Optimizing ORCAs NMO sensitivity with PID classes

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Recap[1]: Goal

- Goal: optimize the sensitivity of ORCA to Neutrino Mass Ordering signal
- Method: introduce some binning scheme in PID variable q and calculate the sensitivity
- Issue: decouple changes in sensitivity due to statistics of Response Matrix or due to signal
- Property: When hypothesis testing using a RM [2]:

$$\langle \Delta\chi^2 \rangle (N_{MC}) \approx \Delta\chi^2_\infty + \frac{K}{N_{MC}}$$

[1]https://indico.cern.ch/event/808541/contributions/3453565/attachments/1860152/3061014/collaboration_meeting_infinity_20190614.pdf
[2]Neutrino oscillations and Earth tomography with KM3NeT-ORCA, S. Bourret, 2018

Recap: Fit to chi2 of sampled response matrix

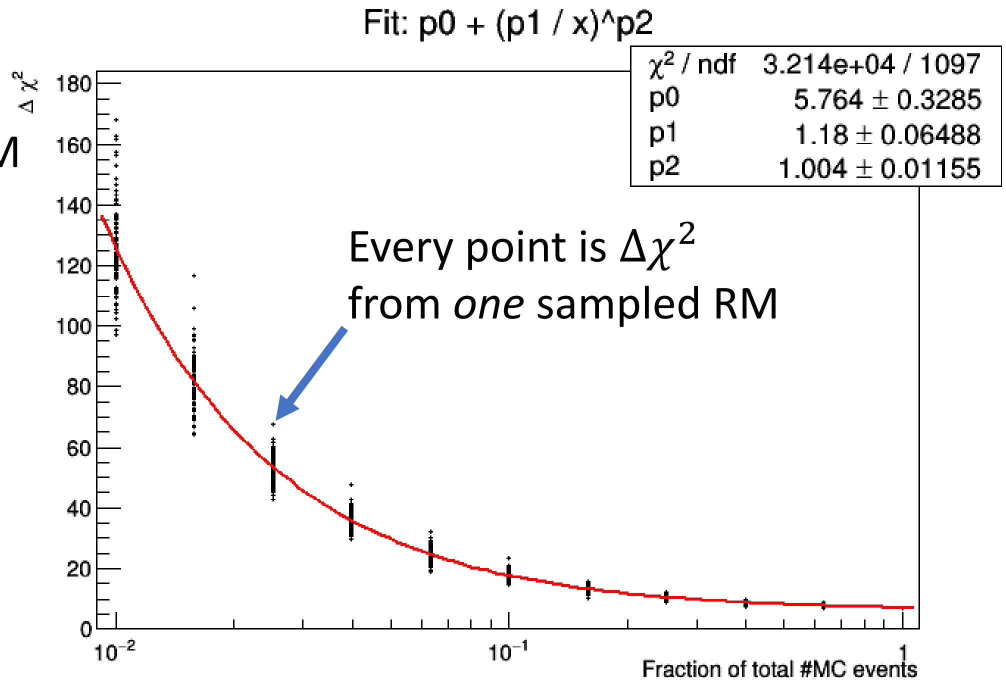
1. Create response matrix with ***fraction*** of all MC events
2. Calculate sensitivity with ***sampled*** RM
3. Do 1. and 2. many times
4. Sensitivity behaves as

$$\langle \Delta\chi^2 \rangle \approx \Delta\chi^2_\infty + \frac{K}{N_{MC}}$$

5. Fit to function **p0 + (p1 / N)^p2** as a check on the behavior: p2 = 1

6. Fit to function **p0 + (p1 / N)**

$$\Delta\chi^2(1) = 7.65$$
$$\Delta\chi^2_\infty = 5.66$$



Recap:

- Under criterium 5. the 5 and 10 PID classes extrapolation procedure does not work. This is also visible in the shape of the curve.

