

PID Calibration

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Scope

Charged PID

How it is done

What will be available to you

Outline of systematic uncertainty application

FAQ

Your questions.

[Daniel's tutorial on using PIDCalib2](#)

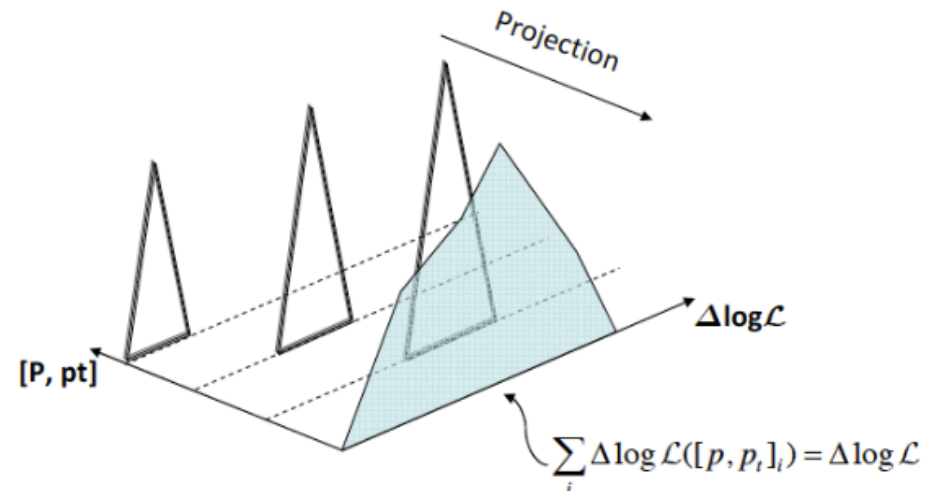
[README has examples](#)

Charged PID

- Simulation PID response doesn't match that of data
- Define a fully data driven method to derive PID efficiencies
- Choose samples of decays where particle type can be determined **without** PID selection (ideally at all, in practice at least no PID on that track)
- Desired properties
 - High purity
 - High yields
 - Broad kinematic coverage
 - A rate that doesn't saturate the bandwidth of the calibration stream

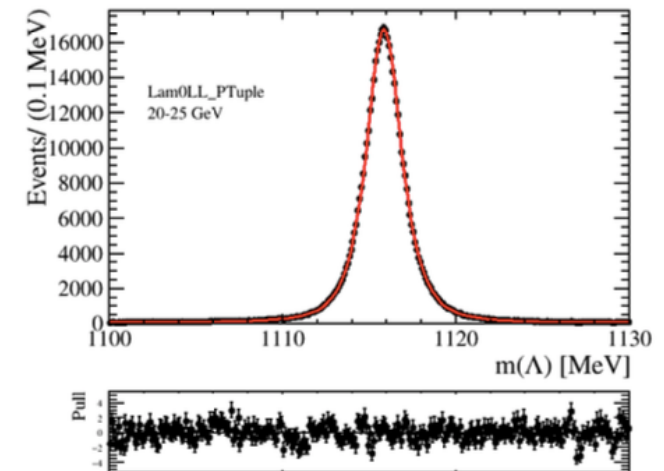
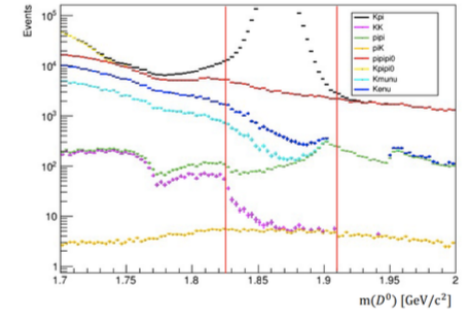
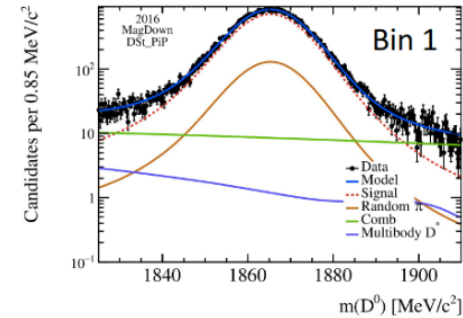
Basic Premise

