variables for
NClusters_Clusters:

- NClusters_Clusters_Mean
- NClusters_Clusters_MeanRF0,
- NClusters_Clusters_MeanRF0,
- NClusters_Clusters_MeanRFL,
- NClusters_Clusters_MeanRFL_Med
- NClusters_Clusters_MeanRFL_Std



Defining models:

- varying parameter of models, input variables and local statistics

Global (varListG) and **local regression (varListLocal)** extracting for basic calibration and QA properties of ALICE TPC calibration and QA variables

- global φ symmetric model, local model **without φ symmetry**
- **Automatic alarms - data "out of range" | data-prediction | $< n\sigma$ without "reason" (other calibration, masking known problems)**

Robust local statistics - median and local std estimator for the outlier tagging and PDF description