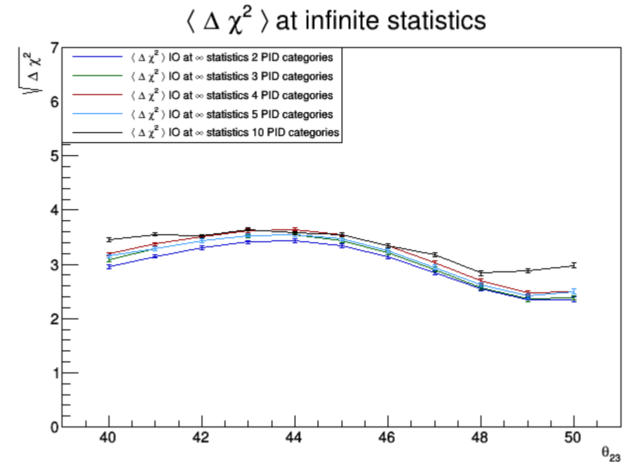


Figure: example of extrapolated sensitivity curve behaving unexpectedly for $N_q = 10$

- Cross-checks: removing q information removes improvements in sensitivity

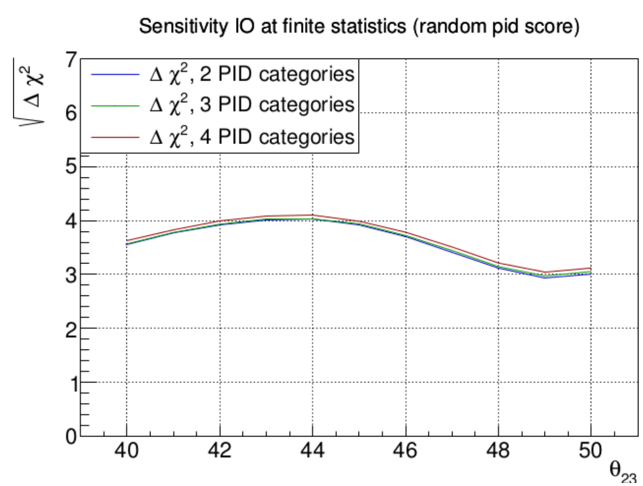


Figure: example of removing q information yields overlapping curves

Metric and method

- Metric needed for finding optimal sensitivity
- Define "integrated sensitivity":

$$S_I = \int_{\theta_{23}=40}^{\theta_{23}=50} S^{NO} + S^{IO} d\theta_{23}$$

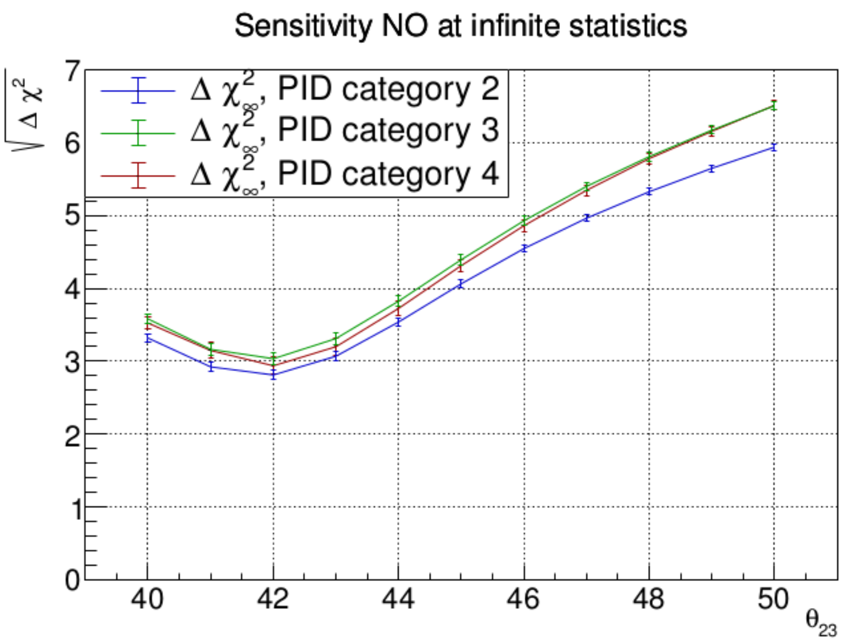
  - Remove θ_{23} dependence
  - Combine NO / IO cases (remove Δm^2_{31} dependence)

