

Current Statistical Practices at Long Baseline Accelerator Experiments

Asher Kaboth

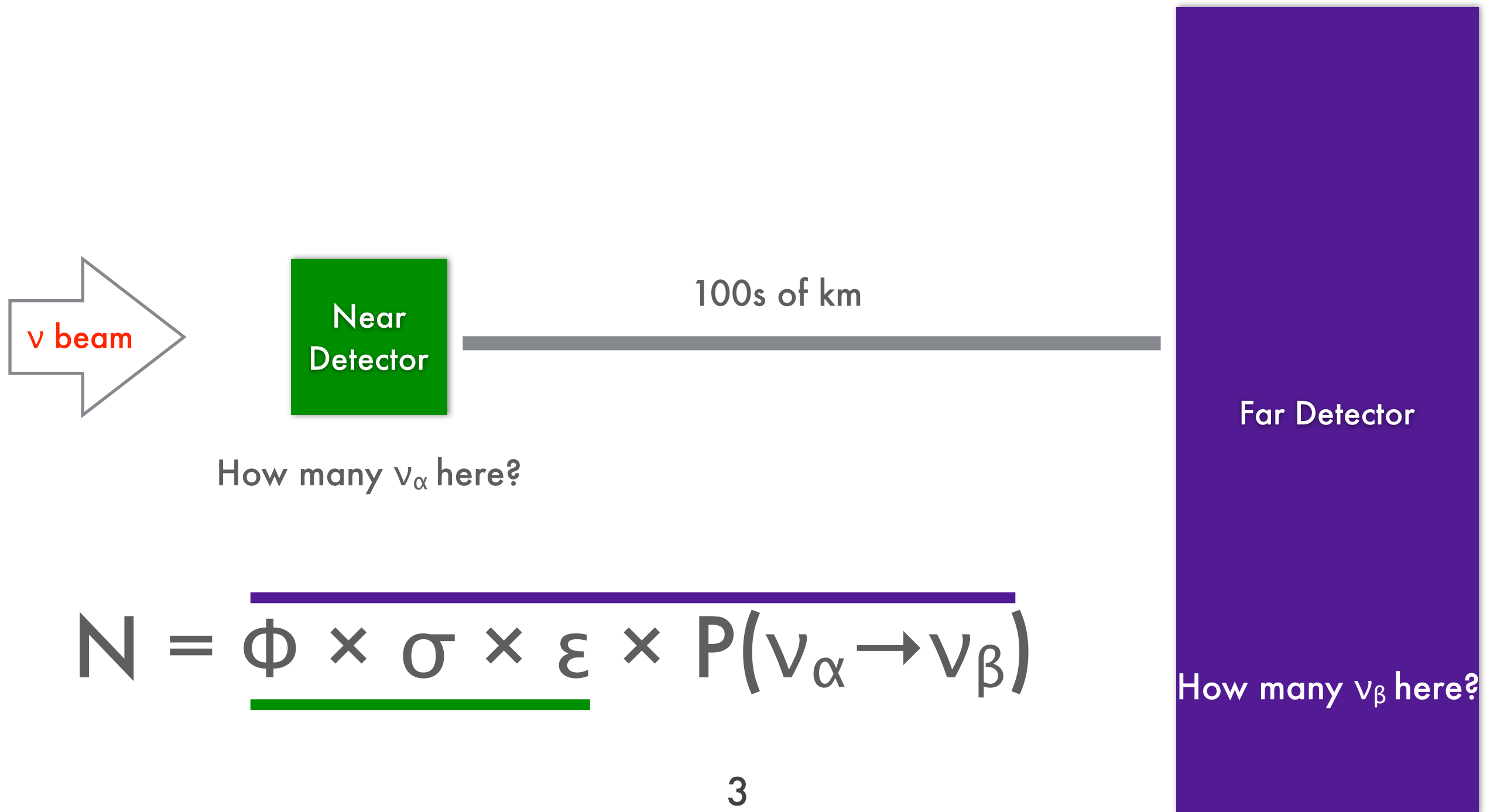
PhyStat-v

30 May 2016

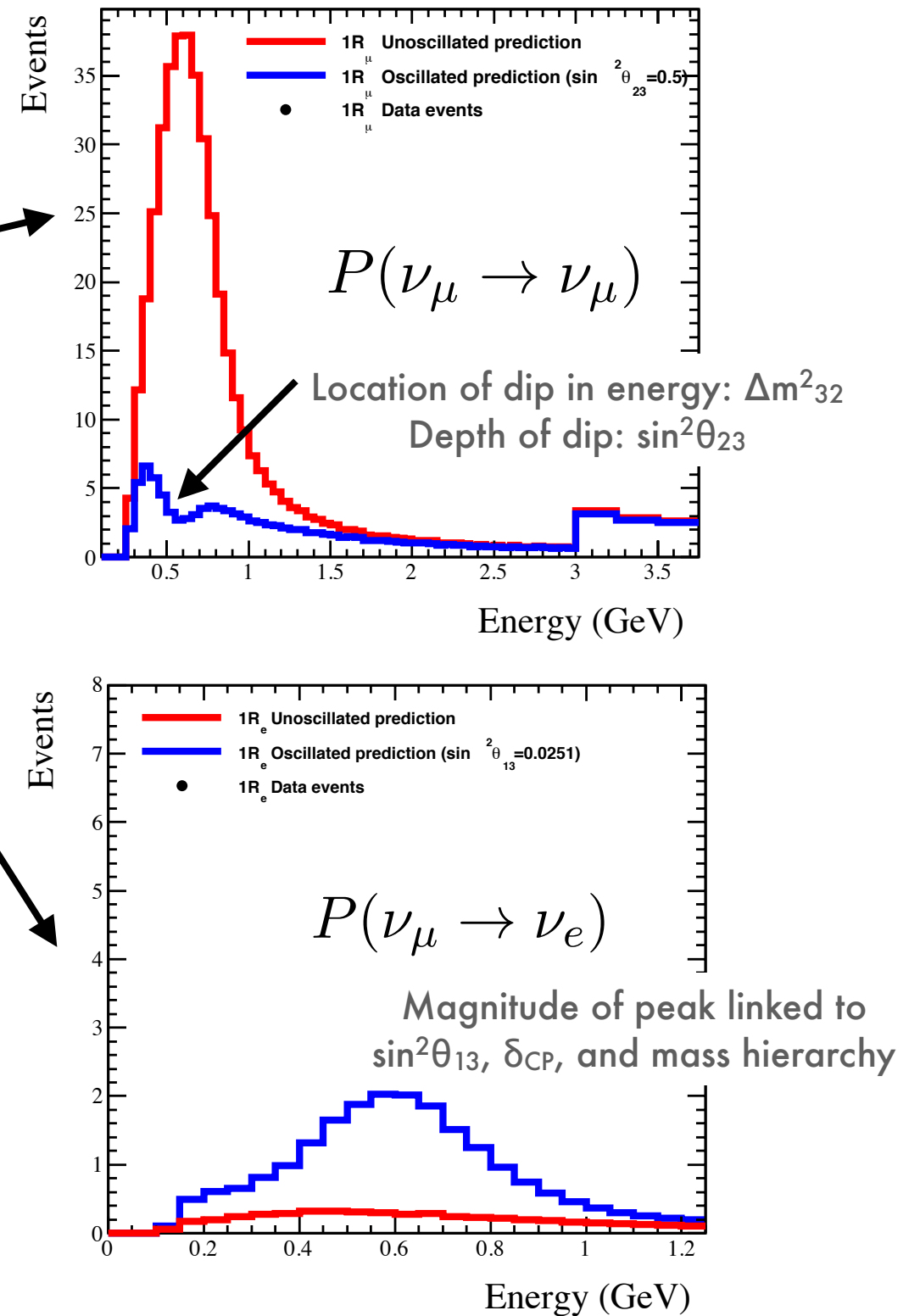
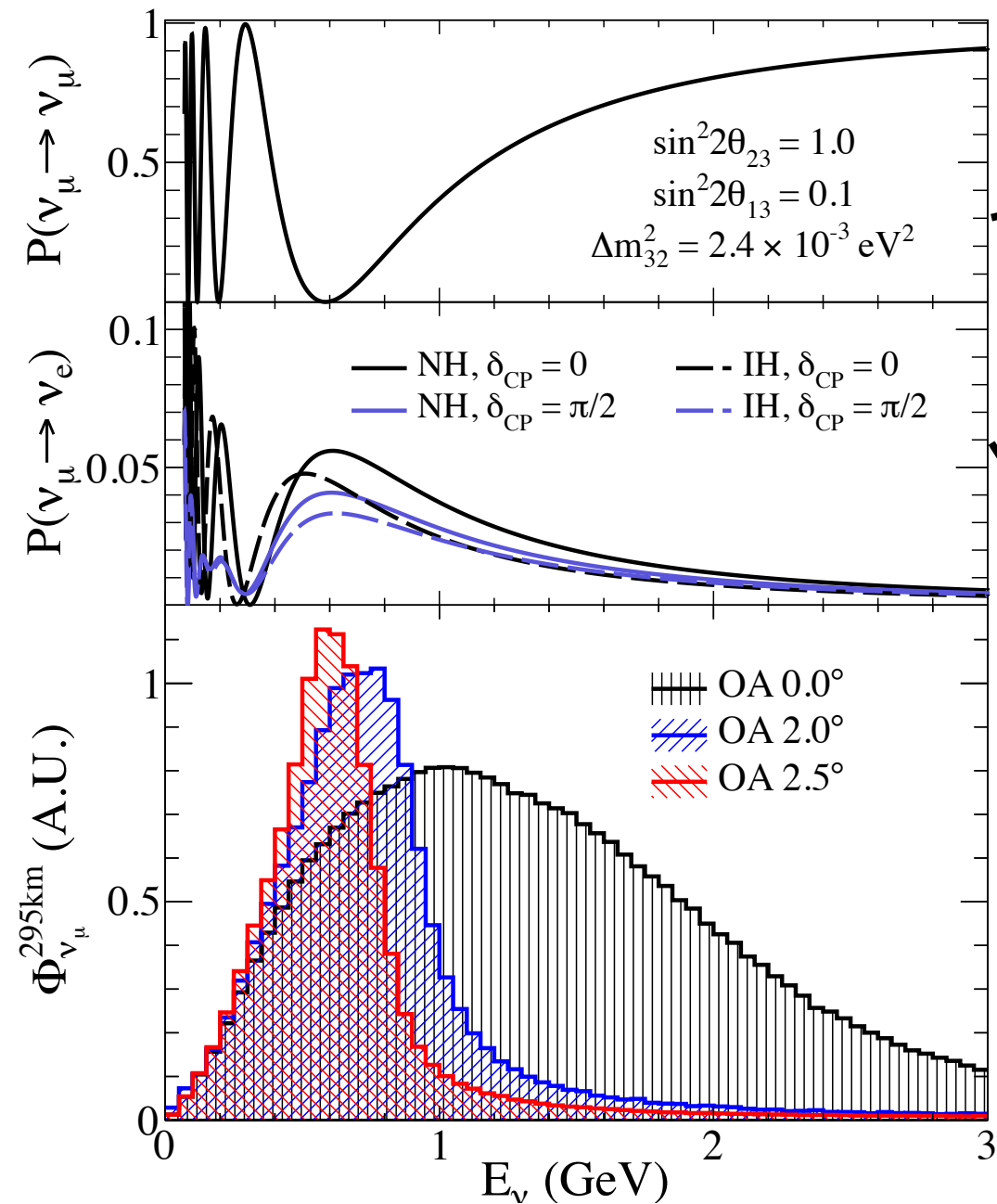
Outline

- Quick Review of LBL physics
- T2K The T2K logo features the text 'T2K' in red, with a green wavy line above it and a blue wavy line below it.
- NOvA The NOvA logo features the text 'NOvA' in a colorful, stylized font, with a green and yellow circular graphic above it.
- Special Issues
- Will not talk about: MINOS, DUNE, HyperK

Long Baseline Experiments in a Nutshell



Long Baseline Neutrino Oscillation



Long Baseline Neutrino Oscillation

$$P(\nu_\mu \rightarrow \nu_\mu) \approx 1 - 4 \cos^2(\theta_{13}) \sin^2(\theta_{23}) [1 - \cos^2(\theta_{13}) \sin^2(\theta_{23})] \sin^2 \left(\frac{\Delta m_{31}^2 L}{E_\nu} \right)$$

$$P(\nu_\mu \rightarrow \nu_e) \approx \sin^2 \theta_{23} \sin^2 2\theta_{13} \frac{\sin^2(\Delta(1-A))}{(1-A)^2} + \alpha^2 \cos^2 \theta_{23} \sin^2 2\theta_{12} \frac{\sin^2 A\Delta}{A^2} \\ + \alpha \cos \theta_{13} \sin 2\theta_{12} \sin 2\theta_{23} \sin 2\theta_{13} \frac{\sin((1-A)\Delta)}{1-A} \frac{\sin A\Delta}{A} \cos(\delta + \Delta)$$

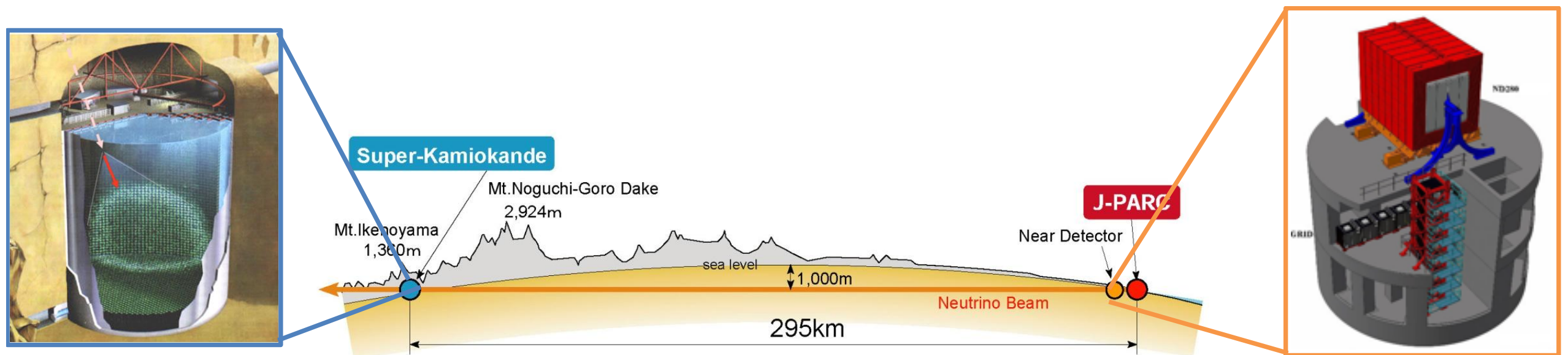
Expanded under
small θ_{13}, α

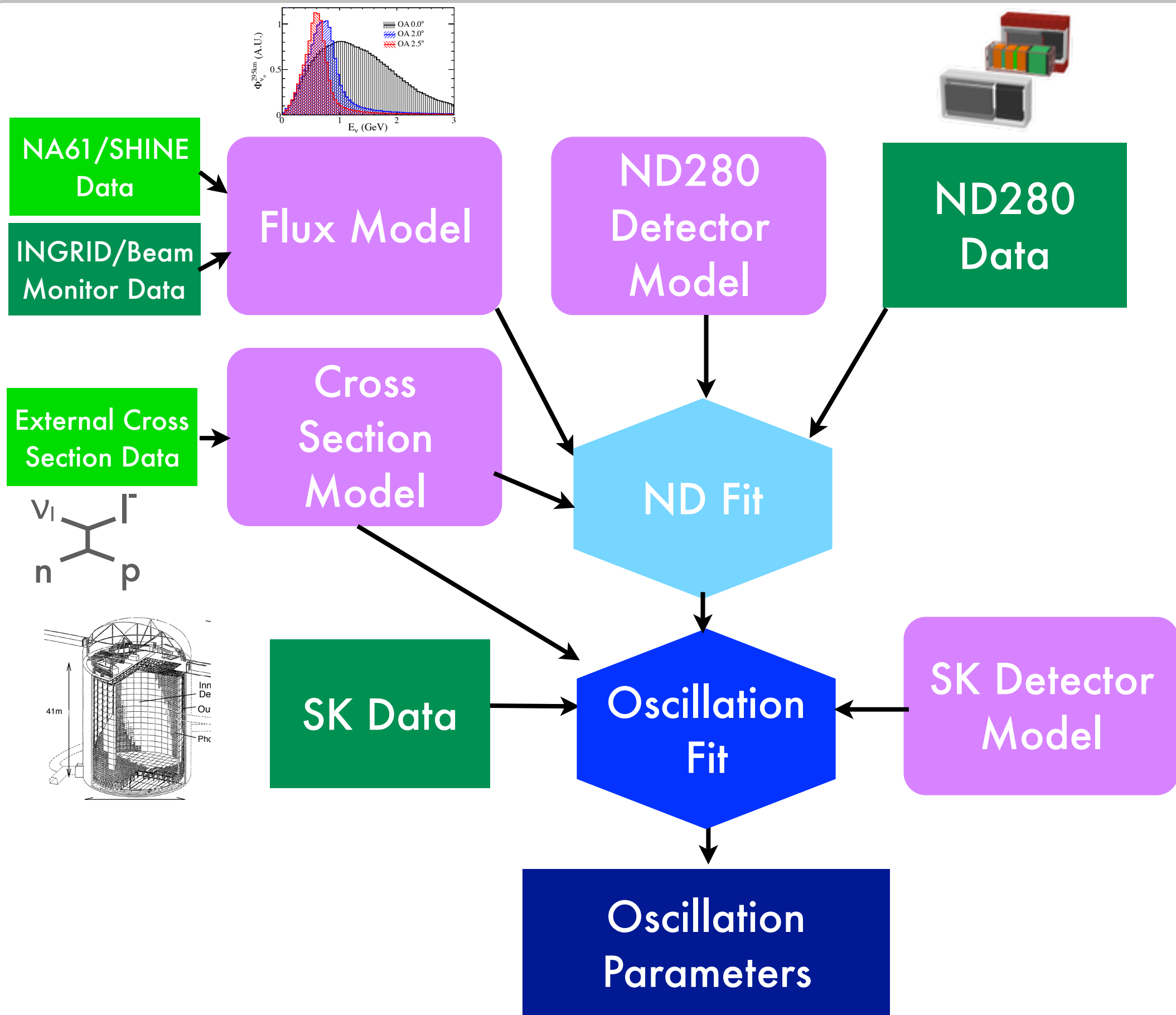
$$A = \pm 2\sqrt{2}G_F n_e E \Delta m_{31}^2 \quad \Delta = \frac{\Delta m_{31}^2 L}{E} \quad \alpha = \frac{\Delta m_{21}^2}{\Delta m_{31}^2} \quad \Delta m_{ij}^2 = m_i^2 - m_j^2$$

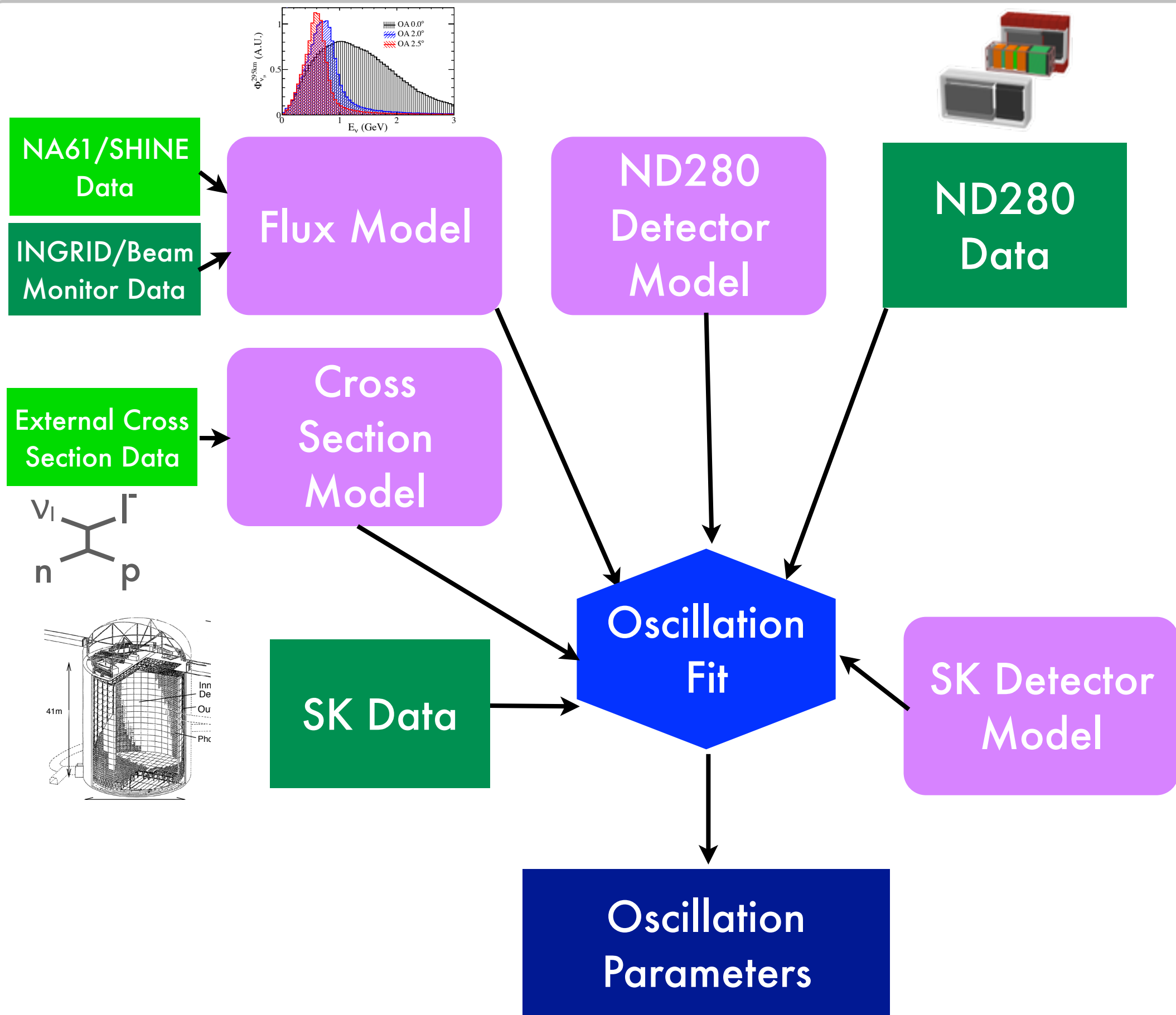
Open Questions

- How well can we estimate the values of θ_{13} , θ_{23} , and Δm^2_{32} ?
- Is δ_{CP} different from 0 and π ?
- Do neutrinos and antineutrinos behave differently?
- What is the mass hierarchy?

