Bayesian neutrino reconstruction in Super-Kamiokande

...and other Bayesian methods in neutrino experiments

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The Super-Kamiokande (SK) detector

Imperial College London

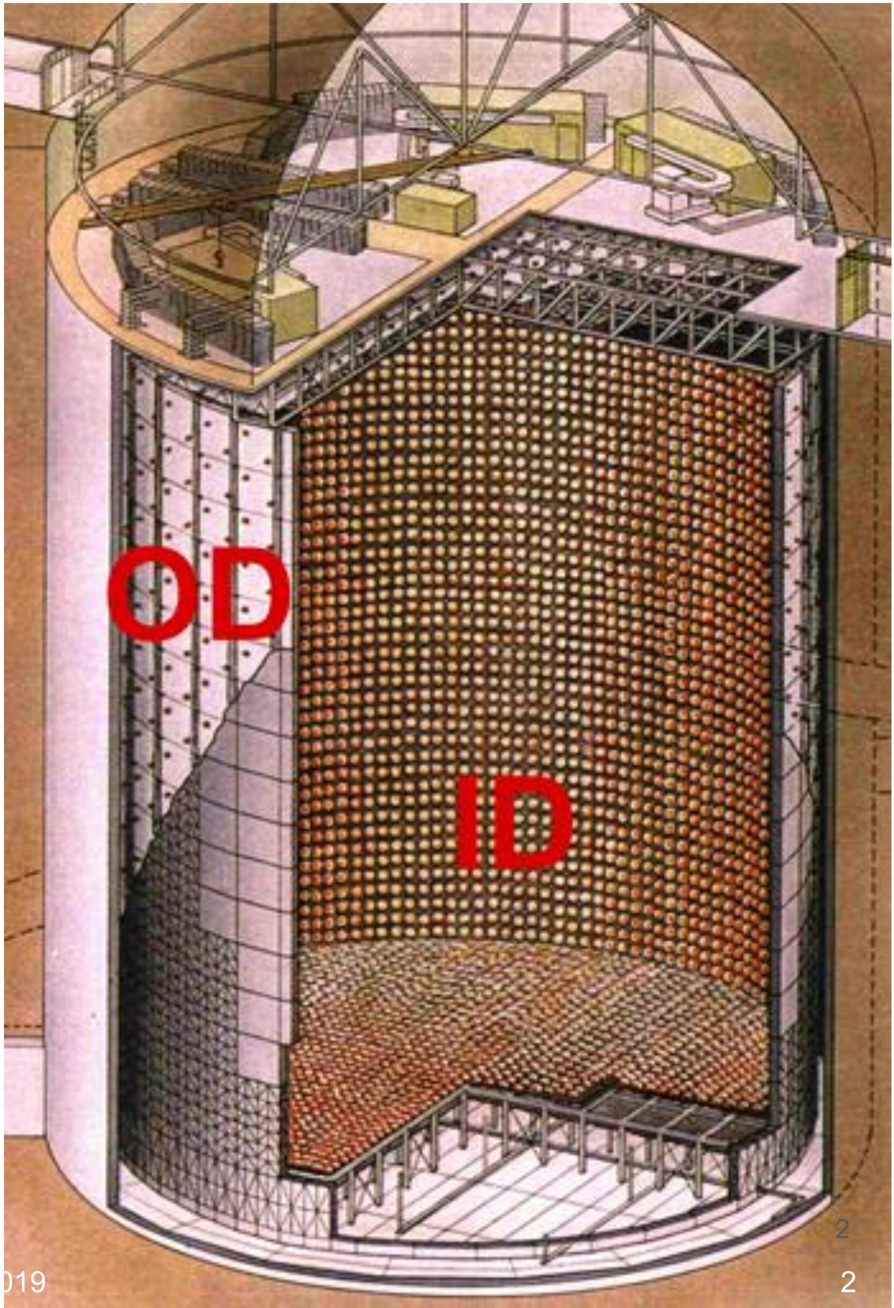
- Super-Kamiokande is a 50 kton (32 fiducial) water-cherenkov detector in Japan

- Separated into inner and outer parts to veto interactions outside the detector;
  - Radioactivity in the rock
  - Cosmics
  - Exiting events

- ~2k 8” photomultiplier tubes (PMT’s) on the outer detector (OD)