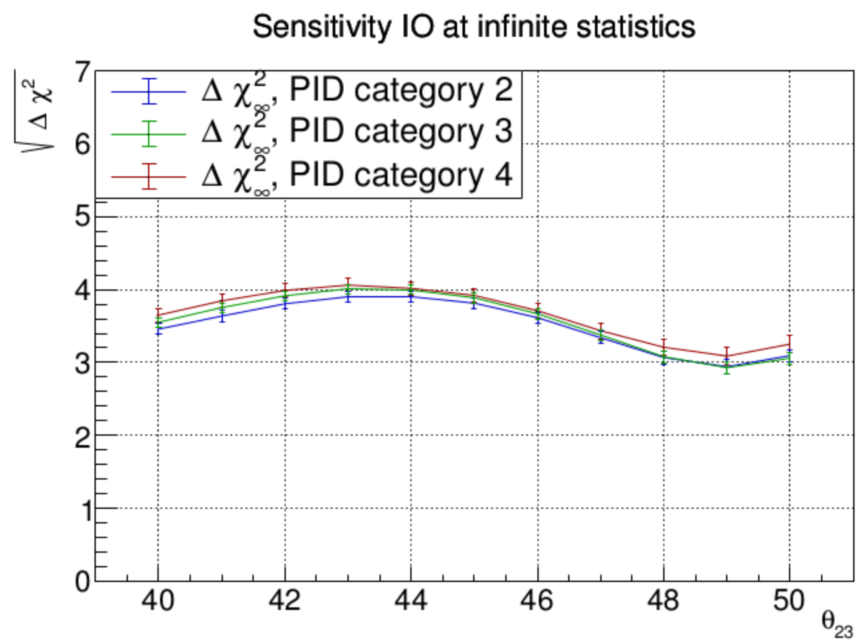
- Brute force different PID set-ups: 2, 3 and 4 classes
- All combinations of cuts with steps of $\Delta q = 0.1$
- Reconstruction information used is always:
  - 2 classes: [shower, track*]
  - 3 classes: [shower, shower, track*]
  - 4 classes: [shower, shower, track*, track*]

*[ORCA meeting 20180827] Use shower energy if available else track energy, rest is track reconstruction

Sensitivity curves for best int. sensitivity

- Comparing 2, 3 and 4 PID classes:





- NO: 3 and 4 perform significantly better than 2
- NO, IO: 3 and 4 have overlapping error bars

Results

- For the basic 2 PID category case:
  $q = 0.7$ is slightly better (+2.5%) than $q = 0.6$

- The cuts providing the largest int. sensitivity are:

#Classes	Cuts	Int. Sens.
2	0.7	76.8
3	(0.3, 0.7)	80.9
4	(0.3, 0.7, 0.8)	81.2

- NB: Int. sensitivity differs <0.5% between 3 and 4

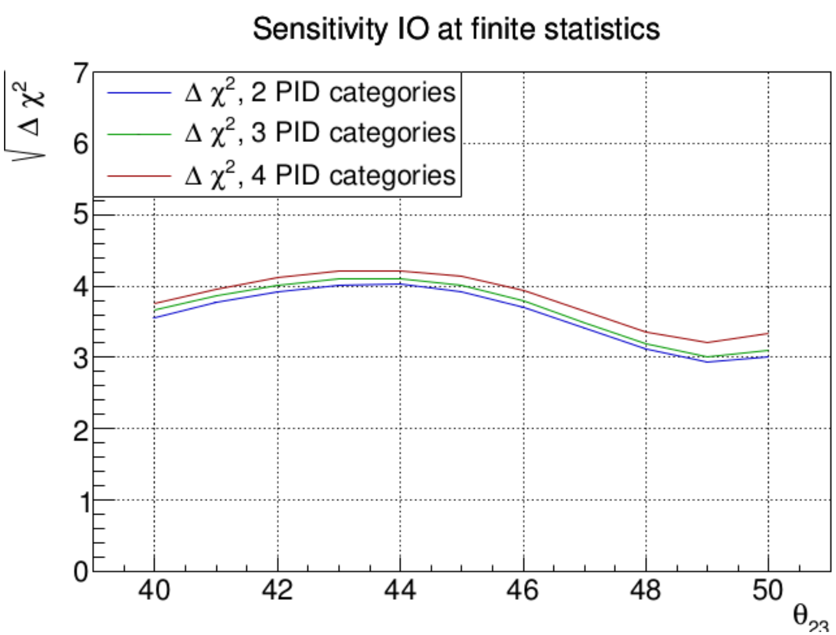
Conclusions and Discussion

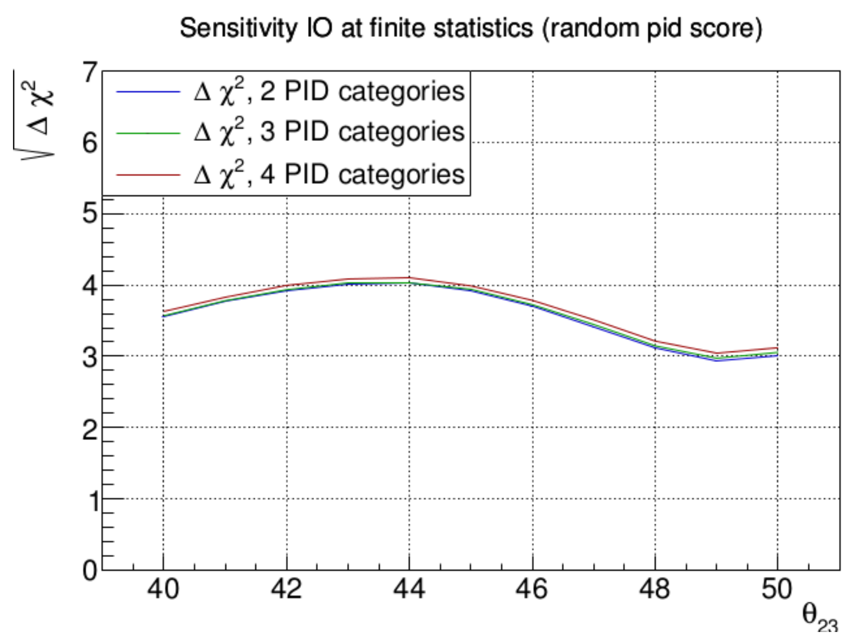
- 3 PID classes is optimal
  - No clear improvement going from 3 to 4 classes
  - Physically it is unclear what the 4th bin adds
    $$q = (0.7, 0.8)$$
  - With sea data less bins is better due to limited statistics
  - Cuts of (0.3, 0.7) give best integrated sensitivity (these are already being used!)

- Statistics used in sampling procedure was 5x lower for bruteforce (this work) than figures shown at Nantes (link on slide 2)

- Document describing procedure coming soon™

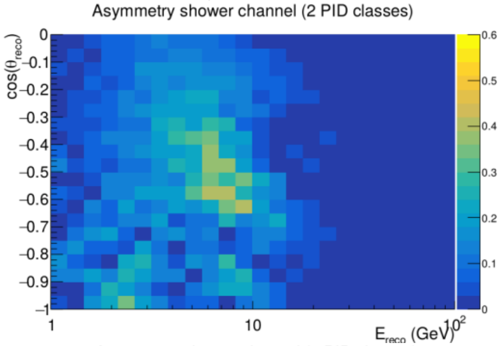
Backup: Sensitivity at finite statistics
Actual PID score used (left) and random PID score used (right)