T2K







Beam Uncertainties

Super-K

1. Proton beam measurement

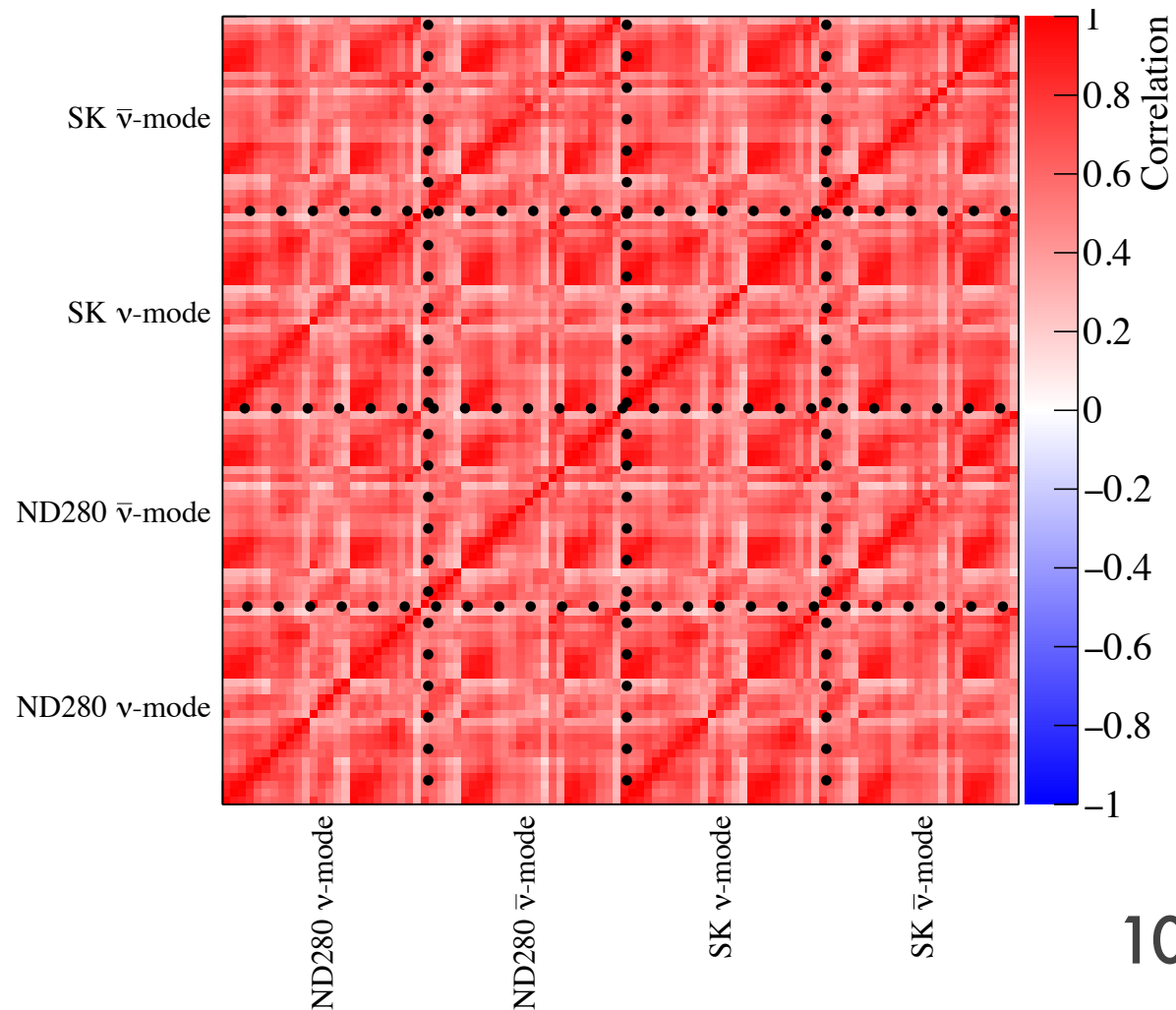
4. Horn current and field

2. Hadron production

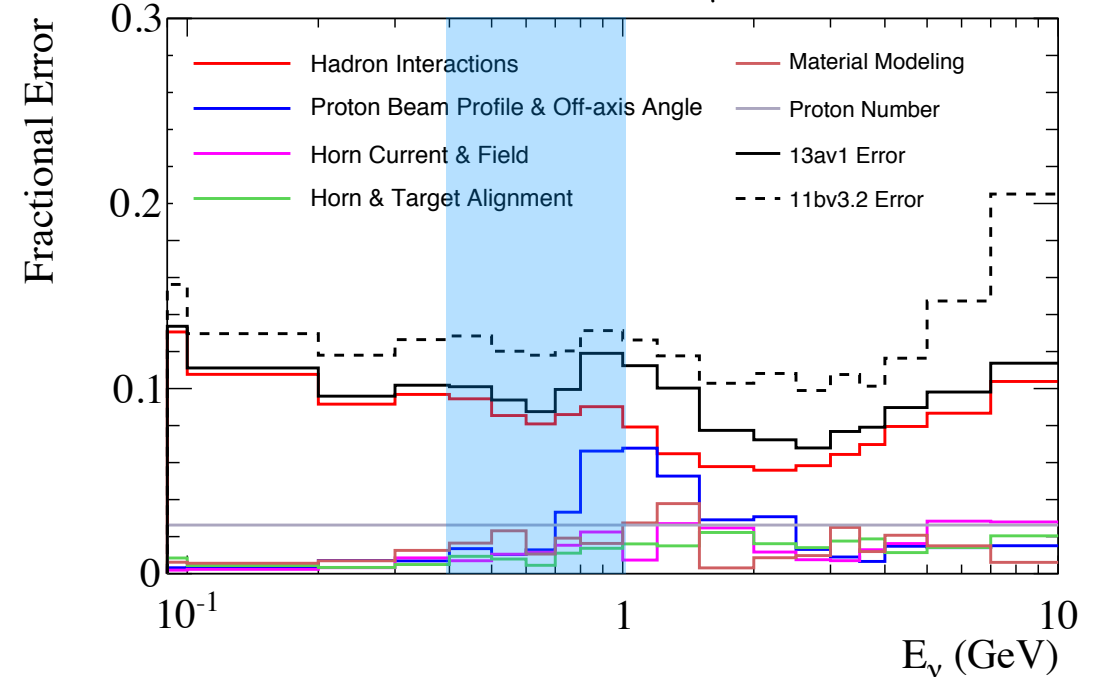
3. Horn and beam alignment

5. Beam direction

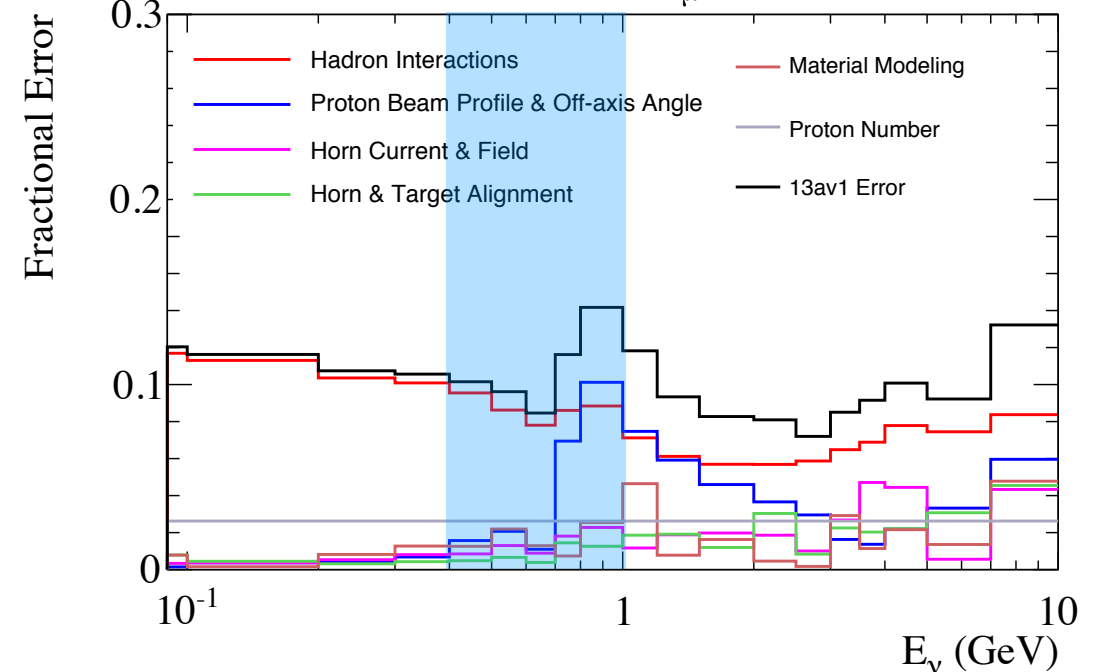
INGRID



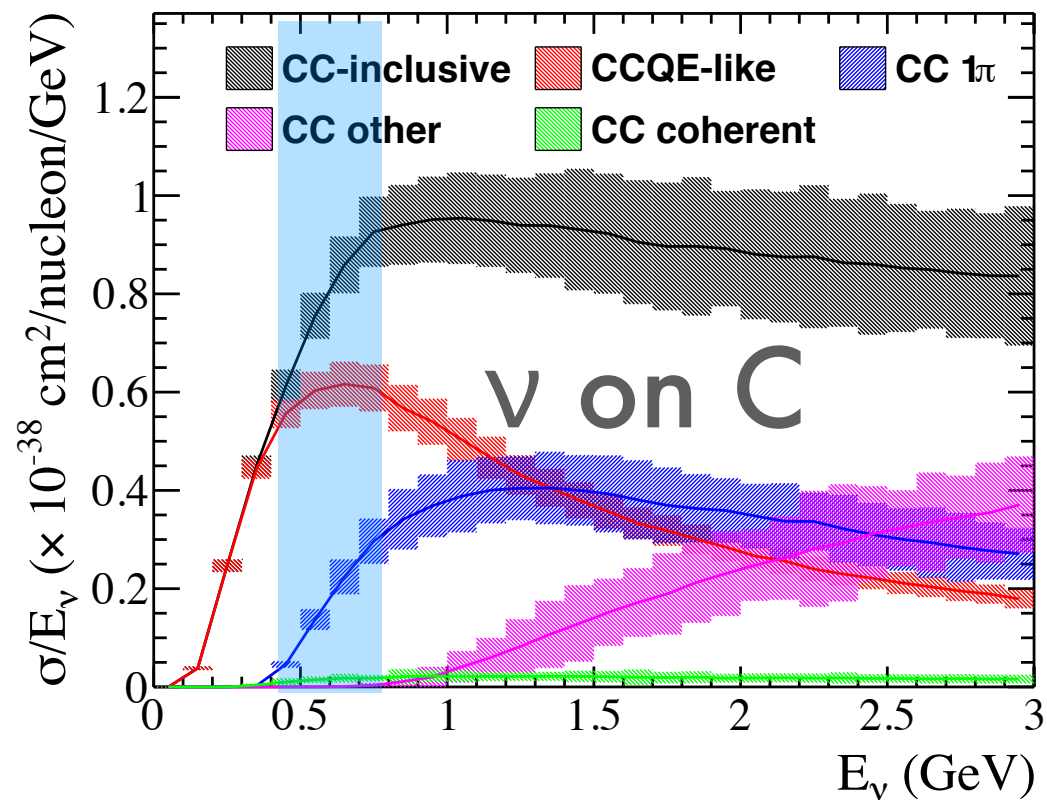
ND280: Positive Focussing Mode, ν_μ



SK: Negative Focussing Mode, $\bar{\nu}_\mu$

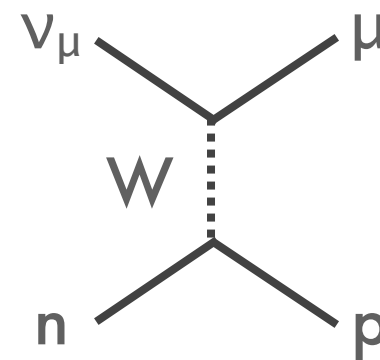


ν -N Cross Section Model

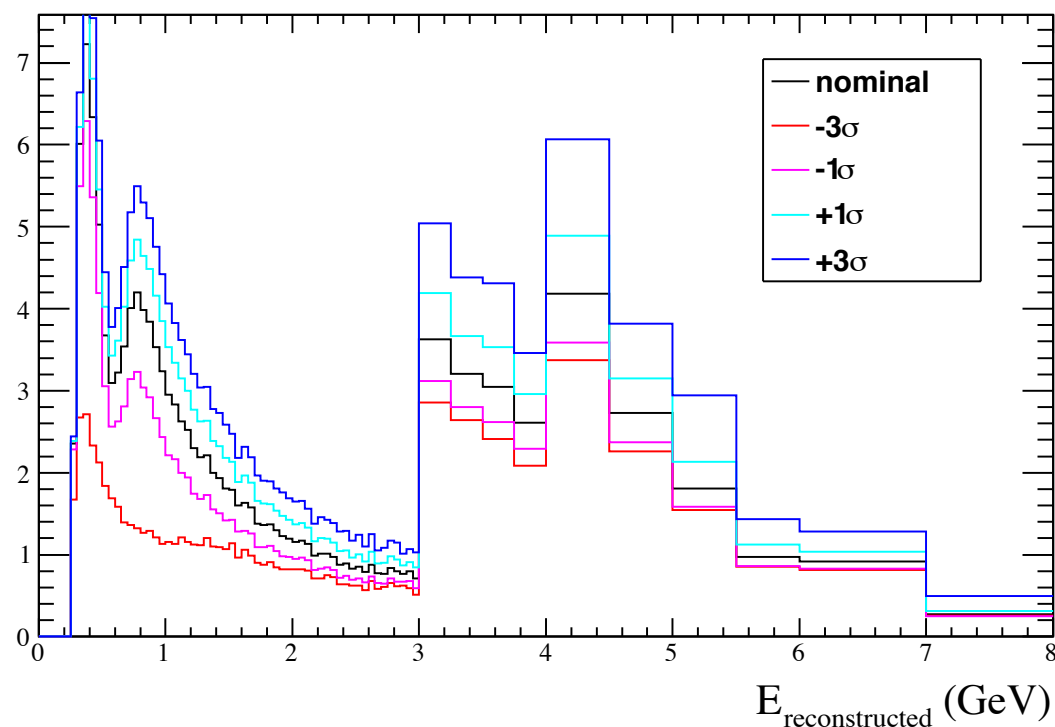


Uncertainties come from underlying model parameters and normalizations

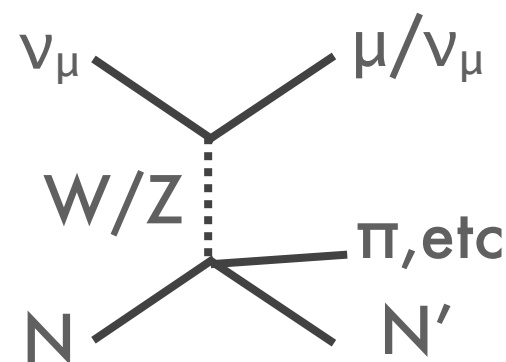
Charged current quasi-elastic



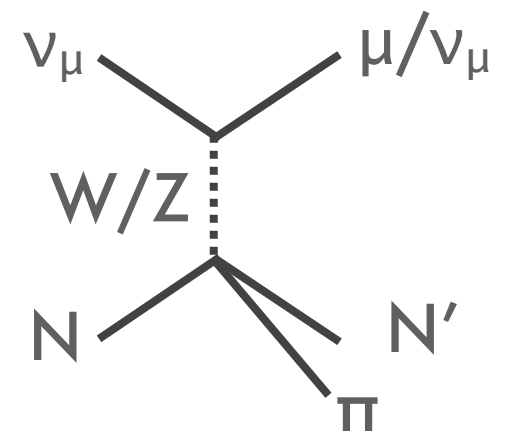
- MAQE
- MARES
- Fermi Mom.
- Binding Energy
- FSI
- 2p2h
- ...