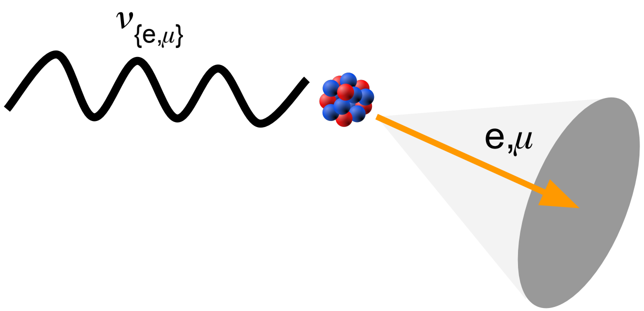
- ~11k 20” PMT’s on the inner detector (ID), with 40% photo coverage

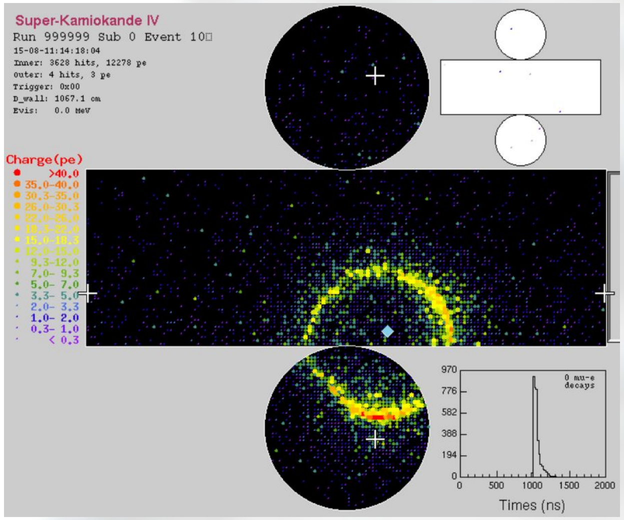
- Fully refurbished in 2018 in preparation for gadolinium doping to add an extra interaction channel



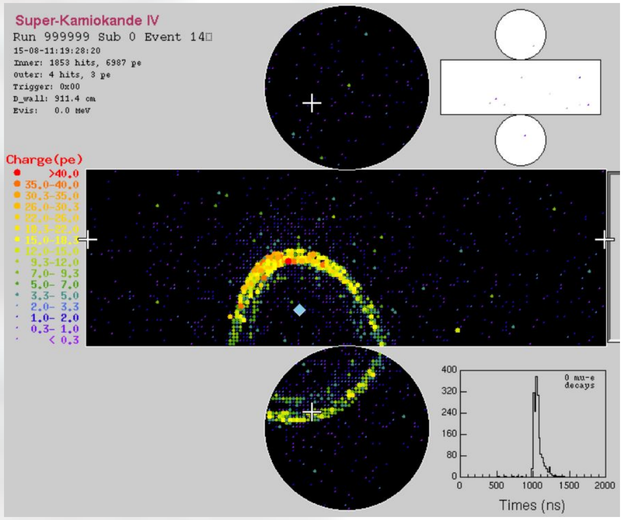
Neutrino interactions at SK

- Neutrinos interact with nucleus/electron, generating muons, electrons, pions, protons etc.
- Charged particles over speed of light in water emit cherenkov light ring along their trajectory
- Muons and electrons/gamma generate different-looking signals - we can differentiate
- Some interactions generate a lot of signal...

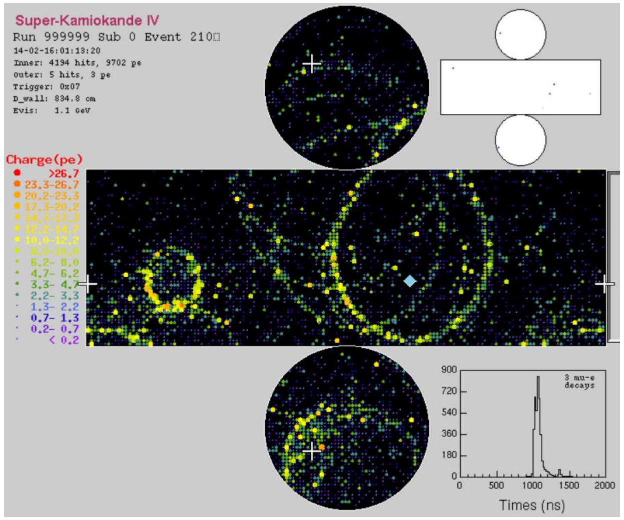




Electron-like ring



Muon-like ring



Hadronic scatter

Neutrino event reconstruction

The likelihood method

- Particles' properties (**x**) to reconstruct: 4-vertex, 2-angle and momentum
  - x, y, z, t, θ, ϕ, p