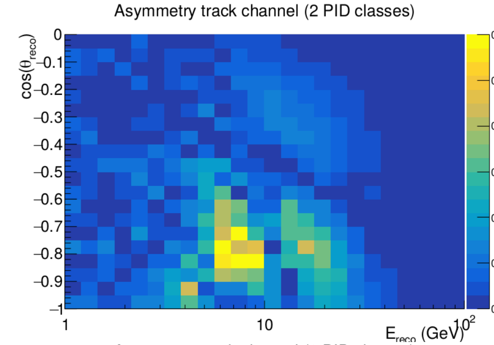




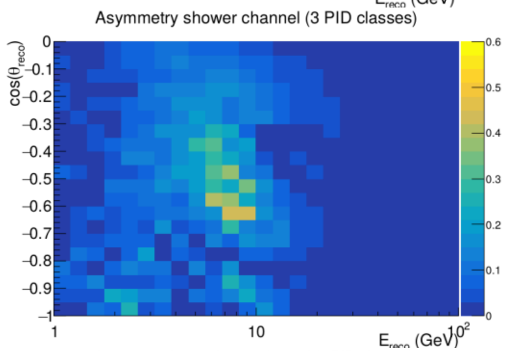
Backup: asymmetries per PID class overview

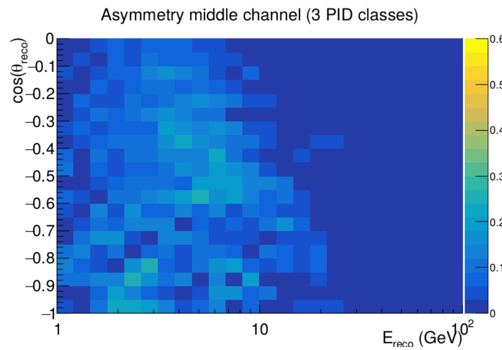
2 classes

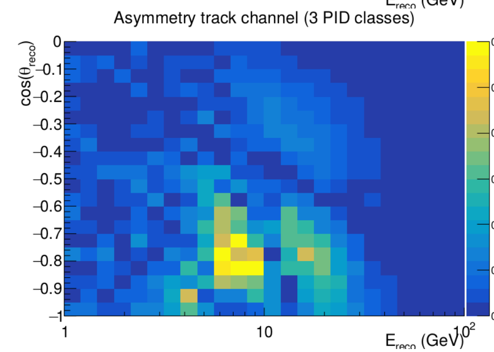