Deep Inelastic Scattering

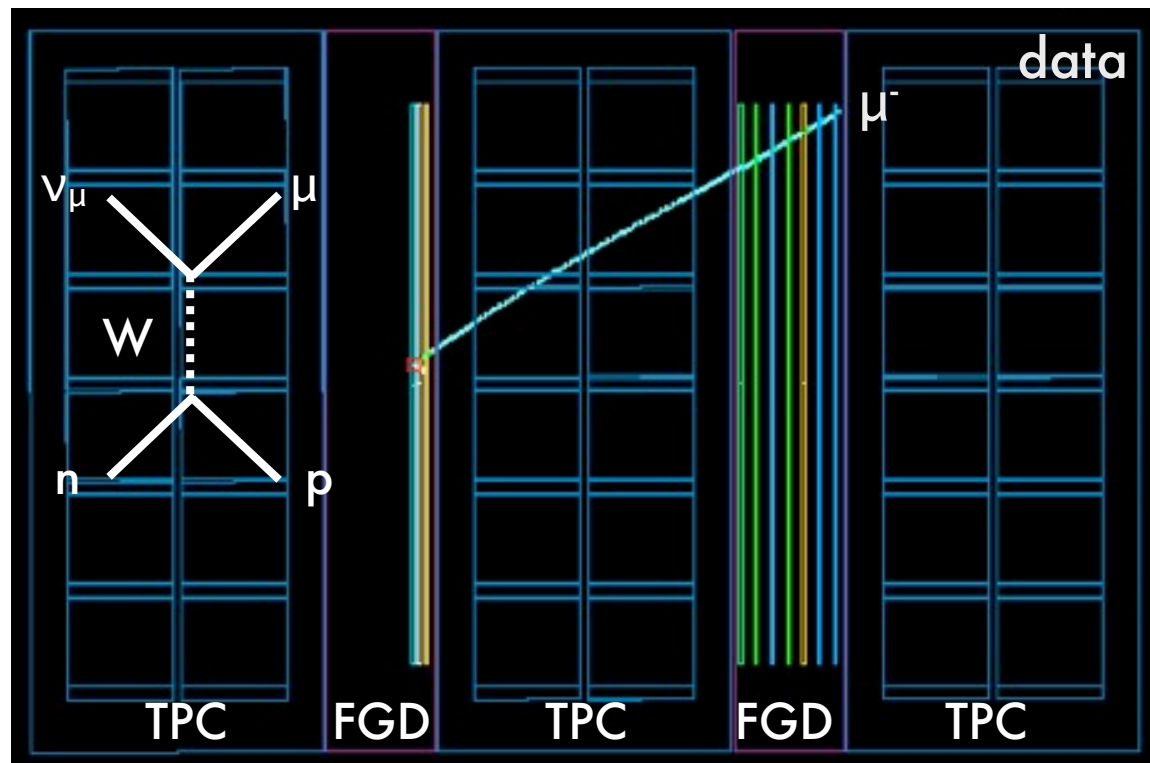


Charged Current 1π

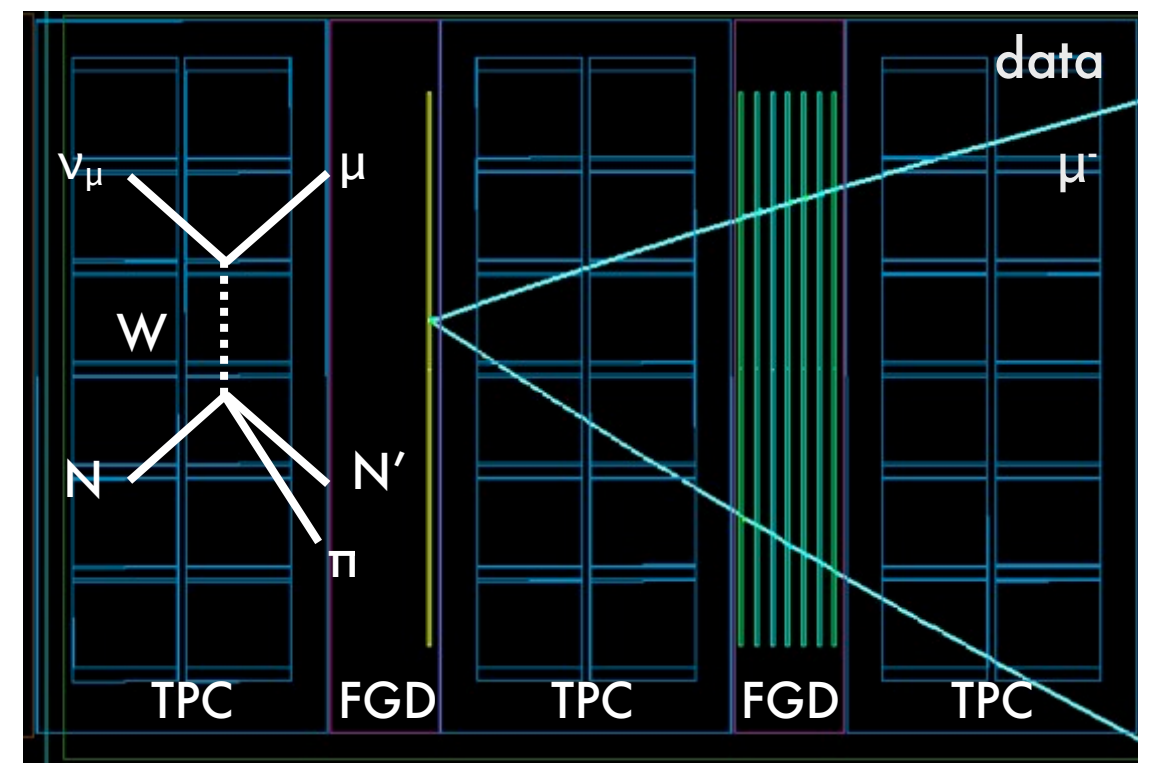


11 Talk by C. Wilkinson and poster by C. Wret on issues with external constraints

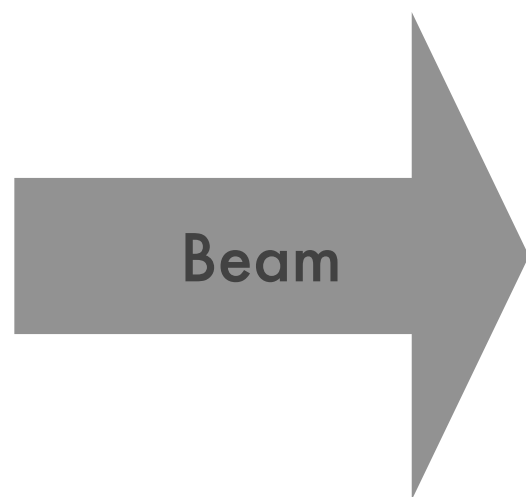
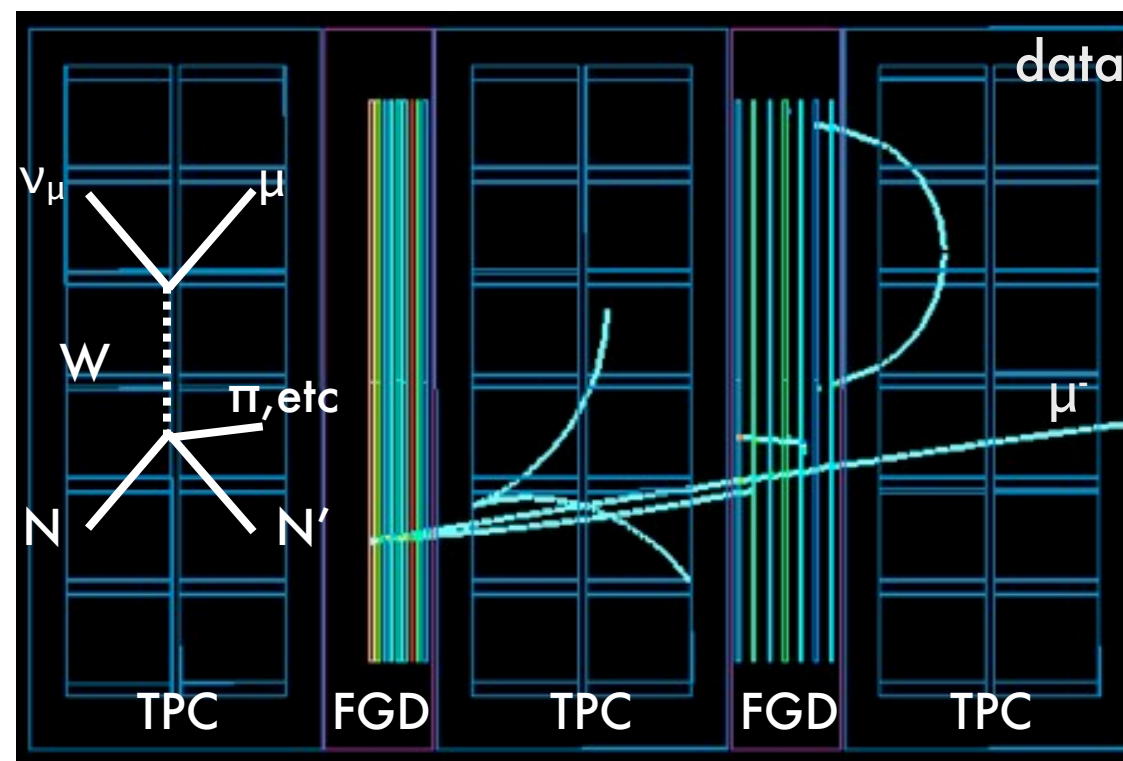
CC0 π



CC1 π^+

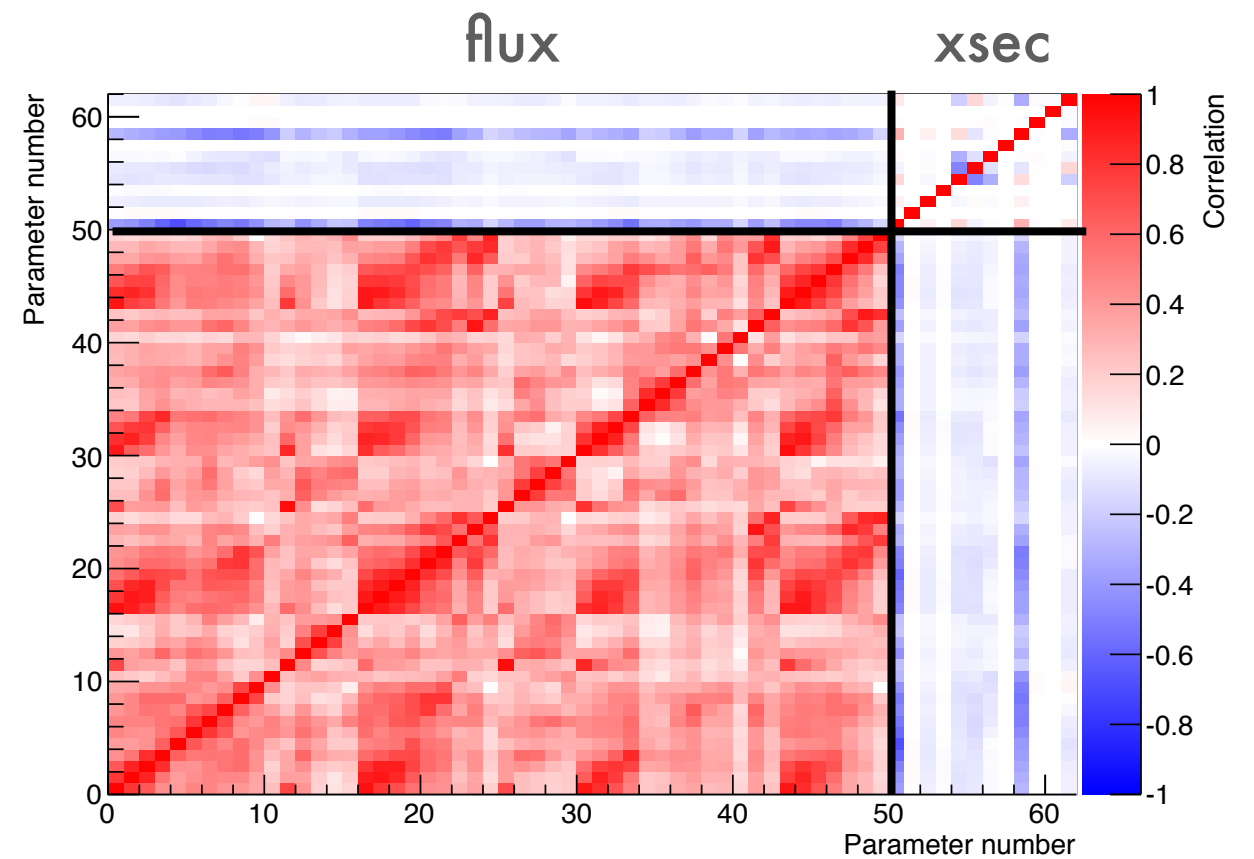
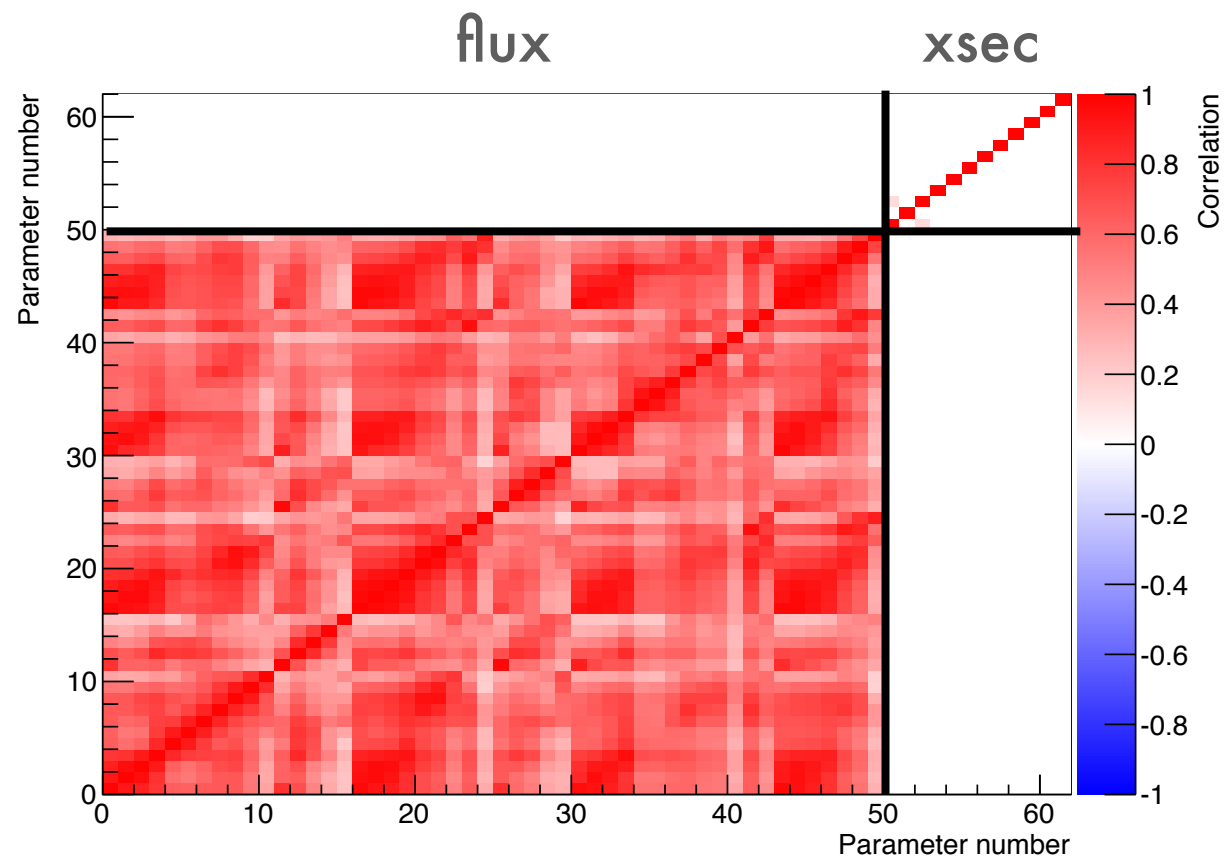


CC other



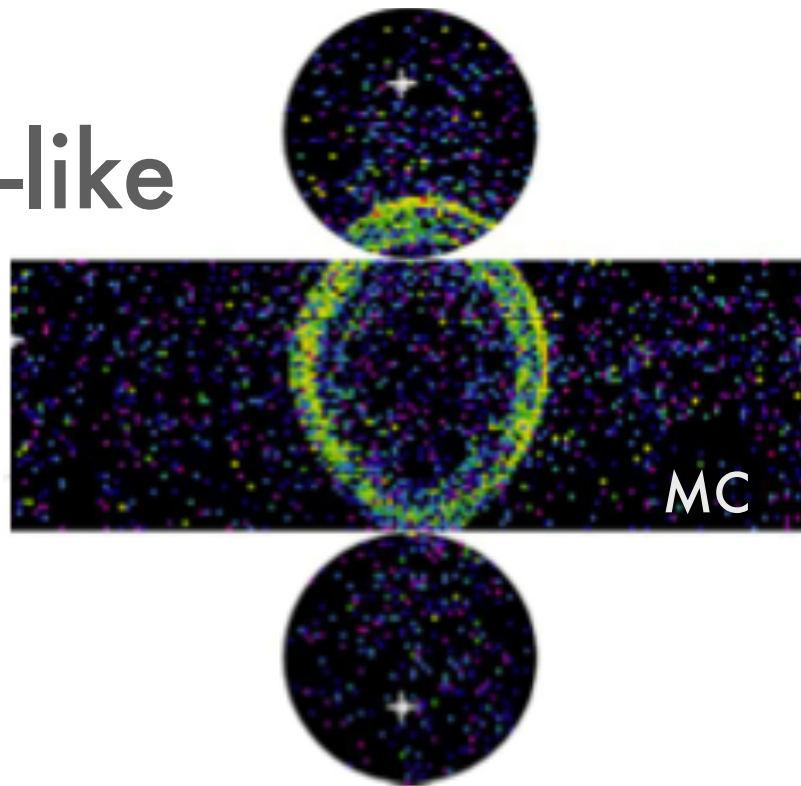
Near Detector Results

- Measure negative correlation between flux and cross section parameters
- Variety of analyses checks that gaussian assumptions are justified

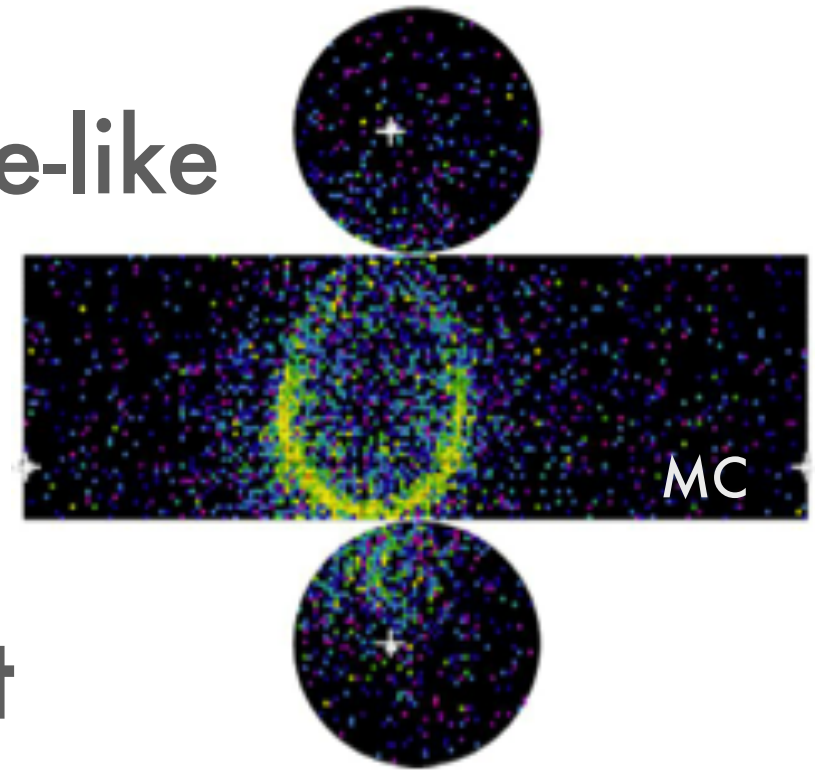


SK Data Samples

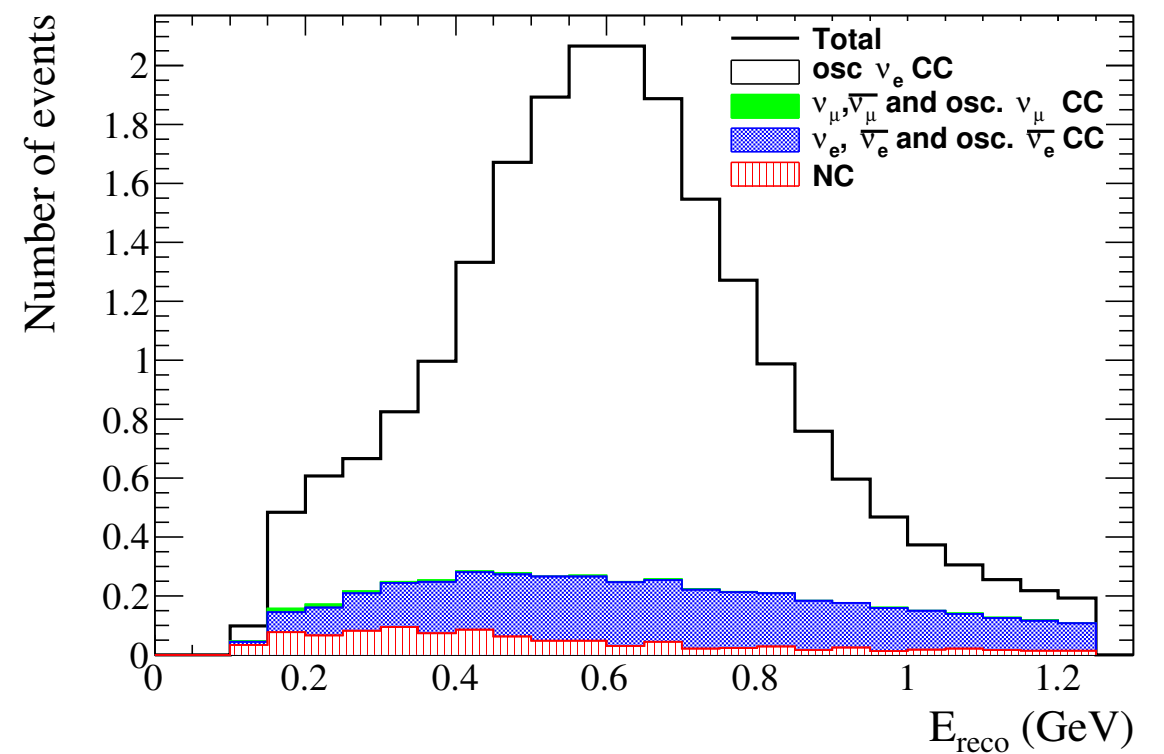
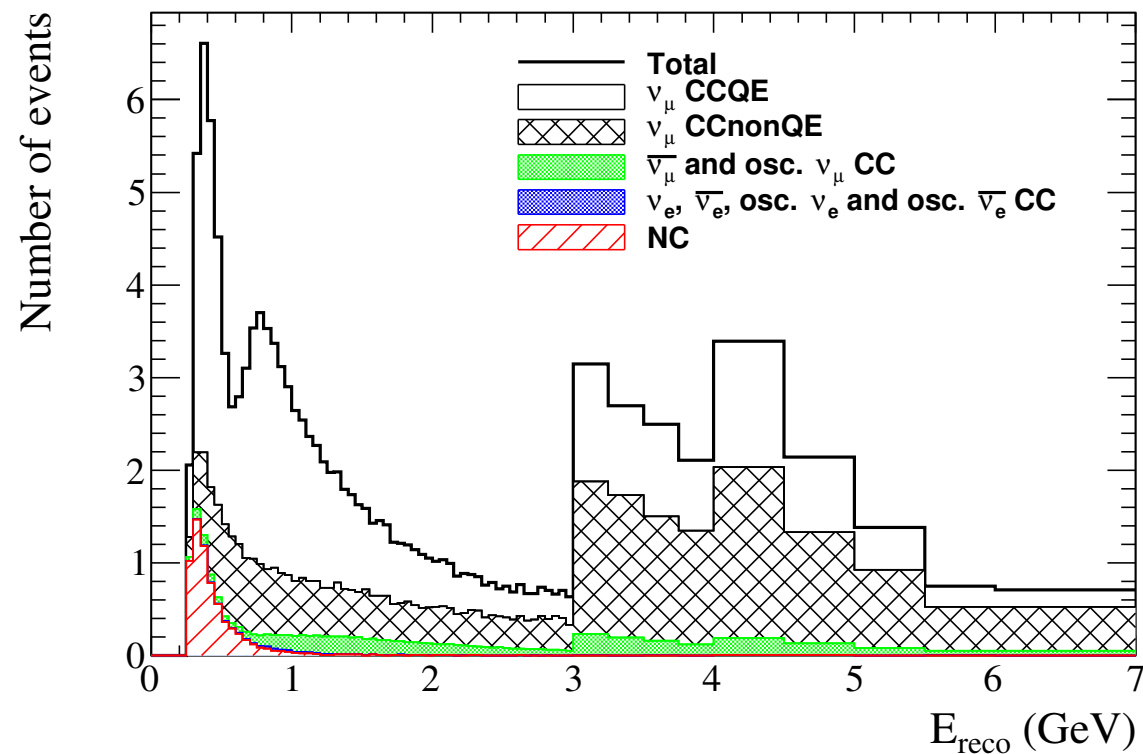
μ -like