- The PID response is track based
- Find the variable to which the PID response is sensitive
- Tracks within a sufficiently small bin of these variables will all have the same PID response



Basic samples (esp for EM)

- For Kaons and Pions: $D^* \rightarrow D^0 \pi^+$, $D^0 \rightarrow K^- \pi^+$
- For Protons: $L0 \rightarrow p \pi^-$
- For Muons: $B \rightarrow J/\psi K$, $J/\psi \rightarrow \mu\mu$
- For electrons: $B \rightarrow J/\psi K$, $J/\psi \rightarrow e e$
- Other possible samples, but unlikely to be available for EM due to complexities requiring extra data validation.



Calibration method

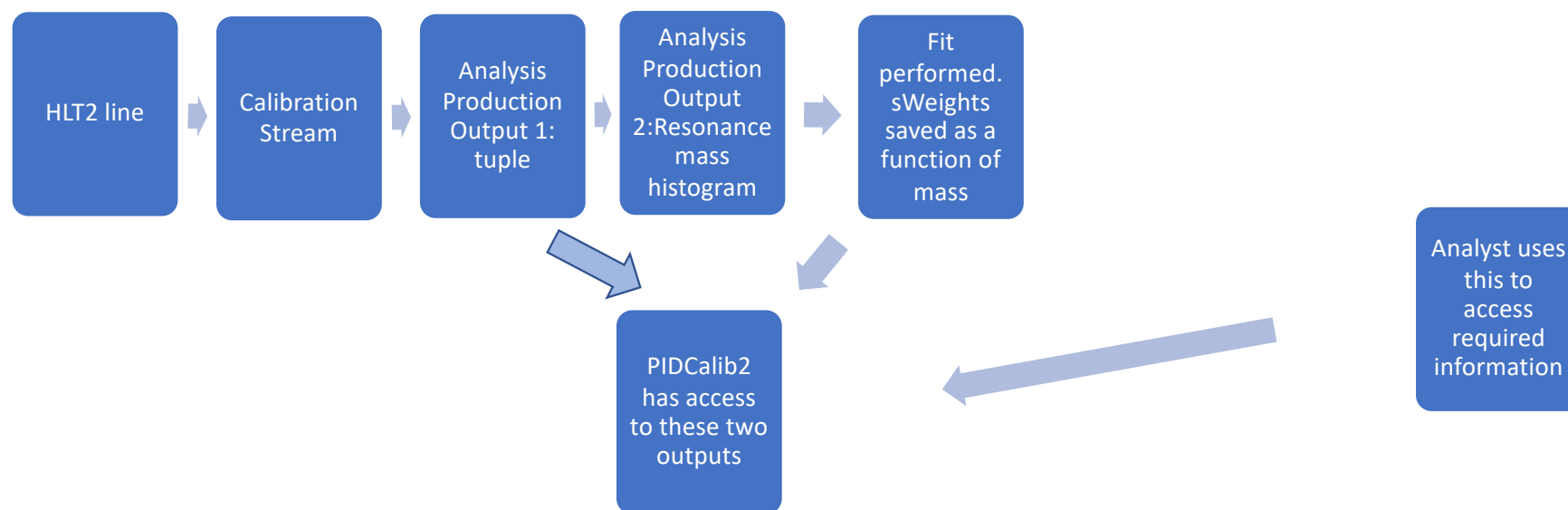
Requirements:

- One cut doesn't fit all – calibration must work for any PID cut choice
- Relatively fast speed – no analysis wants to spend weeks doing this
- Low learning curve – undesirable for every analysis to reinvent the wheel

Design:

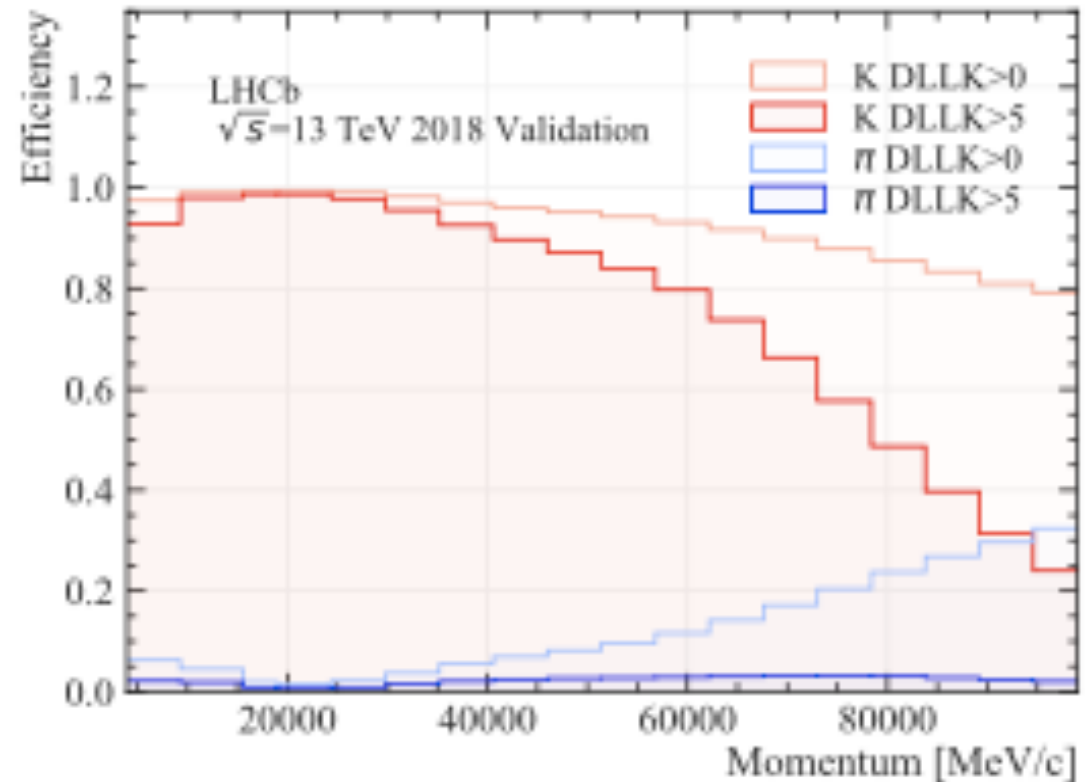
- Extraction of the "track samples" is a dedicated responsibility
- Tracks are assigned signal weights to remove background from sample
- Analyst simply counts weights before and after cut in order to determine efficiency