- What we get in the **data**: accumulated **charge** and **time** distributions **per-PMT**

- Use the **likelihood method** for the **event** parameter **reconstruction**

Probability i'th PMT was not hit

$$L(\mathbf{x}) = \prod_{j}^{\text{unhit}} P_j(\text{unhit}|\mathbf{x}) \prod_{i}^{\text{hit}} \{1 - P_i(\text{unhit}|\mathbf{x})\} f_q(q_i|\mathbf{x}) f_t(t_i|\mathbf{x})$$

Data from PMT's

Probability i'th PMT was hit

- Time and charge PDF distributions ($f_q(q_i|\mathbf{x})$ and $f_t(t_i|\mathbf{x})$) built from MC

Neutrino event reconstruction

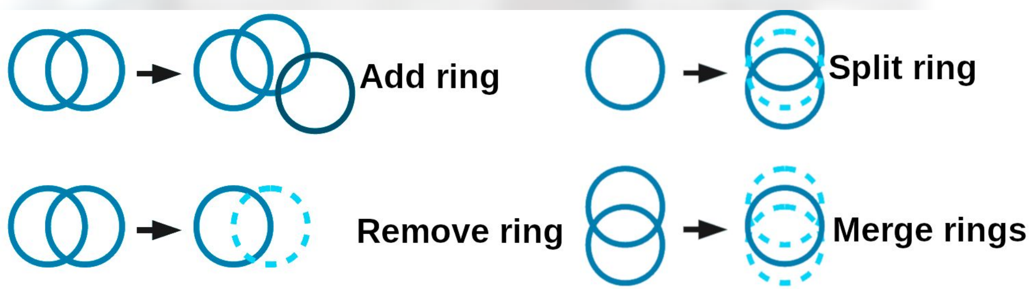
Reverse-Jump Markov Chain Monte Carlo

- ➢ MCMC is a ~~minimizer~~ **sampler**; it "steps" around the parameter space **recreating** the underlying **posterior density**

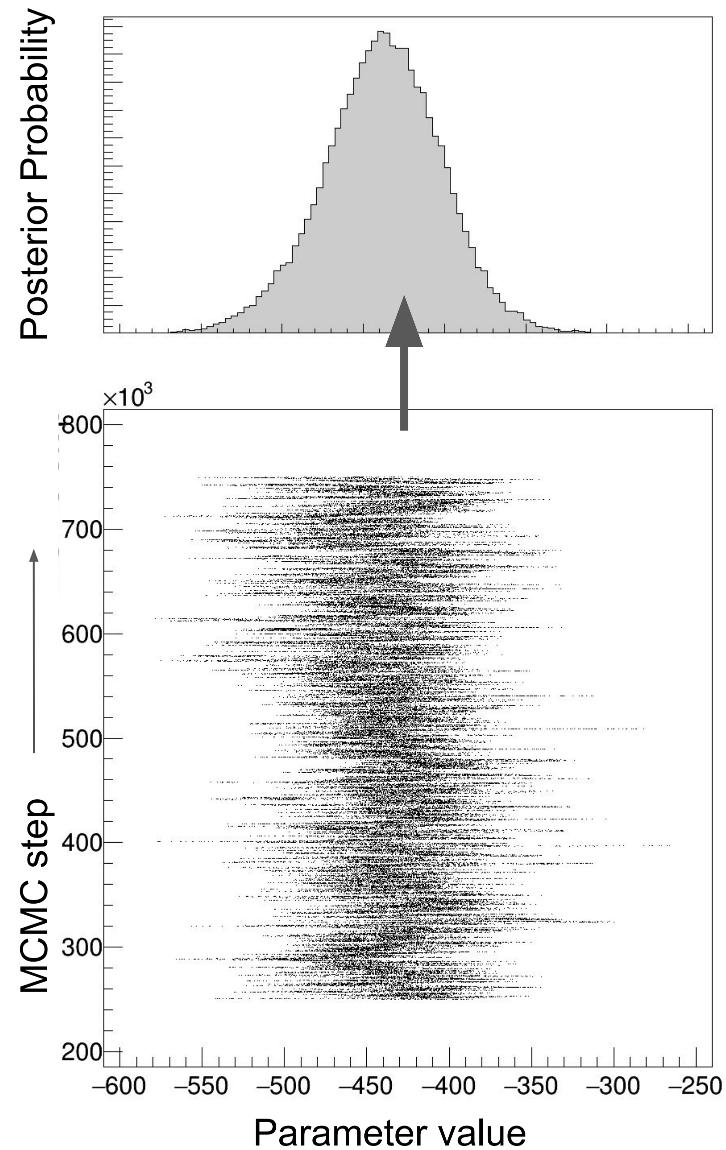
- ➢ We **bin the steps** to make properly marginalized 1D/2D **posterior probability** distributions