e-like



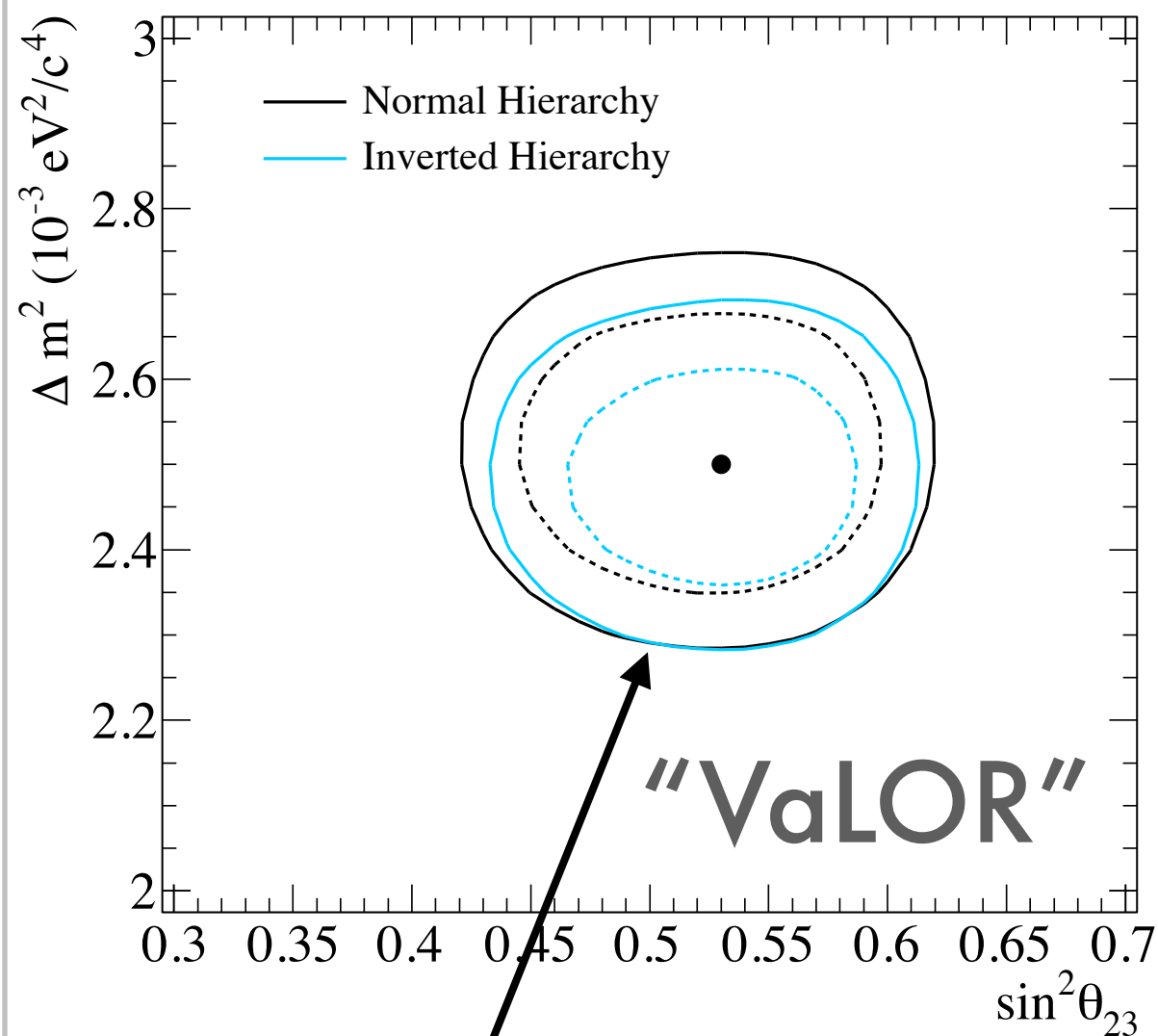
Binned ML Fit



Results

See posters by: L. Haegel, D. Sgalaberna, and R. Shah

T2K loves all statistical methods!

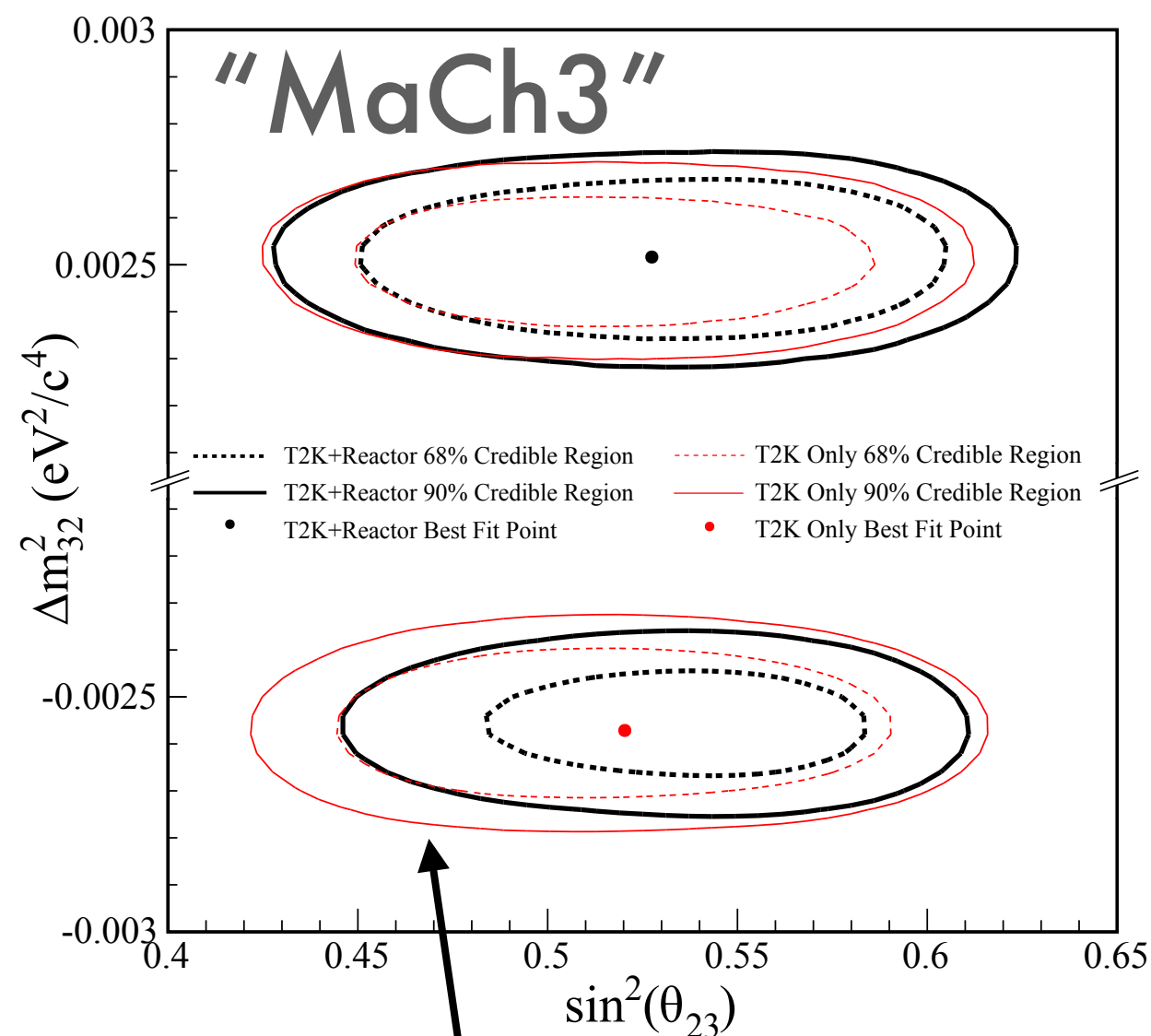


confidence level contours

constant $\Delta\chi^2$

Profiling treatment of systematics

Gradient descent



credible interval contours

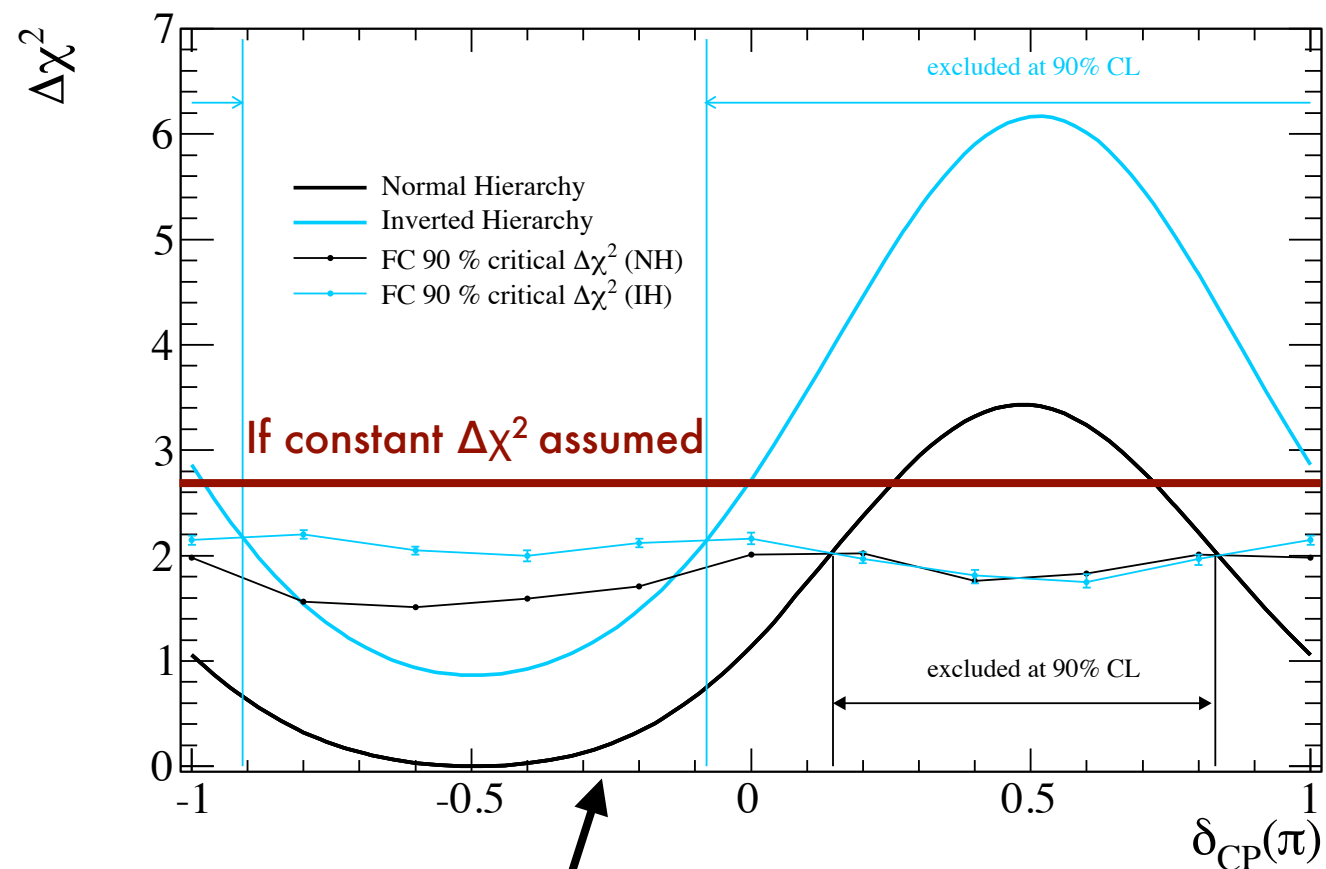
highest posterior density method

Marginalization treatment of systematics

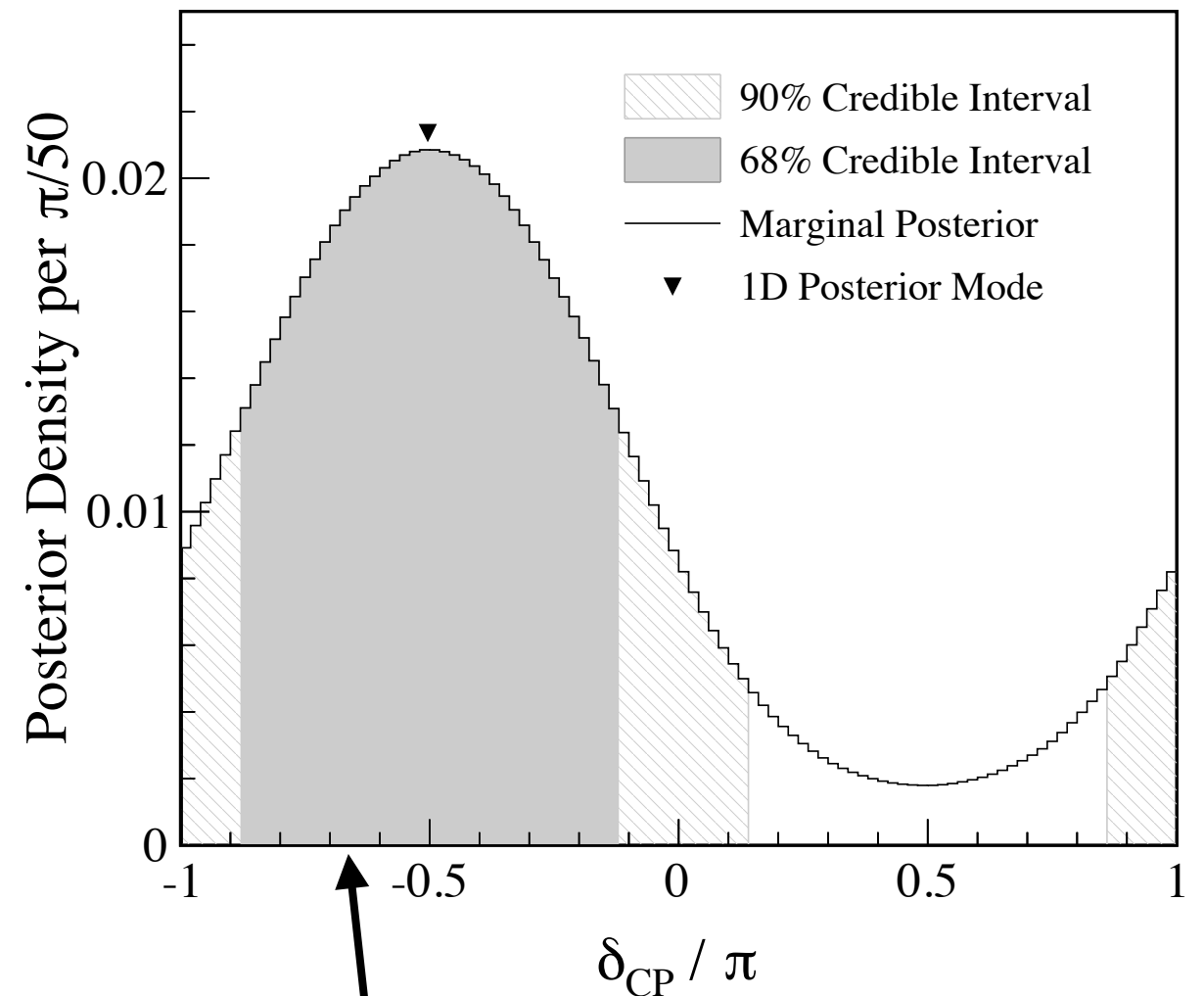
15 Markov Chain MC (Metropolis-Hastings)

Results

See posters by: L. Haegel, D. Sgalaberna, and R. Shah



confidence level interval
Feldman-Cousins-Highland
separate for NH/IH



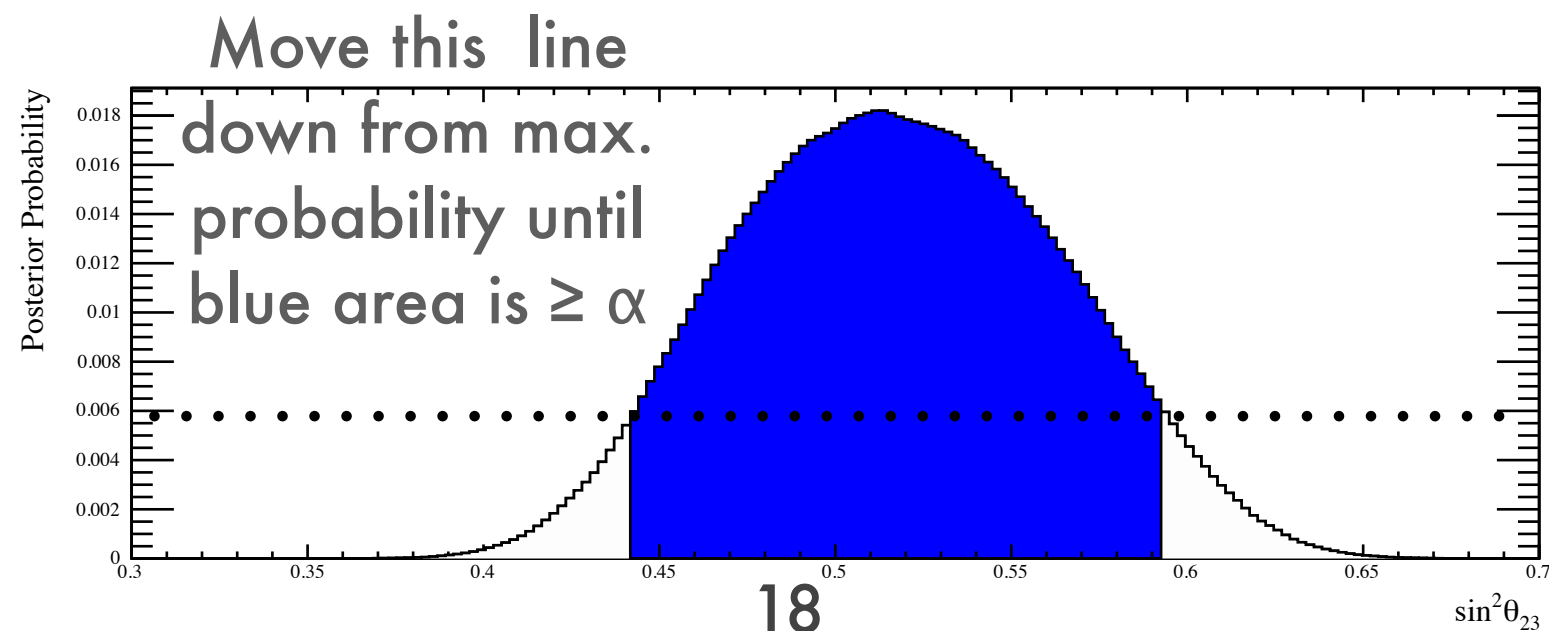
credible interval interval
highest posterior density method
marginalized over hierarchy

A Brief Review of F-C-H

- ◉ Scan over your parameter space
- ◉ At every point, generate many toy MC experiments, including systematic parameter variations
- ◉ Fit your toys and generate the distribution of the test statistic
- ◉ Find the value of the test statistic where $\alpha\%$ are excluded; this is the critical value of the test statistic at that point in the parameter space
- ◉ For the distribution of your data test statistic over your parameter space, draw a contour to exclude those where the data test statistic is greater than the critical value

A Brief Review of HPD Credible Intervals

- Build your posterior in your parameter space of interest
- Draw your contour such that the integral of the probability inside your contour is $\alpha\%$, and such that the posterior density at any point inside the contour is higher than any point outside the contour
- This minimizes the size of the contour