Run 3 vision

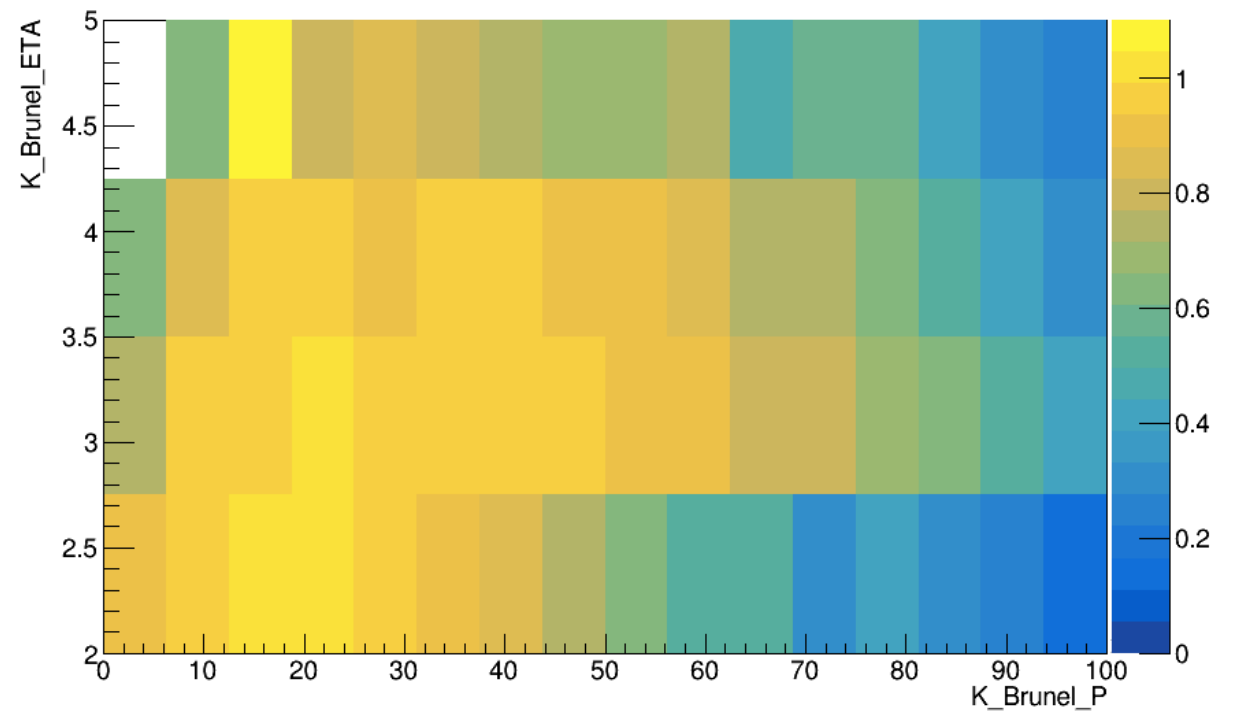


First you need binned efficiencies

- Create efficiency table:
- You enter the cuts of choice
- You enter the defined bins
- PIDCalib2 looks up the calibration tracks in each bin and counts all sWeights and those that pass the cut. Saves information of efficiency
- Can put these into a root histogram if you wish.



In 2
dimensions



Ntracks or not?

- If your reference sample is MC, then it is likely that your Ntrack distribution doesn't match that of data.
- In this case it can make sense to only bin in P , η or P_t . You then assume that the calibration sample has similar multiplicity to your own data, and therefore assume an integration over this variable



What to think about:

- Traditional binning variables: P , P_t or η , N_{tracks} (may not need)
- ProbNN variables may have some dependence on other track quantities
- Where to place the bins should depend on the kinematic dependence of the tracks in your analysis.
 - Trade between small bins vs being sensitive to statistical fluctuations due to yields of calibration data.

Next: Calculate the efficiency for your analysis

- Essentially, find the average efficiency over all tracks in your physics analysis
- PIDCalib2 can accept your input tuple, and add to it efficiency information from the histograms you created in Step 1.

Demo

```
dev/pidcalib2-test 8s
pidcalib2.ref_calib --sample Turbo18 --magnet up --ref-file data/user_ntuple.r
bin-vars '{"P": "P", "ETA": "ETA", "nTracks": "nTracks"}' --ref-pars '{"Bach": [
user_ntuple_PID_eff.root
[8 ref_calib:191] Running PIDCalib2 ref_calib with the following config:
[08 utils:116] =====
[08 utils:119] sample      : Turbo18
[08 utils:119] magnet       : up
[07:08 utils:119] bin_vars      : {"P": "P", "ETA": "ETA", "nTracks": "nTracks"}
[07:08 utils:119] histo_dir     : pidcalib_output
[07:08 utils:119] output_file    : user_ntuple_PID_eff.root
[07:08 utils:119] ref_file       : data/user_ntuple.root
[07:08 utils:119] ref_tree       : DecayTree
[07:08 utils:119] ref_pars       : {"Bach": ["K", "DLLK > 4"]}
[07:08 utils:119] merge         : False
[07:08 utils:119] compatibility  : False
[07:08 utils:119] verbose        : False
[07:08 utils:119] version        : 0.5.2
[07:08 utils:120] =====
[07:08 ref_calib:214] Loading reference sample 'data/user_ntuple.root' ...
[07:08 utils:251] Events out of binning range: 1 (1.00%)
[07:08 ref_calib:233] Average per-event PID efficiency: 88.13%
[07:08 pid_data:592] Efficiency tree saved to user_ntuple_PID_eff.root
```