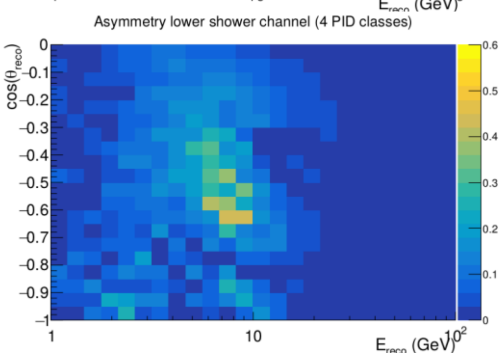
3 classes

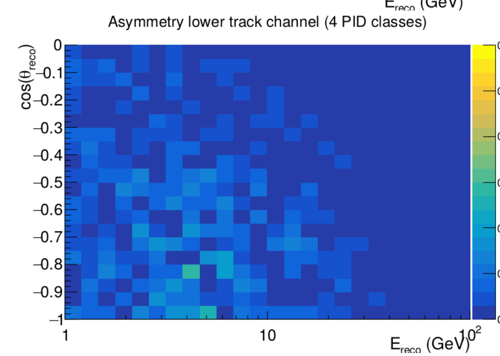




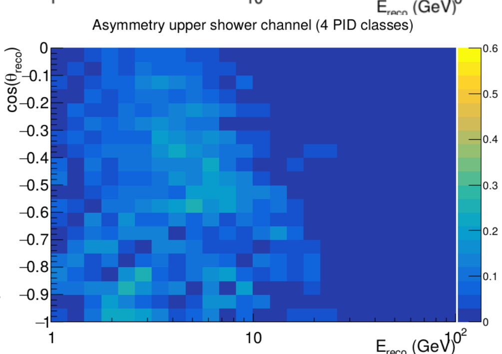


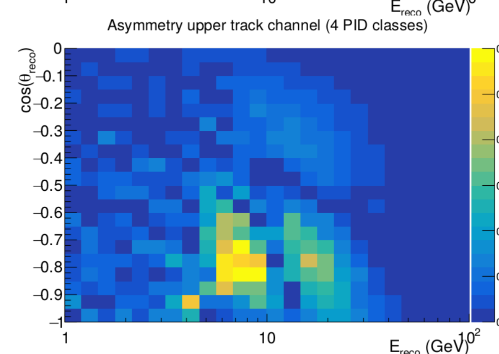
4 classes



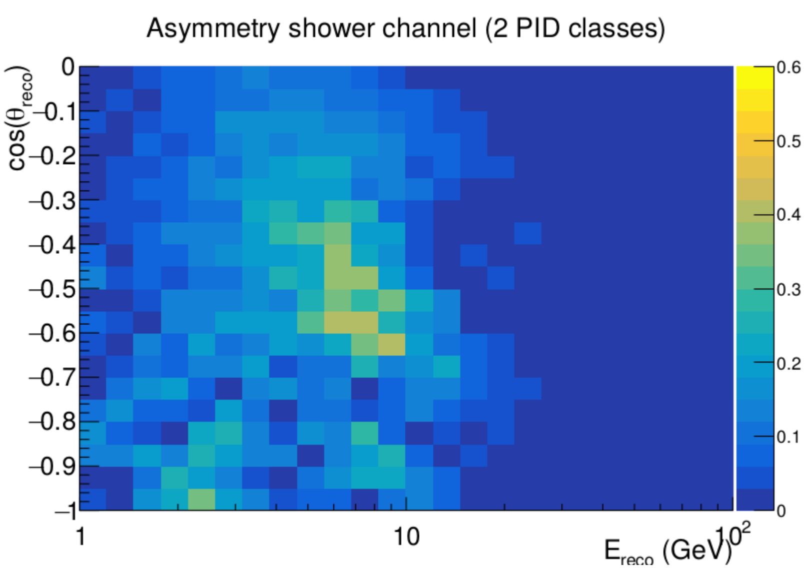