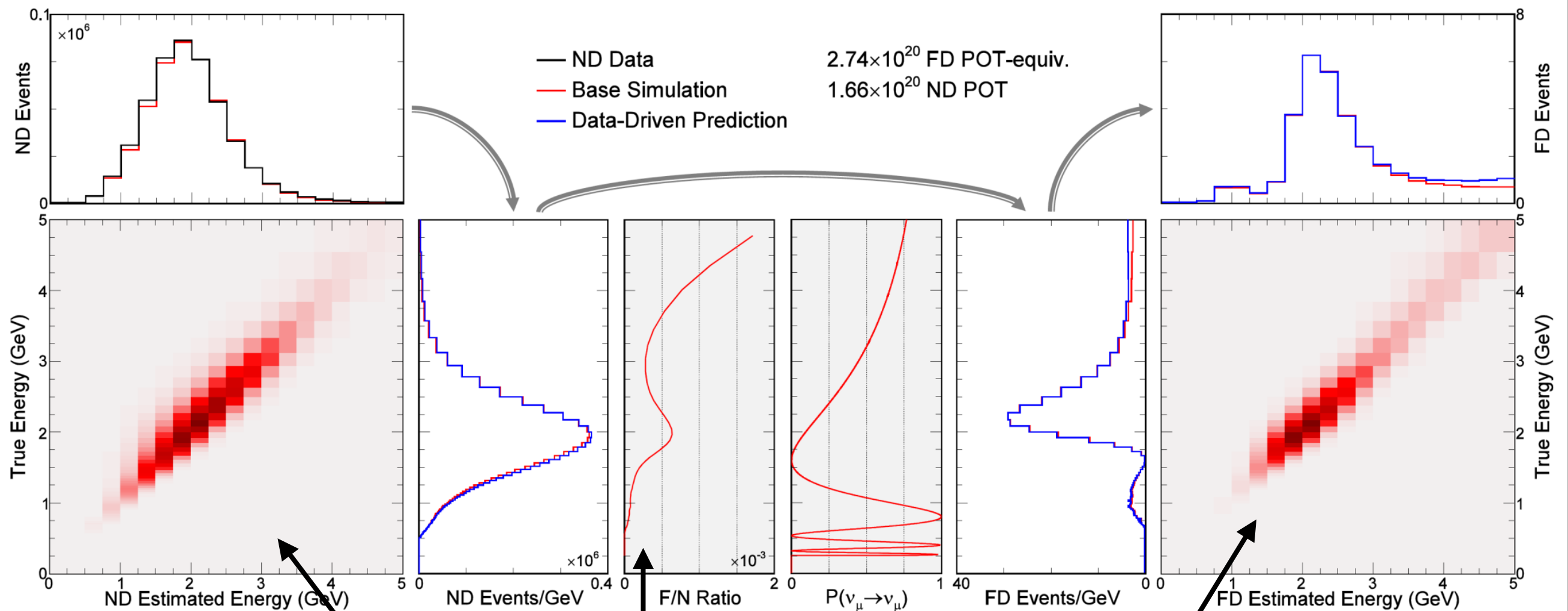


NO ν A

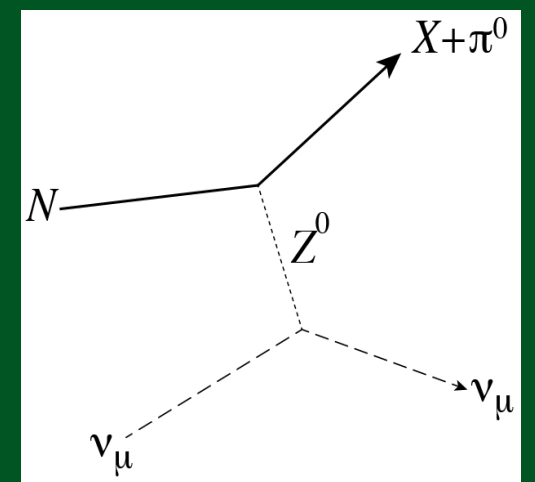
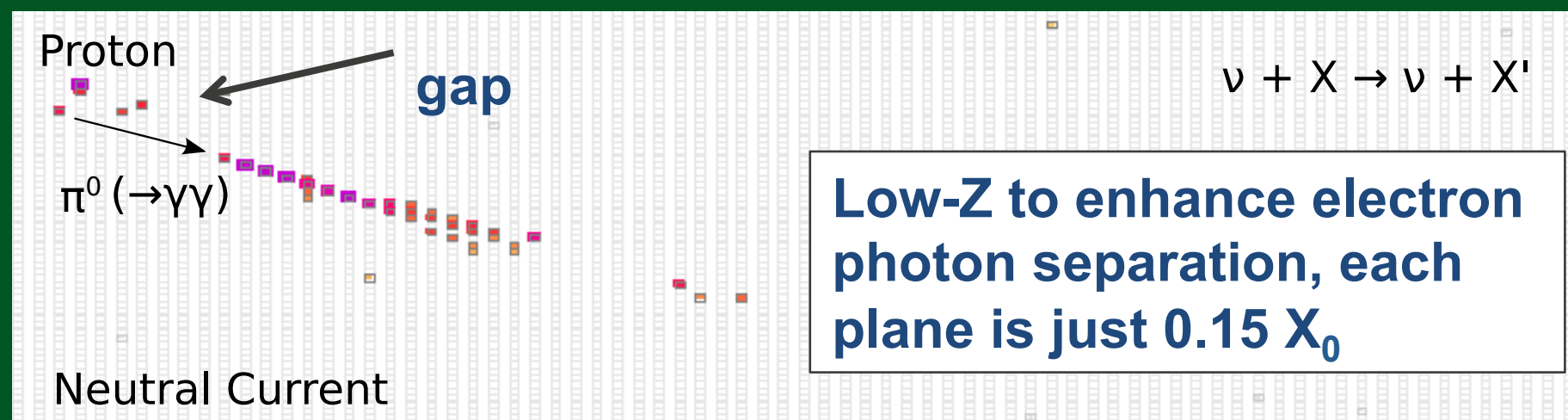
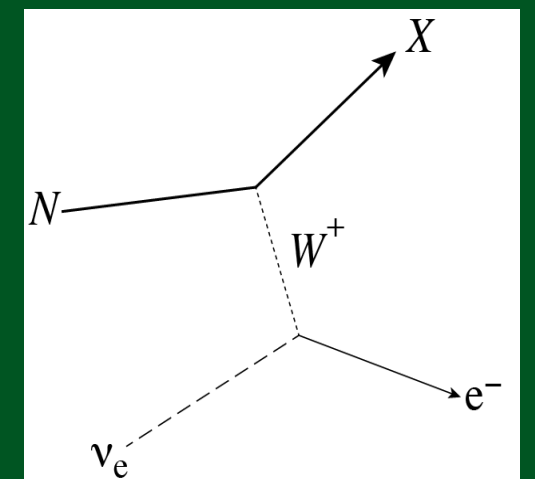
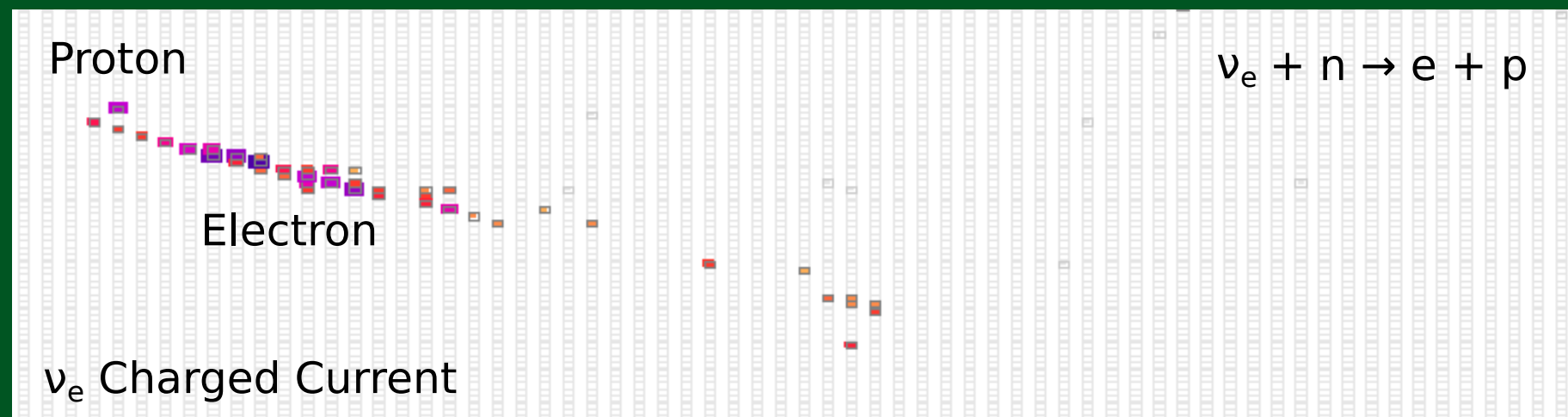
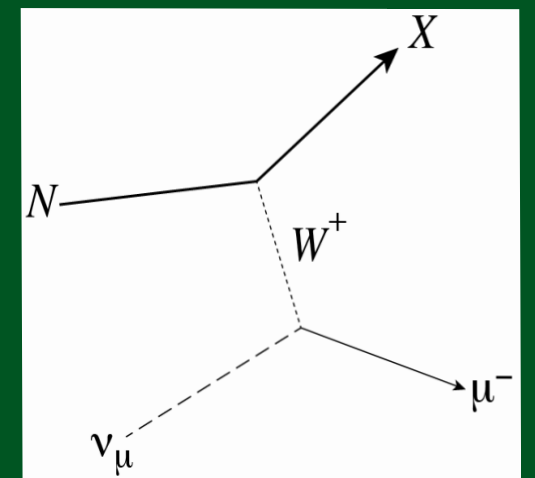
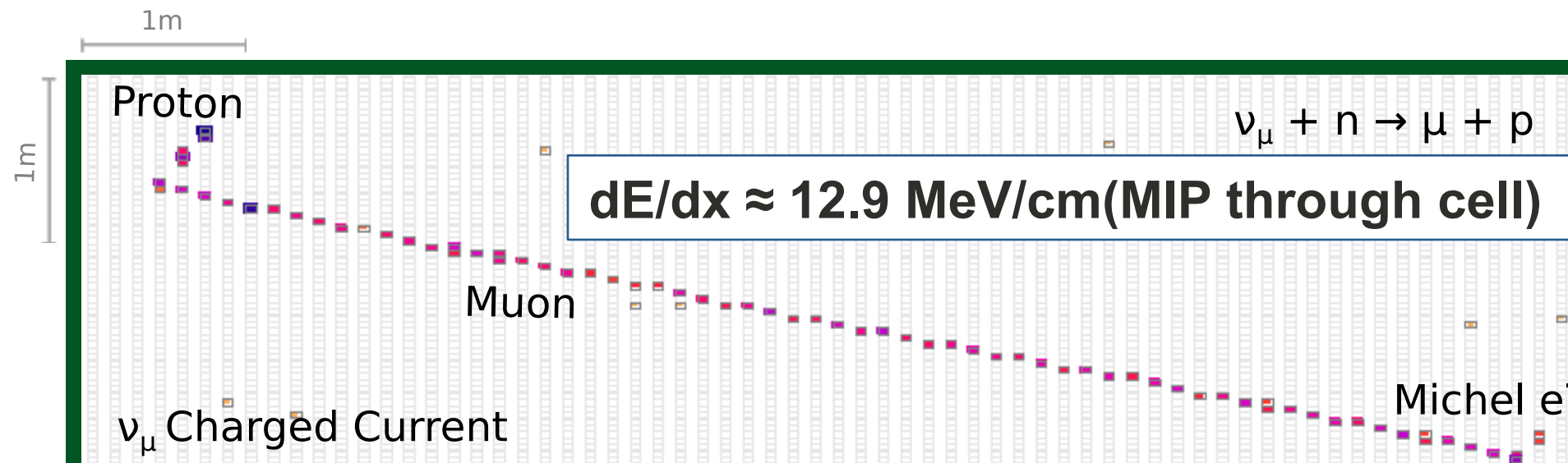


Select CC inclusive

Select CC inclusive



Estimated from simulation
Use a binned ML method



Energy estimation

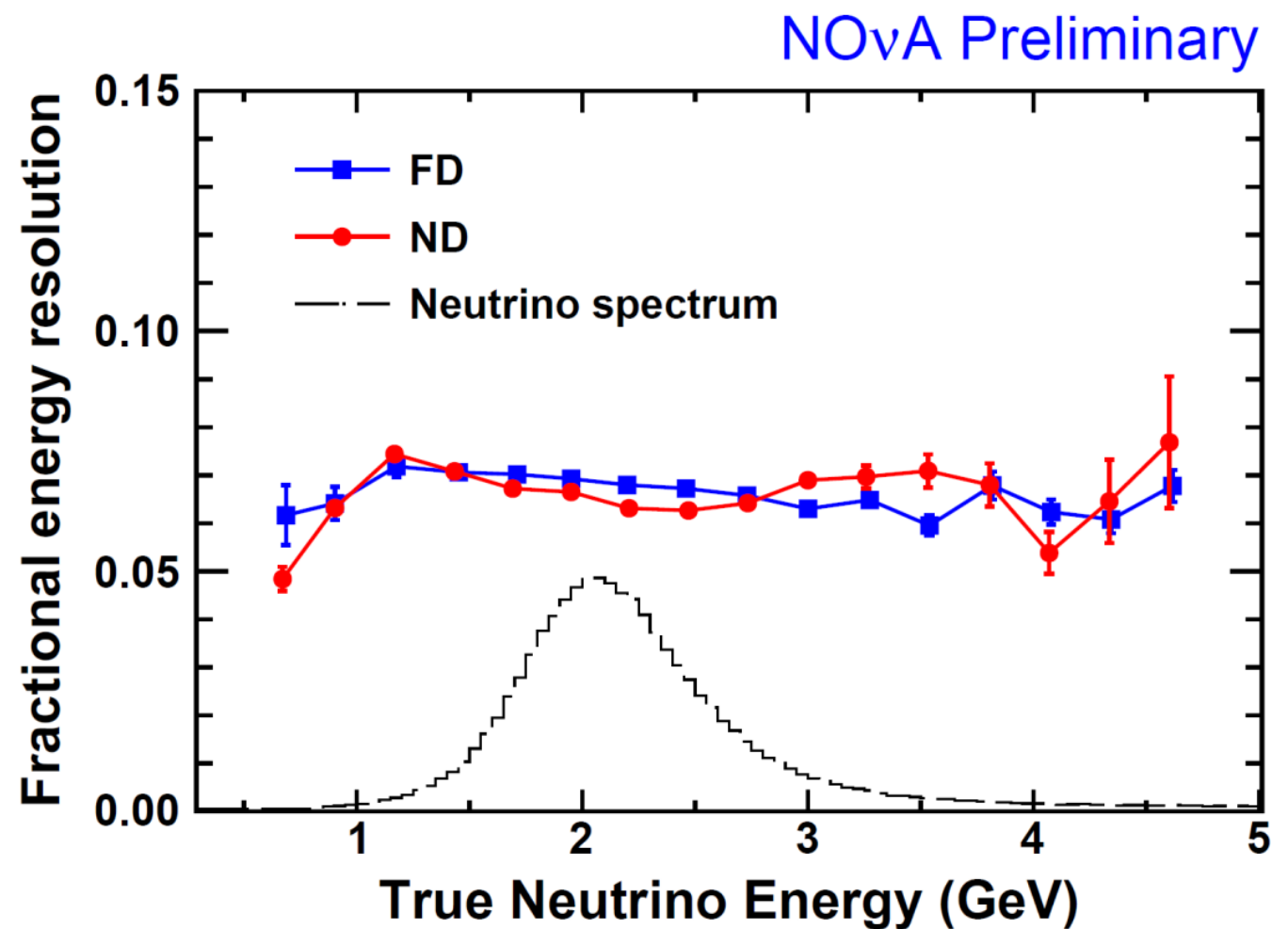
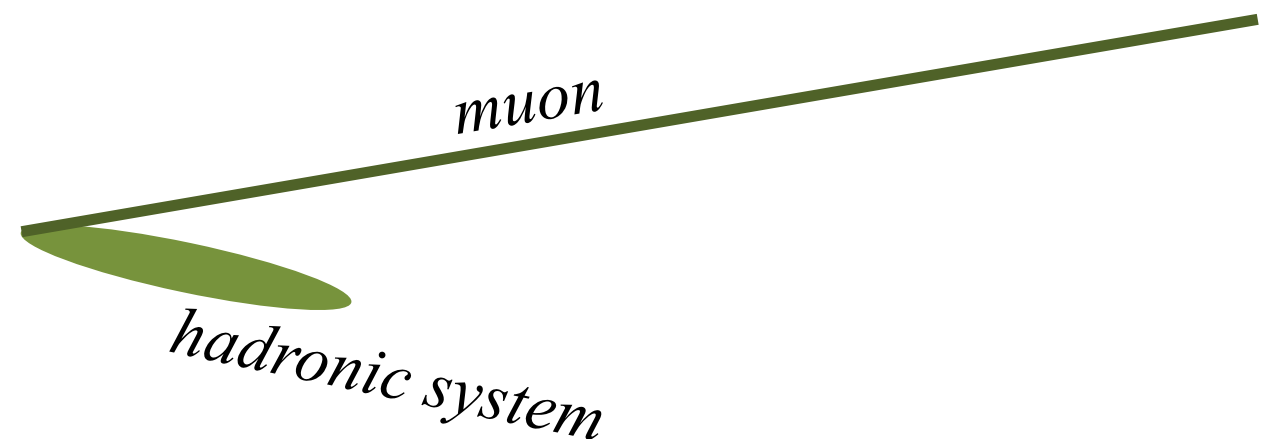
Reconstructed muon track:
length $\Rightarrow E_\mu$

Hadronic system:
 $\sum_{\text{cells}} E_{\text{visible}} \Rightarrow E_{\text{had}}$

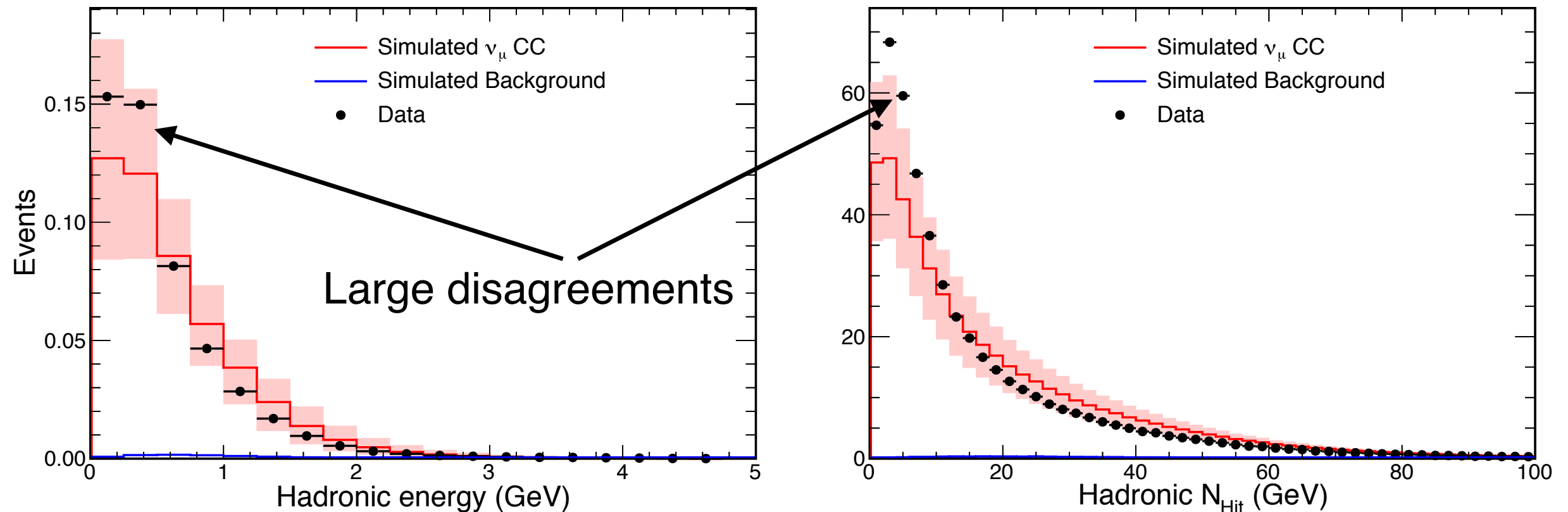
Reconstructed ν_μ energy is
the sum of these two:

$$E_\nu = E_\mu + E_{\text{had}}$$

*Energy resolution at
beam peak $\sim 7\%$*

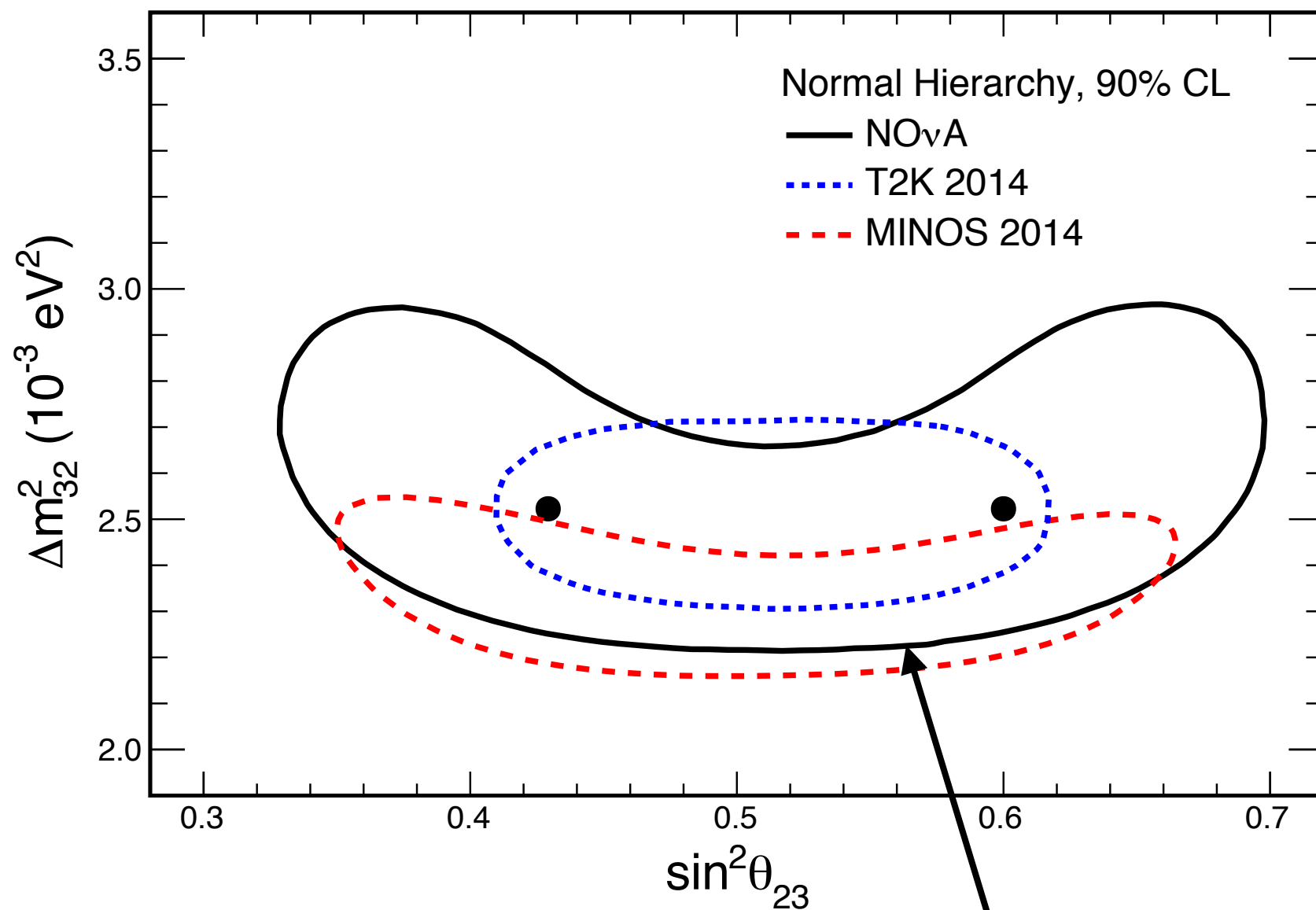


Cross Section Uncertainties



- Change underlying parameters in neutrino model, similar to T2K
- NOvA uses a CC-inclusive sample, so individual modes are less important
- However, see a large uncertainty in the hadronic energy component which is currently a major systematics driver