- ➢ Reverse-Jump MCMC can propose steps with different dimensionality

- ➢ We can add, substract, merge and split rings, changing their number - all in one MCMC run



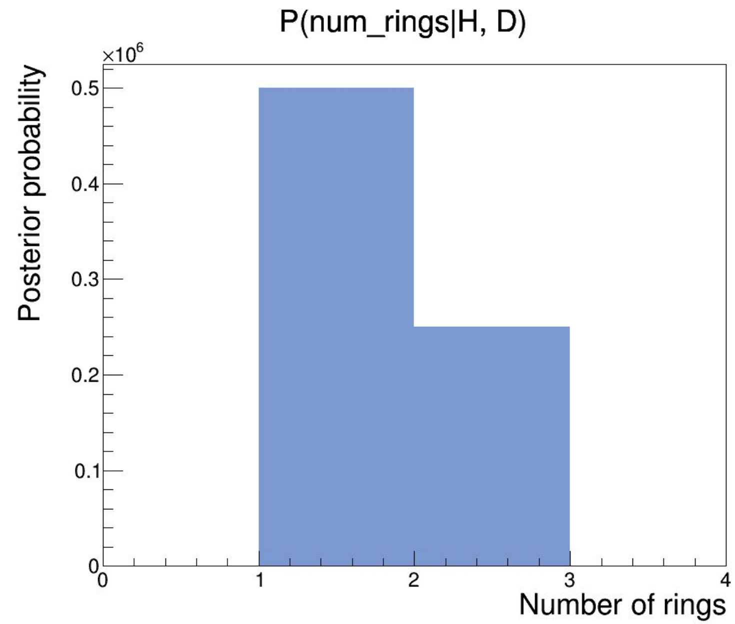
Dimension change step proposals

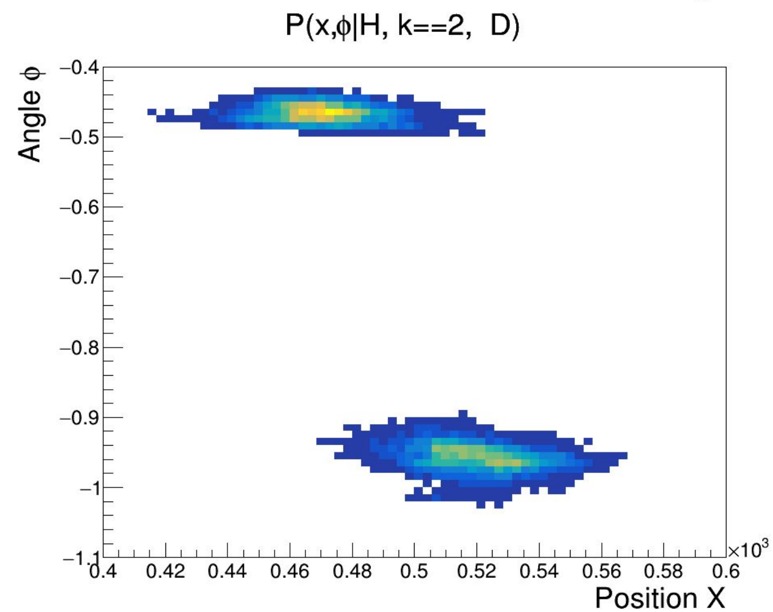


Neutrino event reconstruction

Bayesian inference

- **Currently** used method requires **many** separate **runs** for each hypothesis
  - Hypothesis selection more **difficult**; arbitrary cuts on likelihood ratios
- We can sample all the PID/number of rings hypotheses in one run
- **Posterior probabilities** allow us for an **easy hypothesis selection** - simply choose the highest bin
- A lot of **new information**; properly marginalized posterior allows for more detailed analysis