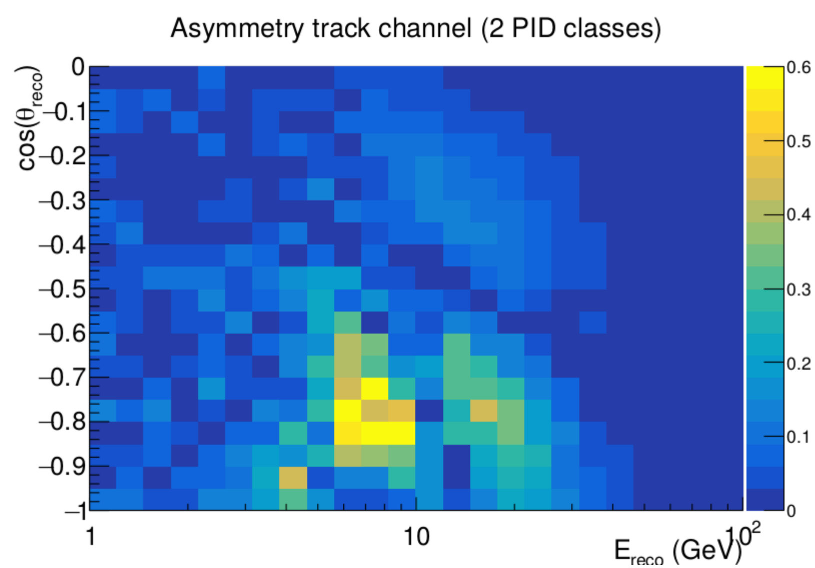
4 classes



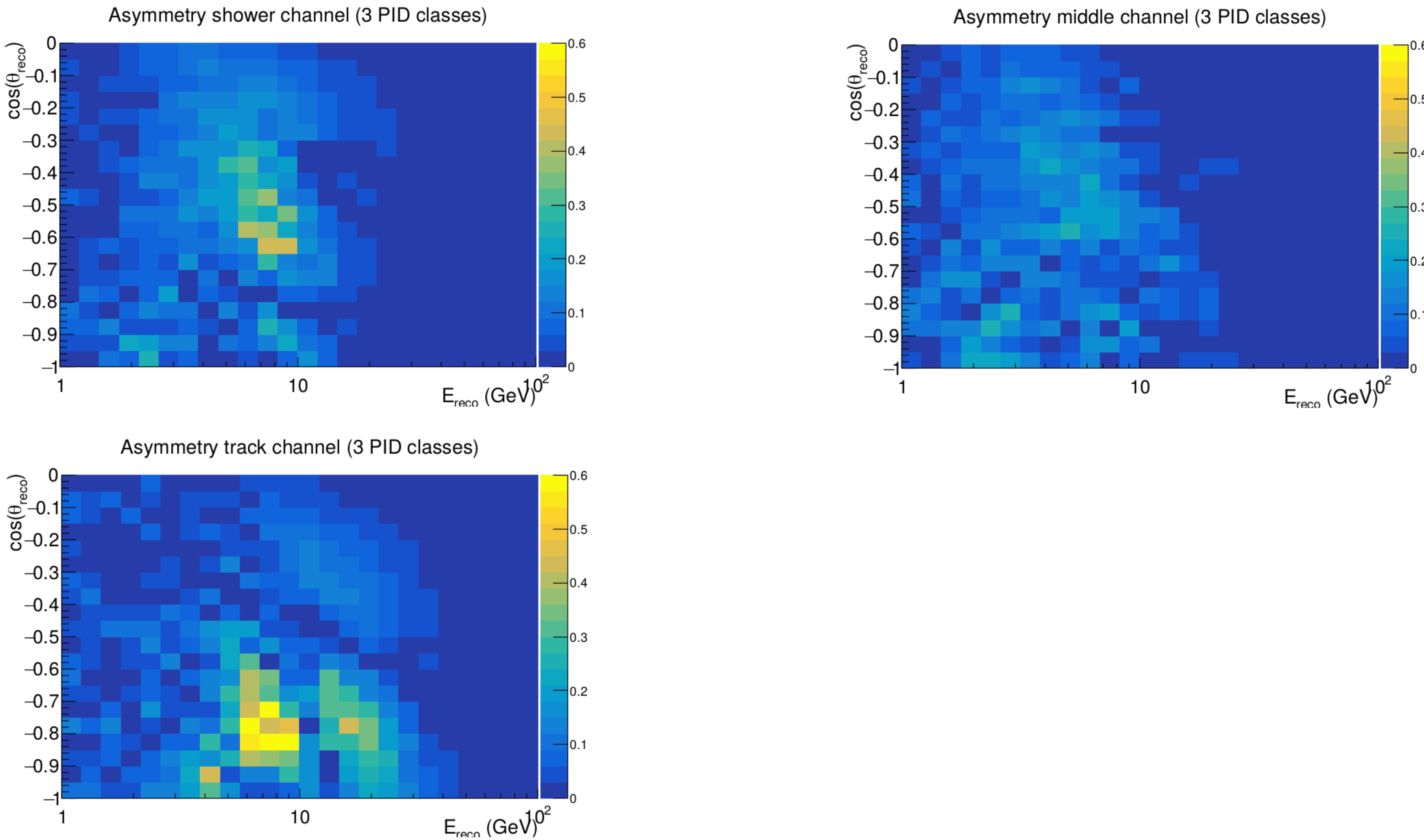


Backup: asymmetries per PID class: 2





Backup: asymmetries per PID class: 3



Backup: asymmetries per PID class: 4