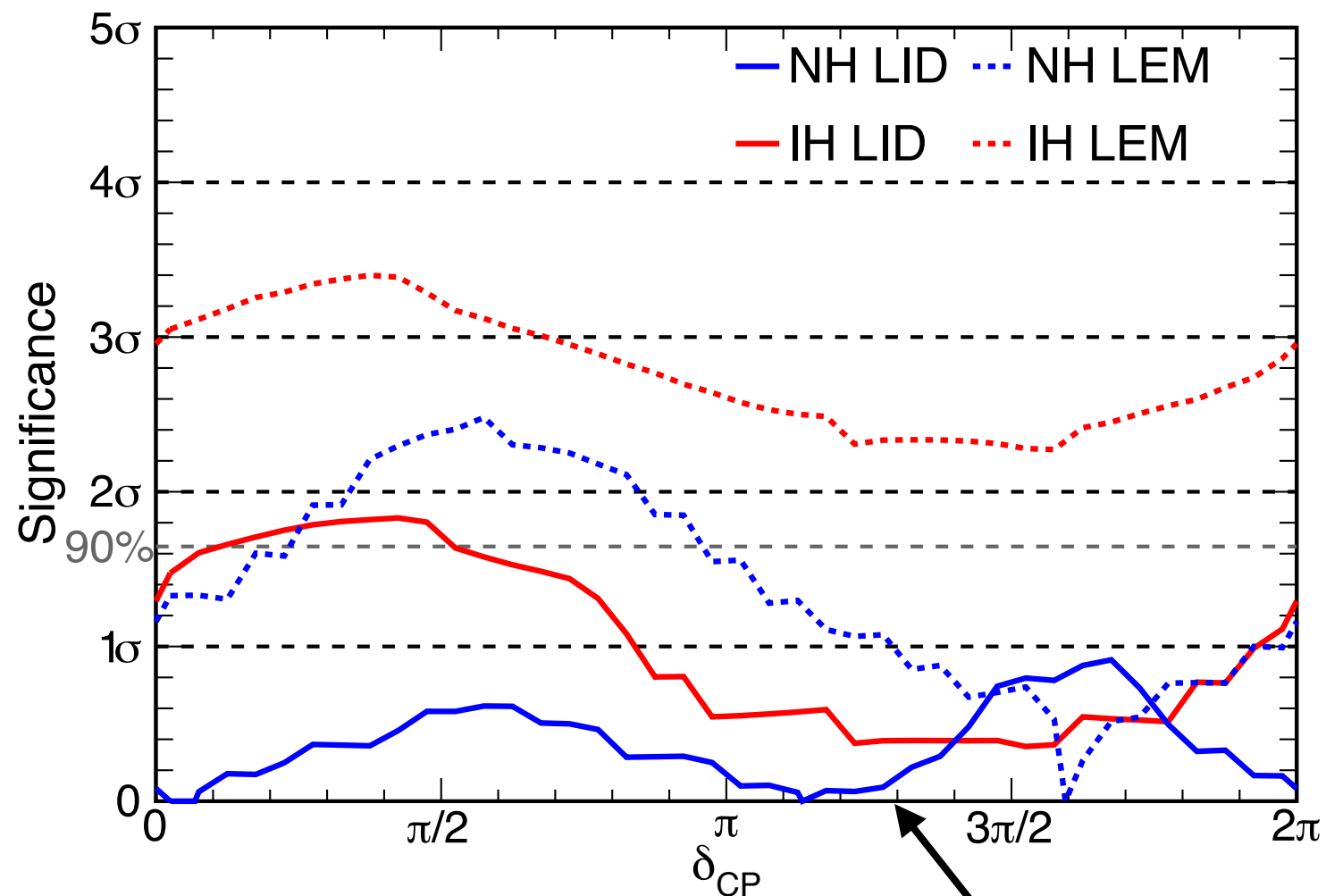
Results



Adamson, P., et al. "First measurement of muon-neutrino disappearance in NOvA." *arXiv preprint arXiv:1601.05037* (2016).

confidence level contours
Feldman-Cousins
Profiling treatment of systematics
Gradient descent

Results

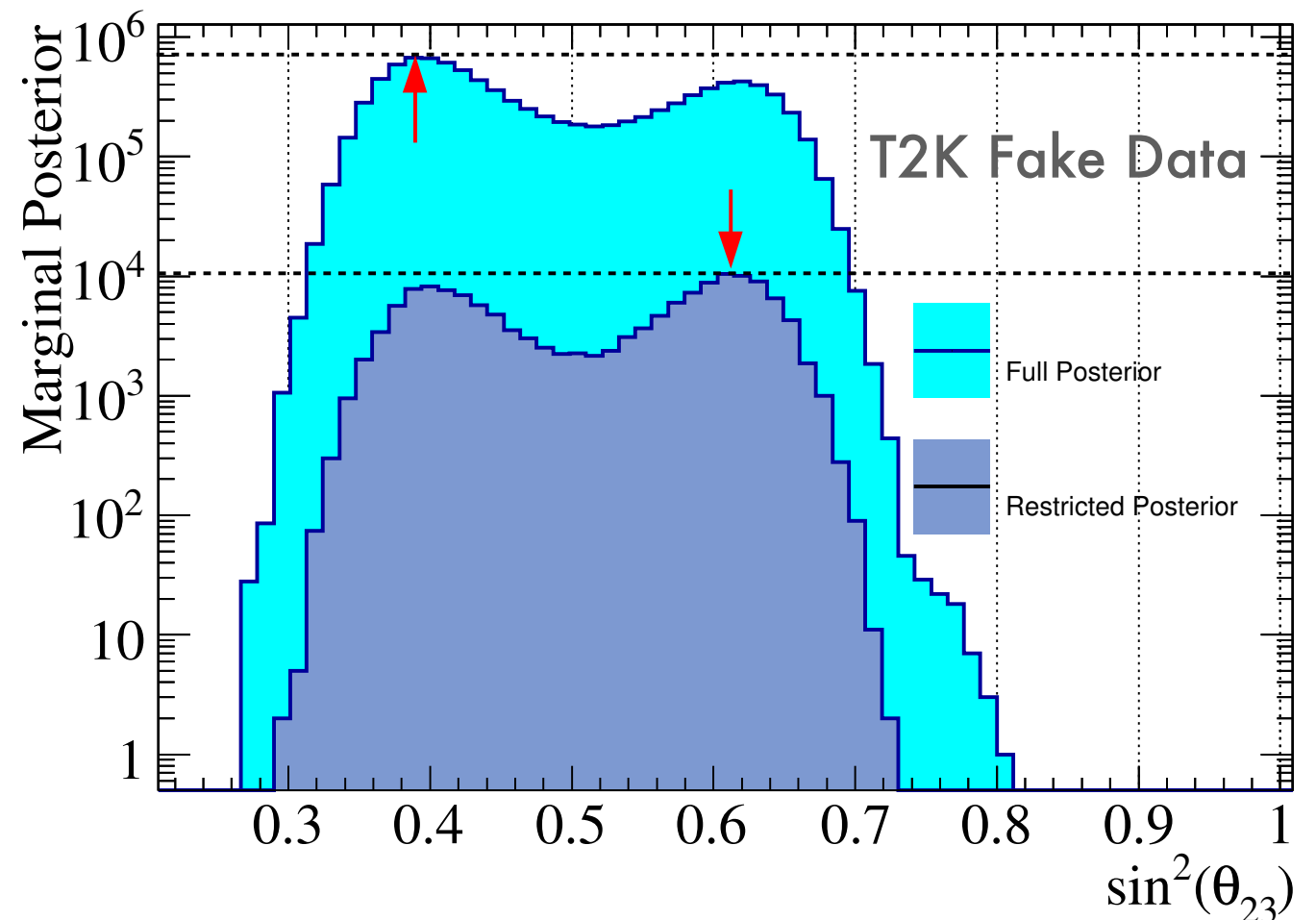


Adamson, P., et al. "First measurement of electron neutrino appearance in NOvA." *arXiv preprint arXiv:1601.05022* (2016).

Special Issues

Marginalization vs Projection

- T2K found that treatment of systematics can have noticeable effects on analyses, especially when treating oscillation parameters, which are very non-gaussian
- T2K has moved to marginalization for all oscillation analyses, using both MCMC and likelihood averaging over toys

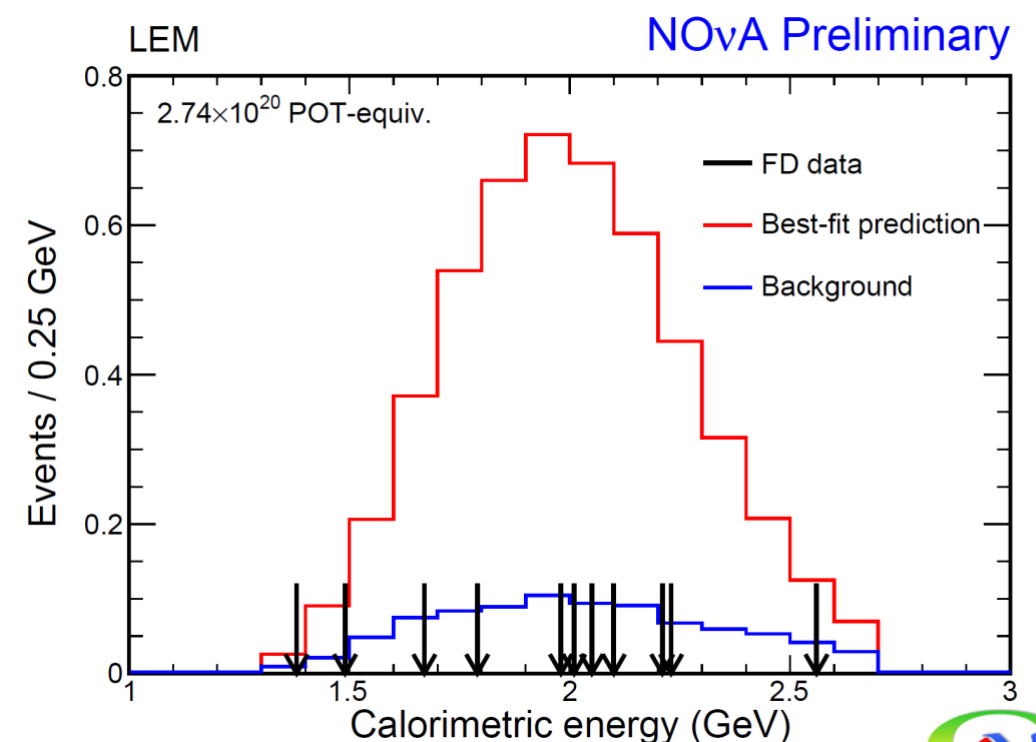
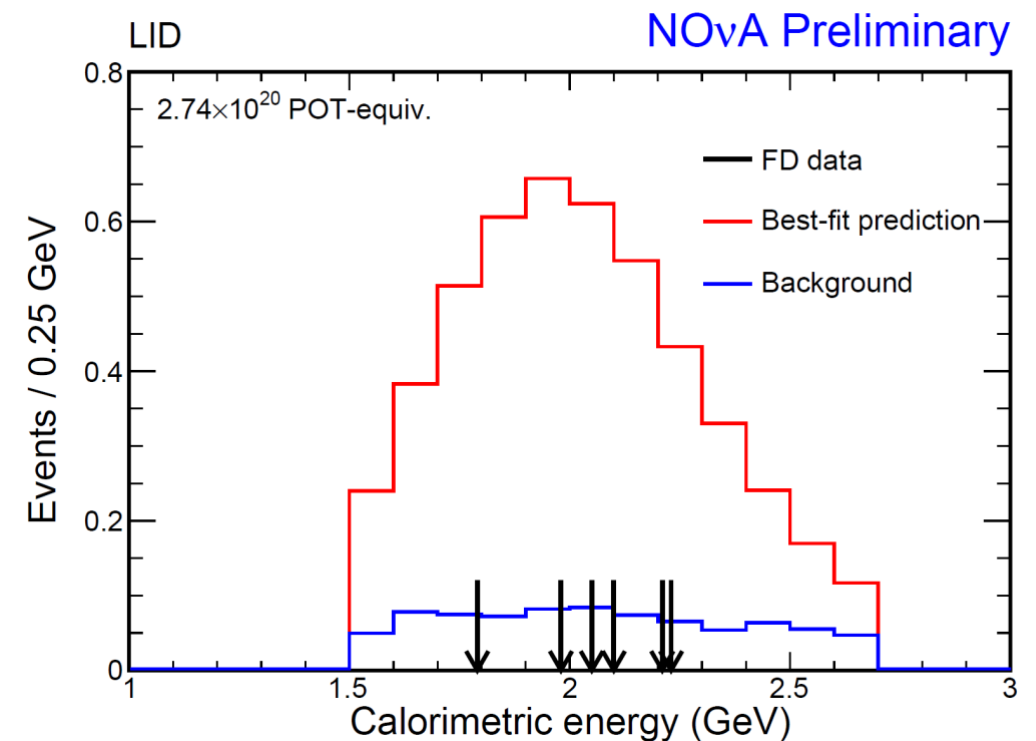


$$f_{\text{marg}}(x) = \int dy f(x, y)$$

$$f_{\text{proj}}(x) = \max_y f(x, y)$$

Selections with Tension

- NOvA has two event selections:
 - Likelihood Identification (LID) with 6 events
 - Library Event Matching (LEM) with 11 events
- All 6 LID events are in the LEM selection
- The predicted number of events for the two selections was roughly equal (5.6 vs 5.9)
- Should we be worried?



Selections with Tension

- Use MC to estimate p_1 , p_2 , and p_3 for signal and background separately, and calculate P for $N_b=0,1,2,\dots$
- What is the total probability for combinations which are less probable than the data combination?

Probability of LEM only
 $n_2=5$

Probability of LID only
 $n_1=0$

$$P = \frac{n!}{(n_1!)(n_2!)(n_3!)} p_1^{n_1} p_2^{n_2} p_3^{n_3}$$

Probability of LEM and LID
 $n_3=6$

Selections with Tension

$$\begin{aligned}
 B = 0, S = 11 &\rightarrow p_{1,B=0}, p_{2,B=0}, p_{3,B=0} \rightarrow P(0/5/6 + |B = 0) = 6\% \\
 B = 1, S = 10 &\rightarrow p_{1,B=1}, p_{2,B=1}, p_{3,B=1} \rightarrow P(0/5/6 + |B = 1) = 7.1\% \\
 B = 2, S = 9 &\rightarrow p_{1,B=2}, p_{2,B=2}, p_{3,B=2} \rightarrow P(0/5/6 + |B = 2) = 8.3\%
 \end{aligned}$$

...

where

$$p_{1,B=N_b} = p_1^b N_b / 11 + p_1^s (11 - N_b) / 11$$

and

$$P(B = 0) = 20.9\%$$

$$P(B = 1) = 35.2\%$$

$$P(B = 2) = 26.9\%$$

...

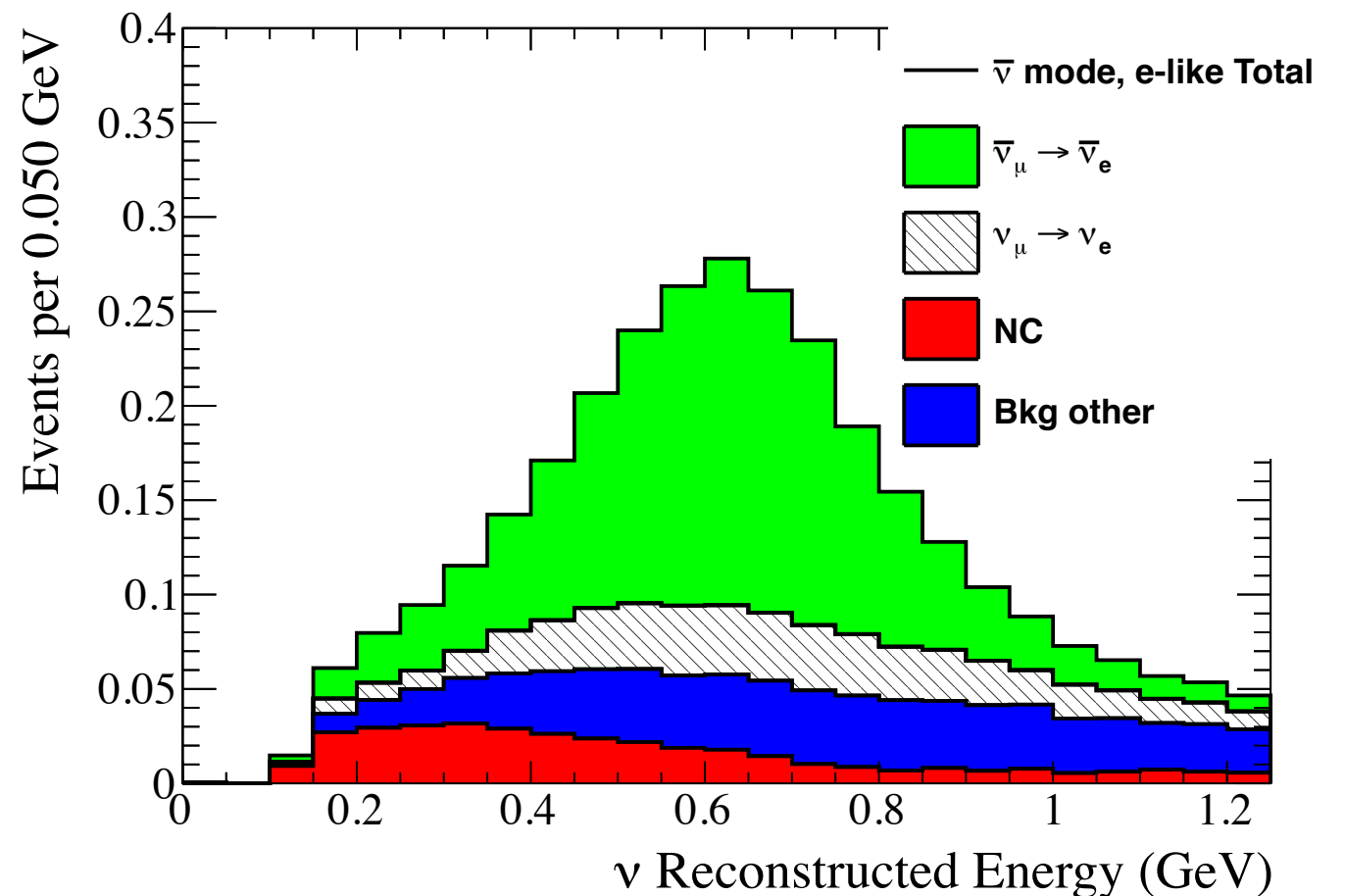
so

$$P = \sum_B P(0/5/6 \text{ or worse} | B) P(B) = \boxed{7.8\%}$$

Uses central value of
background prediction

Parameterizing $\nu/\bar{\nu}$ Differences

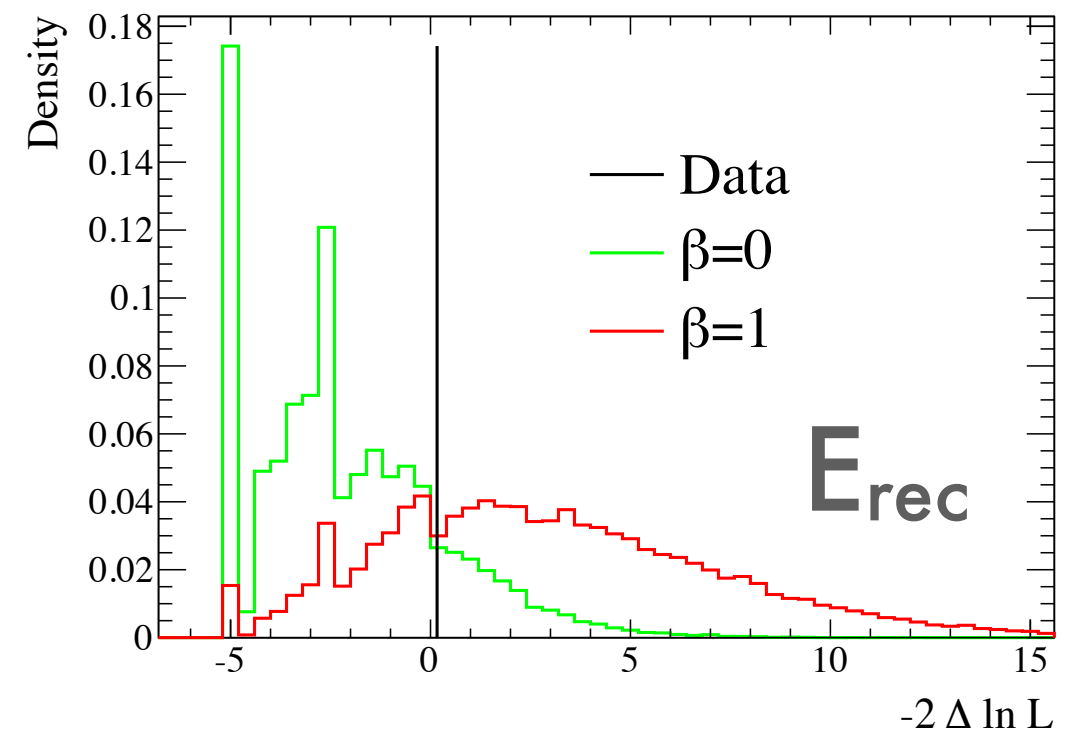
- After establishing ν_e appearance, T2K wanted to analyze $\bar{\nu}_e$ appearance
- How to build a model that is “minimally” CP-violating?
- Decided to introduce a parameter β that multiplies $P(\bar{\nu}_\mu \rightarrow \bar{\nu}_e)$ while keeping all other oscillation parameters the same between ν and $\bar{\nu}$
- Allow β to only take the values 0 (no $\bar{\nu}_\mu \rightarrow \bar{\nu}_e$ oscillation) and 1 ($\bar{\nu}_\mu \rightarrow \bar{\nu}_e$ oscillates as $\nu_\mu \rightarrow \nu_e$)