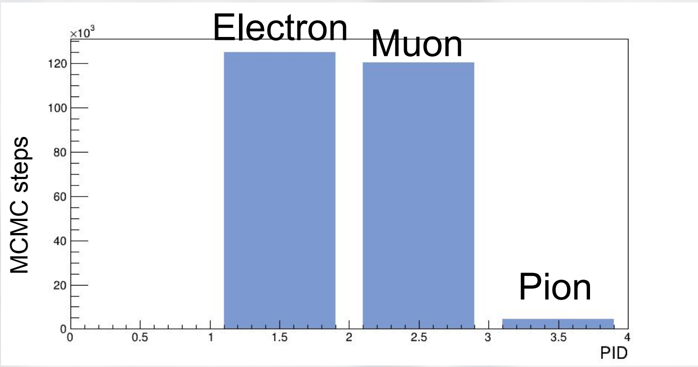


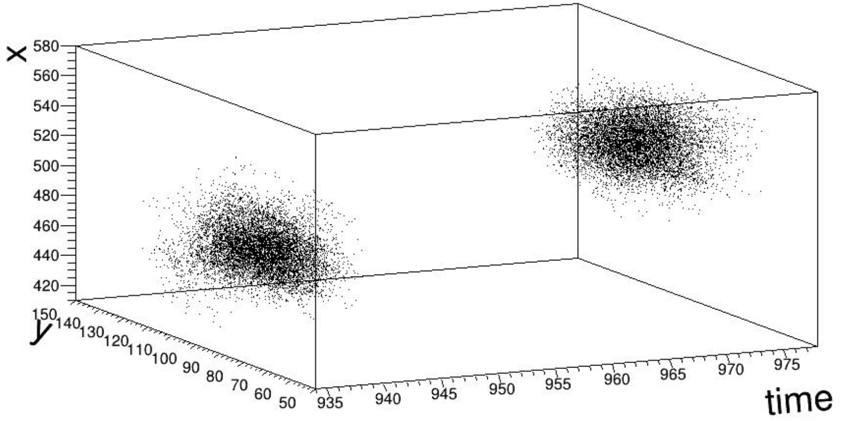


- Work originally started by Richard Cannald (IPMU)

Neutrino event reconstruction

- We now have a new Bayesian method of the neutrino event reconstruction for large Water-Cherenkov detectors
- We obtain not only the **best-fit** parameter **kinematics**, but also a properly **marginalized posteriors**
- This can be used for **better selections/cuts**, e.g. for particles with high position uncertainty near the detector wall
- One fit, all particle hypothesis. Previously over hundred of fits per event, complex likelihood ratios for selections
- Hopefully **better efficiency**, important for e.g. future detectors (**Hyper-Kamiokande**)





Neutrino event reconstruction

Outstanding issues

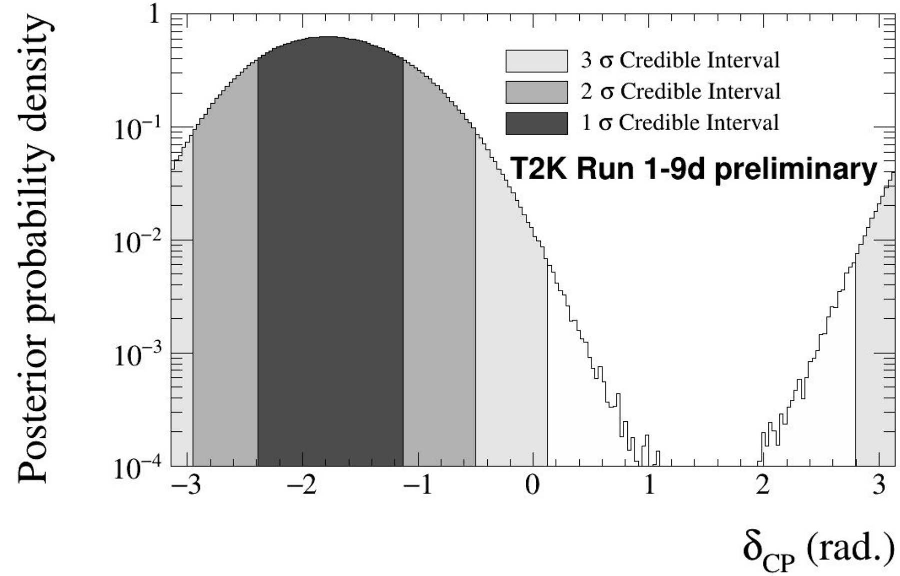
- MCMC can be **difficult to tune**;
  - We need to select MCMC tuning that will be “OK” for all number of particles and particle hypothesis…
  - Or make new tuning criteria for **each hypothesis separately**
- **When** do we **stop** MCMC chain?
  - Need great convergence for **all hypothesis** or just the **most likely** one?
  - Higher number of rings; need **longer MCMC chain**
  - Need a unit of measure to check for the posterior “quality” to **decide** whether to **stop the sampler**.
- Will probably find more as the validations are ongoing!