Calculate efficiency of events with multiple tracks

```
--ref-pars '{"Bach": ["K", "DLLK > 4"], "SPi": ["Pi", "DLLK > 4"]}'
```

--merge to copy the PID efficiency tree to your input file and
add the efficiency tree as a "Friend" of your input tree

Practical Tips (1):

- What if I want to put two PID cuts on a track e.g $DLLK > 5$ and $ProbNNp < 0.2$
 - No problem! The response of the two PID variables is correlated:
 - Do not create separate histograms for the two PID cuts and multiply together
 - Instead ask PIDCalib2 to give you the histogram for the combined cut
- $\varepsilon(DLLK > 5 \ \&\& \ ProbNNp < 0.2)$
 $\neq \varepsilon(DLLK > 5) * \varepsilon(ProbNNp < 0.2)$

Practical Tips (2):

- I have a three track decay, each track has different PID cut applied (e.g $L_c \rightarrow pK\pi$), how do I find the PID efficiency of the decay?
- Multiply the track efficiencies for each event first. Then take the average overall events
- $\epsilon(L_c) = \langle \epsilon(P) * \epsilon(K) * \epsilon(\pi) \rangle \neq \langle \epsilon(p) \rangle * \langle \epsilon(K) \rangle * \langle \epsilon(\pi) \rangle$

How much
calibration
data?
When
available?

- You need to match the run range of calibration data to the run range of your analysis.
 - PID performance is fill dependent, might be stable but might not. You can cut the calibration sample by run if required
 - From experience, calibration yields are sufficient for HF analysis
- AP will be run and take some time (presumably your analysis has the same issue)
 - Hope that fits are sufficiently automated that time from end of AP to availability in PIDCalib2 ~24-48 hours

What's the error?

- Calibration statistical uncertainty should hopefully be too small to worry about. It is however calculable from the PIDCalib2 output. The statistical uncertainty associated to your reference sample should be larger
- There is a systematic associated with your choice of binning scheme
 - The assumption that the efficiency is constant across the bin is an assumption
 - Usually this is a significant contribution
- sWeights come with issues. Run2 estimate $\sim 0.2\%$ absolute. Expect similar in Run 3. The binning systematic is still likely to be bigger

PIDCalib2 or PIDGen

Remember, both derive from the same calibration samples, and the same sTables.

Hence both methods have the same limitations in this respect

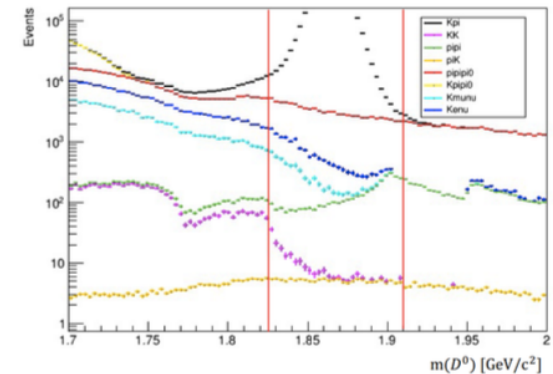
PIDGen – effectively resamples PID distributions from the calibration data and replaces the variable in your tuple dependent on track kinematics. Particularly useful if you want to put the PID distribution into a NN.

PIDCorr – resampling taking into account correlations between PID variables for the same track.

Things PIDCalib won't do for you

- Decay in flight
- Provide samples for physics analyses (there are often veto cuts on the samples to keep rates manageable)
- Replace your own thinking especially when it comes to systematic uncertainties
- Currently doesn't provide an automated Fit & Count derived efficiency

Dealing with this is non-trivial





Questions ?