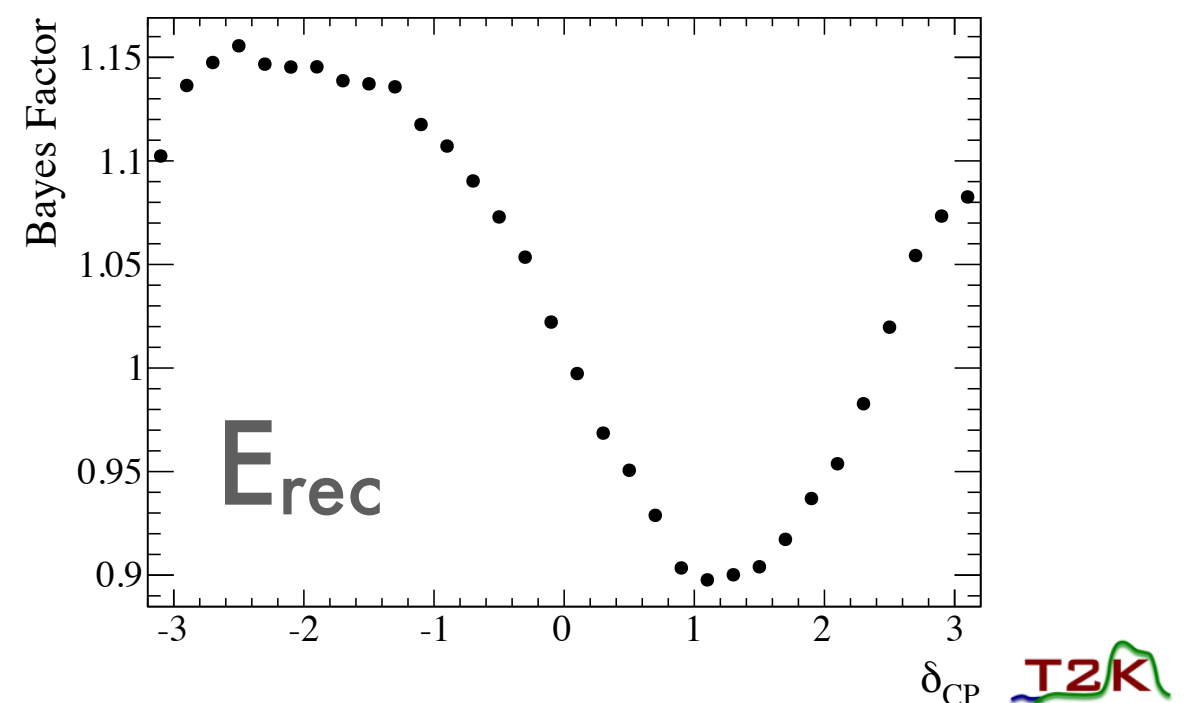
Parameterizing $\nu/\bar{\nu}$ Differences

- Use a test statistic of

$$-2 (\ln \mathcal{L}(\beta = 1) - \ln \mathcal{L}(\beta = 0))$$
- Throw toy data sets for the cases $\beta=0$ and $\beta=1$ and compare what data looks like
- Also calculate a Bayes factor

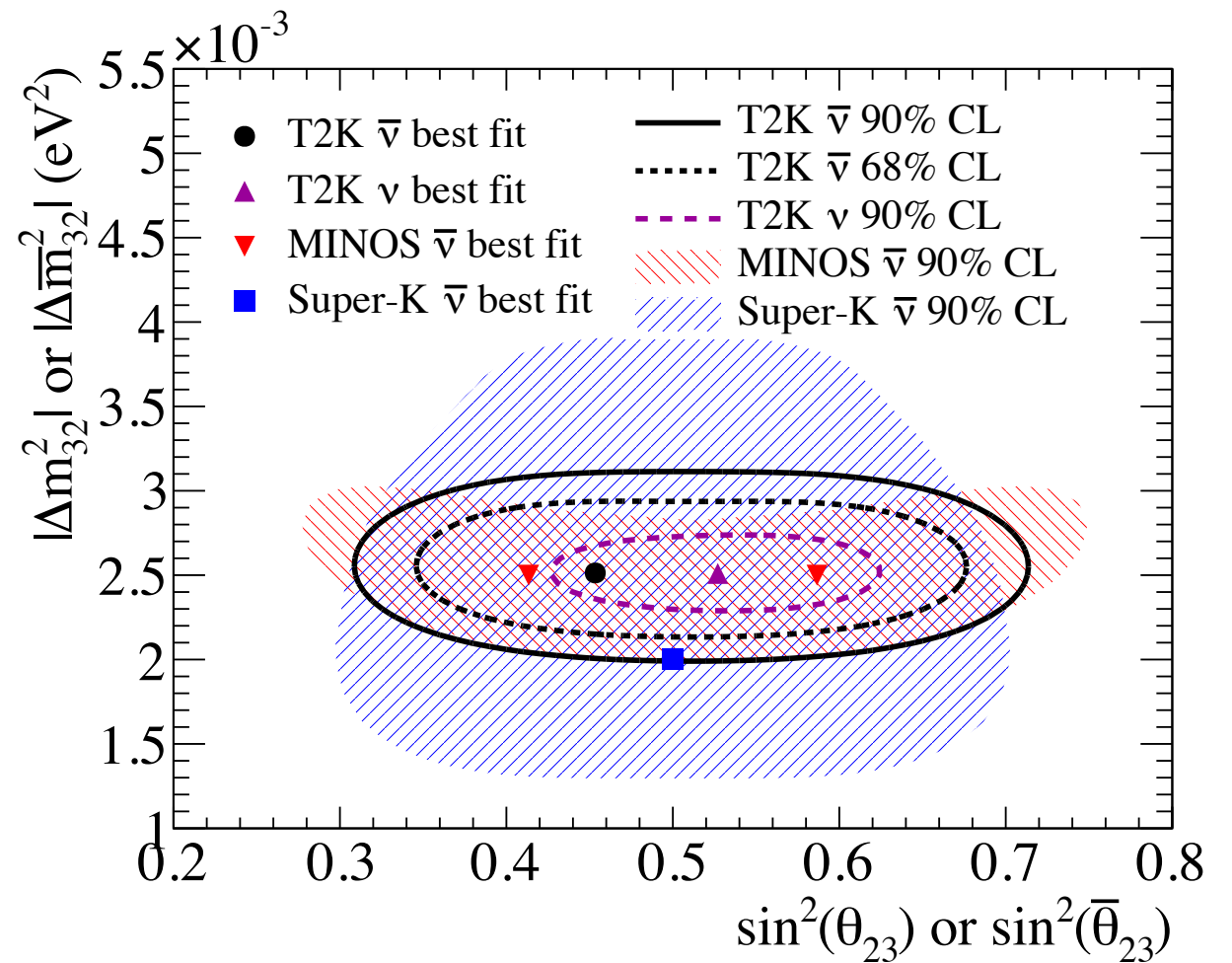


	E_{rec}	p-theta
p-value	0.16	0.34
BF	1.1	0.6

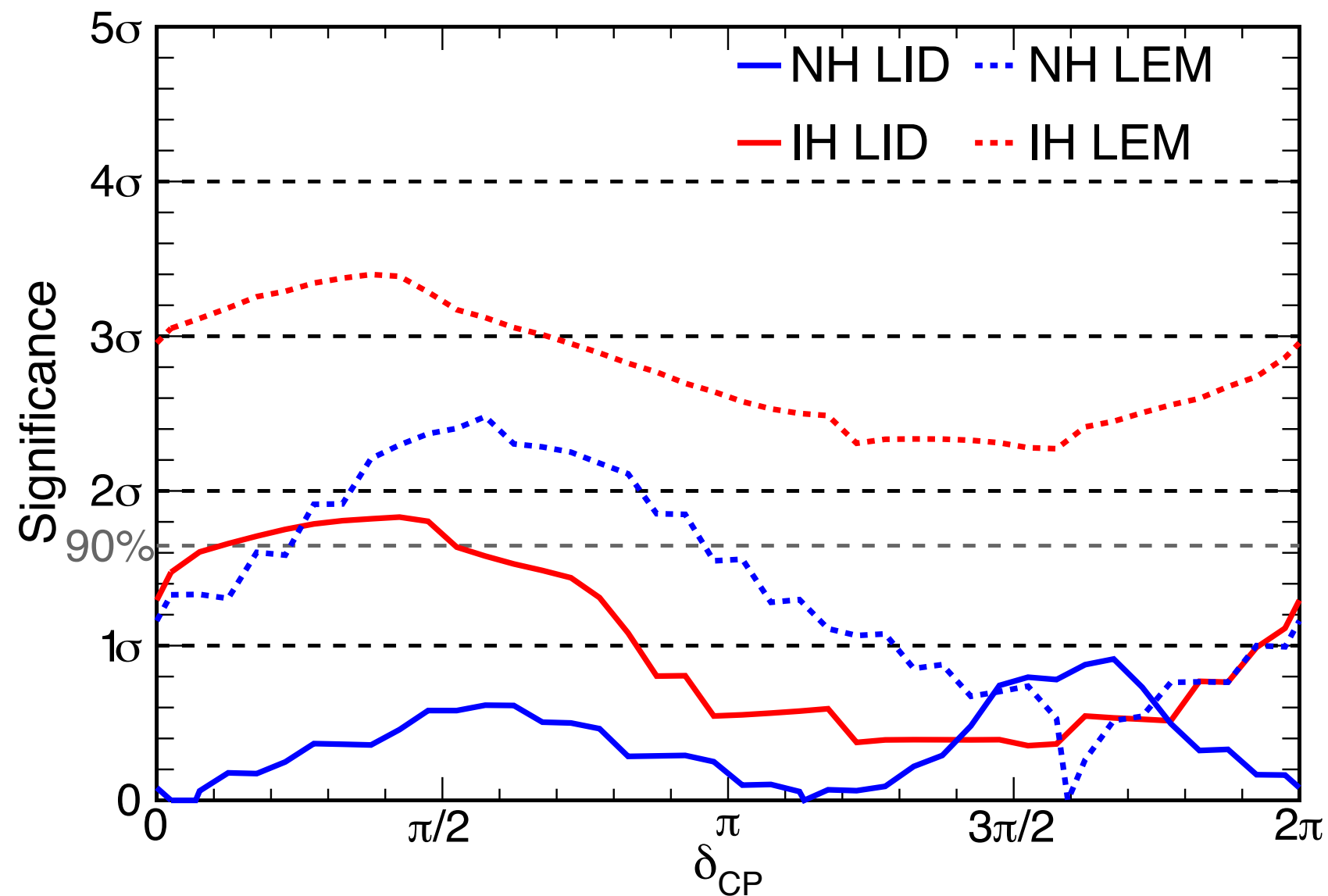


Parameterizing $\nu/\bar{\nu}$ Differences

- For $\bar{\nu}$ disappearance measurements, T2K chose to duplicate the full set of oscillation parameters (θ_{23} , $\bar{\theta}_{23}$, etc.)
- Because of a low statistics sample, all parameters except the 23 parameters were fixed as equal between ν and $\bar{\nu}$; only $\bar{\theta}_{23}$ and $\Delta\bar{m}_{23}^2$ are variable



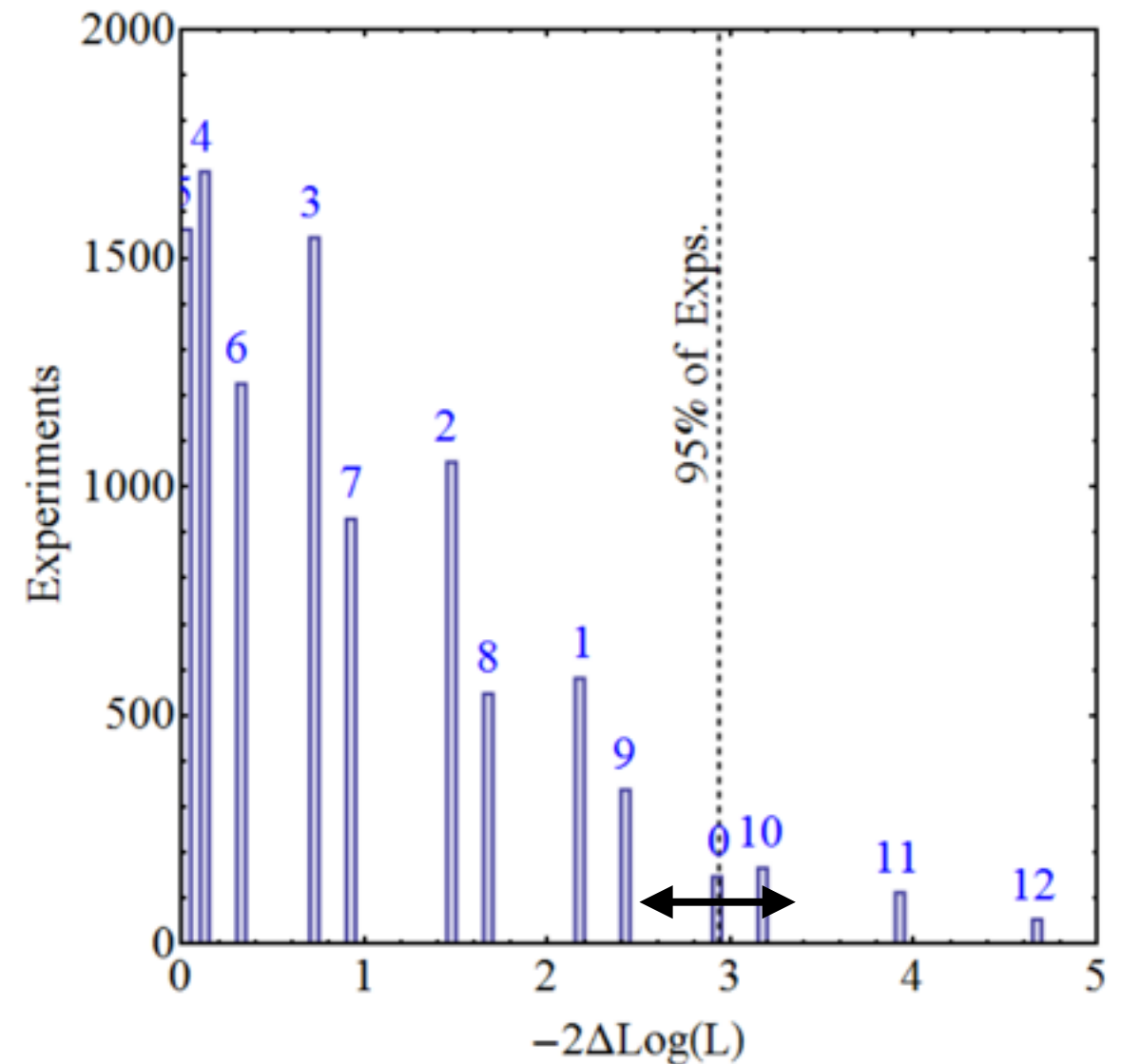
P-Values (1)



Why are these so jagged?

P-Values (1)

- These p-values are generated as a counting rate
- When the assumptions about the oscillation parameters are varied, these spikes can cross the critical value, which causes jaggedness
- Things like shape information and more data will smooth this out



P-Values (2)

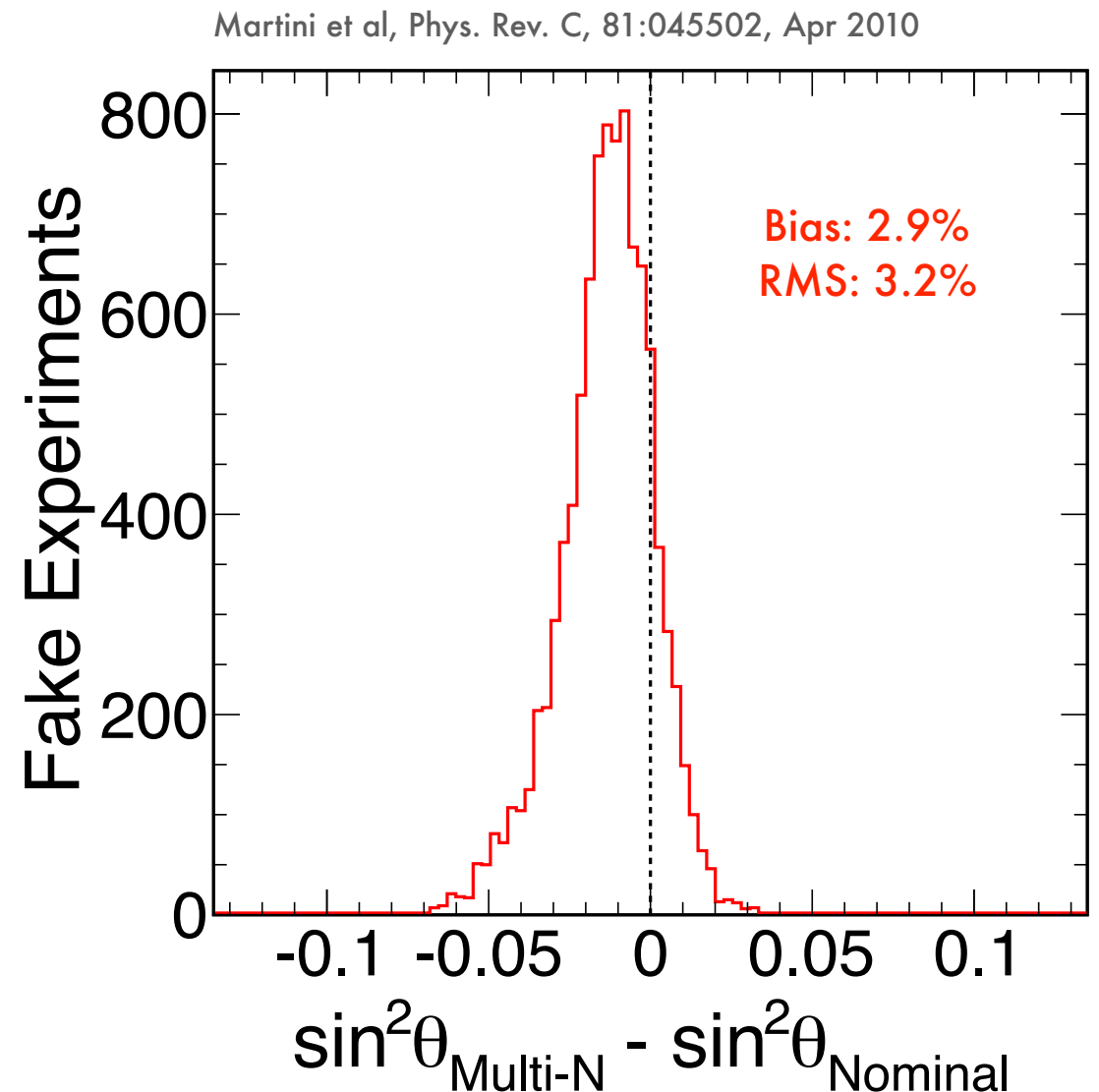
- How do we treat p-values in the presence of systematic uncertainties that may be constrained by the analysis?
- This is an issue for δ_{CP} and mass hierarchy measurements
- T2K has been discussing which of several methods to use: <http://physics.rockefeller.edu/luc/proceedings/phystat2007.pdf> (Thank you to PhyStats of years gone by!)

P-Values (2)

- Two options, both which integrate the p-value over the systematics
 - Prior-predictive
 - $p_{prior} = \int d\nu \pi(\nu) p(\nu).$
 - “A small value of p_{prior} is therefore evidence against the overall model used to describe the data, and could in principle be caused by a badly elicited prior as well as by an invalid likelihood (or unlikely data)”
 - Posterior-predictive
 - $p_{post} = \int d\nu \pi(\nu | n_0) p(\nu)$
 - “Estimates the probability that a future observation will be at least as extreme as the current observation if the null hypothesis is true”
- Ongoing discussion!

Discrete Model Issues

- We do our best to have the best model of cross section, but this is hard
- Test impact using fake data studies—can see bias in parameters
- We may not have complete implementation of a particular model, which makes it hard to use that model to fit data
- How can we include the error from these discrete model differences on our final parameters?

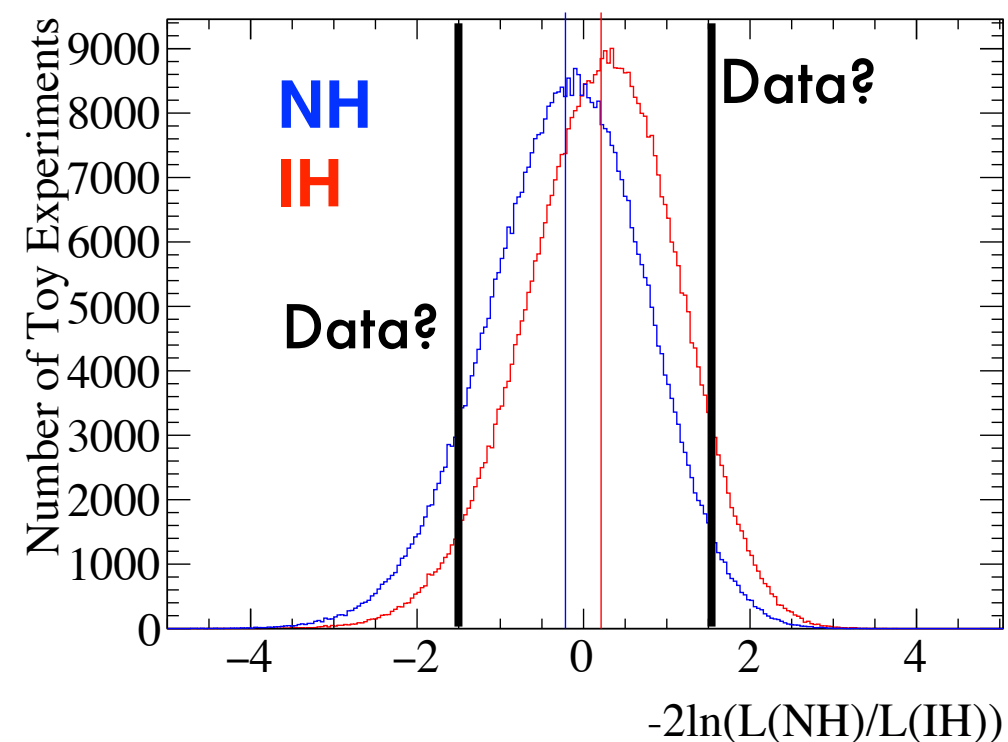


Mass Hierarchy

BF=2.2

- What should we report?
- Answer: report it all!
 - Show distributions for test statistic
 - Show Bayes Factor
 - Show sensitivity (and assumptions)
- Let the consumer make choice—somewhat help them along!

For $P(\text{NH})=P(\text{IH})=0.5$	NH	IH	Total
$\sin^2\theta_{23}\leq 0.5$	17.9%	7.8%	25.7%
$\sin^2\theta_{23}>0.5$	50.5%	23.8%	74.3%
Total	68.4%	31.6%	100%



Questions for Discussion

- Are we doing anything that's flat out wrong?
- Do we need to do anything more?
- How do we best communicate our choices?

Thank You!

Supplementary

Posterior Probability

$$P(\vec{z}|\text{data}) \propto P(\text{data}|\vec{z})P(\vec{z})$$

$$-\ln(P) = c + \sum_i^{ND280bins} N_i^p(\vec{b}, \vec{x}, \vec{d}) - N_i^d \ln N_i^p(\vec{b}, \vec{x}, \vec{d})$$

$$+ \sum_i^{N_\mu \text{ bins}} N_{\mu,i}^p(\vec{\theta}, \vec{b}, \vec{x}, \vec{s}) - N_{\mu,i}^d \ln N_{\mu,i}^p(\vec{\theta}, \vec{b}, \vec{x}, \vec{s})$$

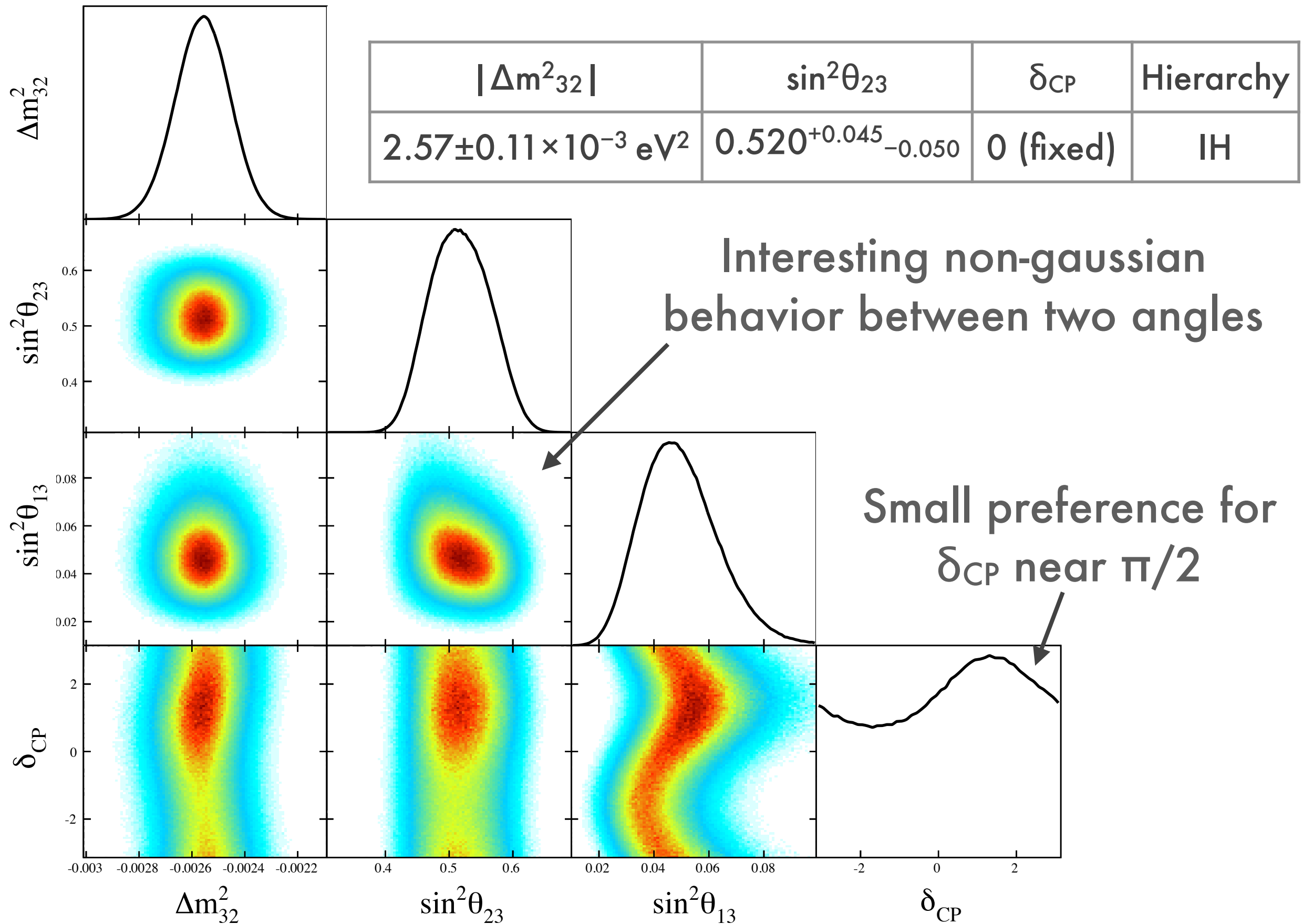
$$+ \sum_i^{N_e \text{ bins}} N_{e,i}^p(\vec{\theta}, \vec{b}, \vec{x}, \vec{s}) - N_{e,i}^d \ln N_{e,i}^p(\vec{\theta}, \vec{b}, \vec{x}, \vec{s})$$

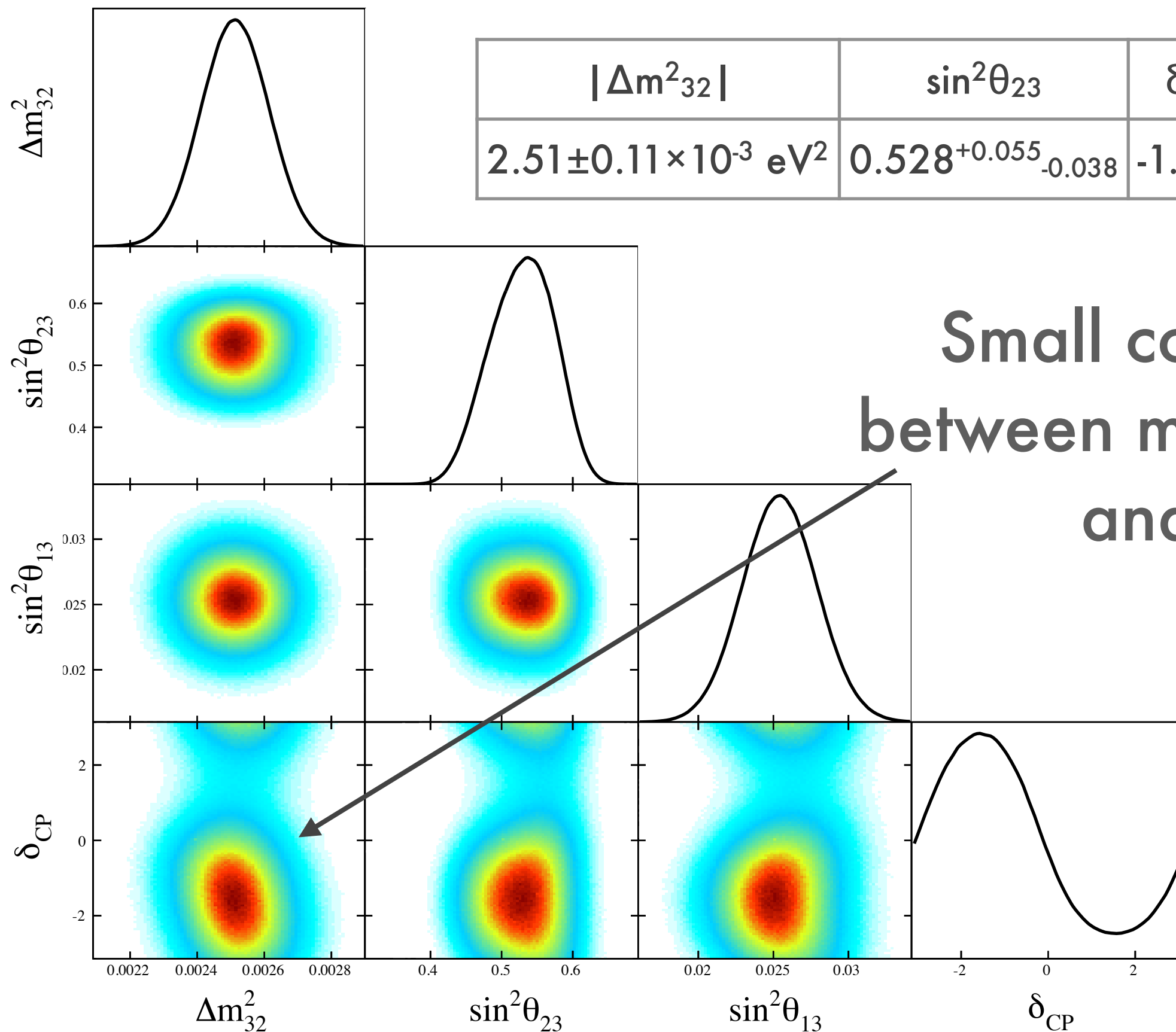
How well does
the data agree
with our
prediction?

$$+ \frac{1}{2} \Delta \vec{b}^T V_b^{-1} \Delta \vec{b} + \frac{1}{2} \Delta \vec{x}^T V_x^{-1} \Delta \vec{x} + \frac{1}{2} \Delta \vec{d}^T V_d^{-1} \Delta \vec{d}$$

$$+ \frac{1}{2} \Delta \vec{s}^T V_s^{-1} \Delta \vec{s} + \frac{1}{2} \Delta \vec{\theta}_{sr}^T V_{\theta sr}^{-1} \Delta \vec{\theta}_{sr}$$

What prior understanding did
we put into our prediction?

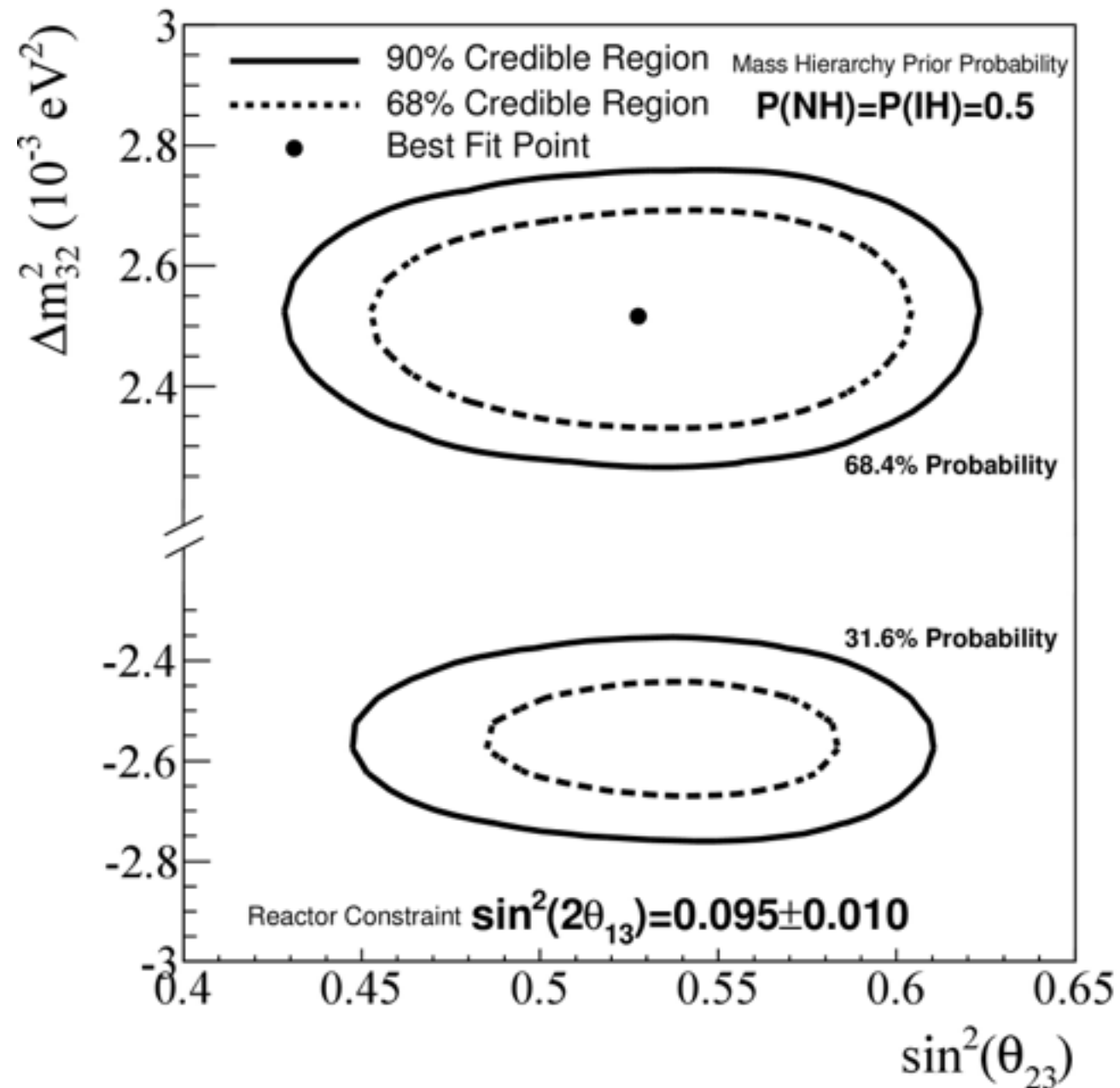




$ \Delta m_{32}^2 $	$\sin^2 \theta_{23}$	δ_{CP}	Hierarchy
$2.51 \pm 0.11 \times 10^{-3} \text{ eV}^2$	$0.528^{+0.055}_{-0.038}$	-1.601	NH

Small correlation
between mass splitting
and δ_{CP}

Mass Hierarchy

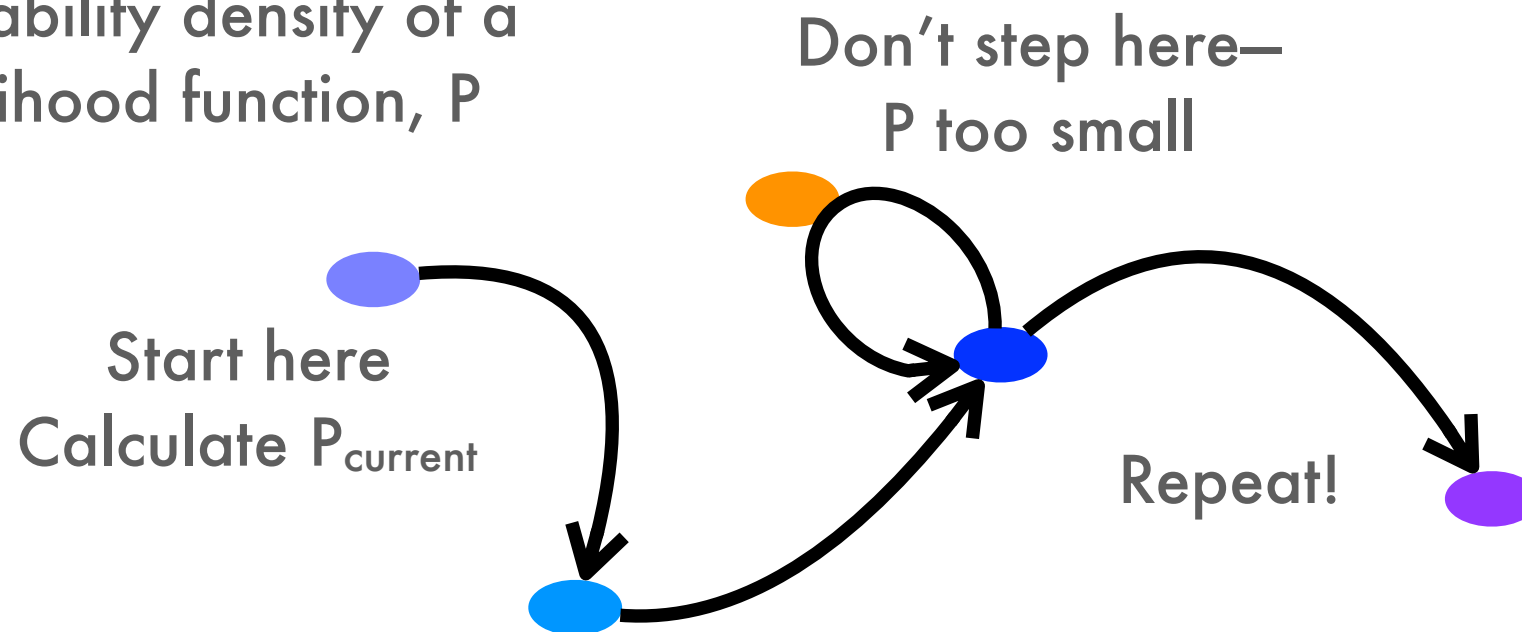


- Markov Chain steps between the two hierarchies
- Relative probability shows any preference for hierarchy

	NH	IH	Total
$\sin^2\theta_{23} \leq 0.5$	17.9%	7.8%	25.7%
$\sin^2\theta_{23} > 0.5$	50.5%	23.8%	74.3%
Total	68.4%	31.6%	100%

Markov Chain Monte Carlo and GPUs

A Markov Chain maps out the probability density of a likelihood function, P



Propose another point
Calculate P_{proposed} ; if better, step to that point
if not, step with probability $P_{\text{proposed}}/P_{\text{current}}$

- High dimensionality problem: 210 parameters
- Use Metropolis-Hastings algorithm with MCMC; doesn't require calculating likelihood derivatives