Other bayesian work

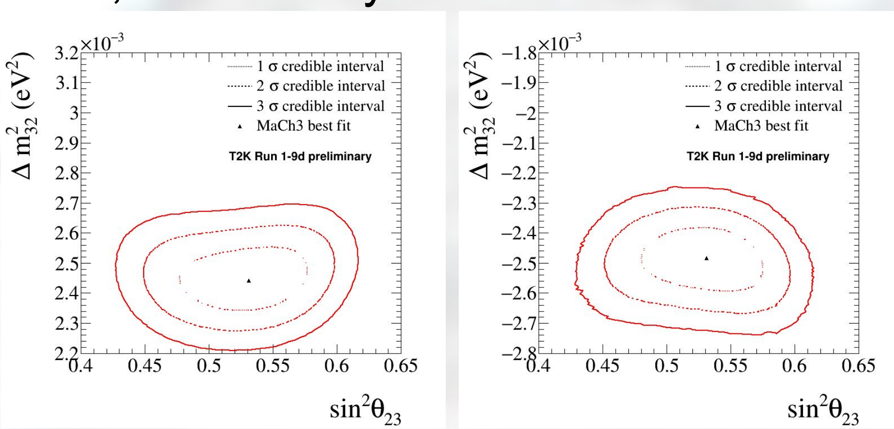
Imperial College London

Official T2K Oscillation Bayesian Analysis

- Measuring neutrino oscillation parameters with T2K dataset using Bayesian statistics
- Part of official results for T2K run 1-9 dataset
- First T2K 1-2-3 sigma posterior plot results for δ_{CP}
- T2K excludes CP-conservation at 2σ, but not 3σ yet.



1D δ_{CP} log-posterior probability marginalized over both mass hierarchies



"Disappearance" parameters: $\pm\Delta m^2_{32}$ and $\sin^2\theta_{23}$

	$\sin^2\theta_{23} < 0.5$	$\sin^2\theta_{23} > 0.5$	Sum
NH ($\Delta m^2_{32} > 0$)	0.184	0.705	0.889
IH ($\Delta m^2_{32} < 0$)	0.021	0.090	0.111
Sum	0.205	0.795	1

Model comparison probabilities from the posterior of run 1-9 T2K data

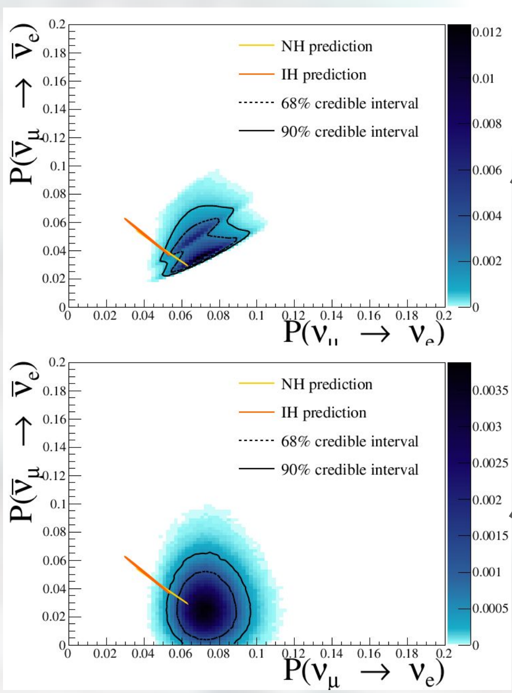
Other bayesian work

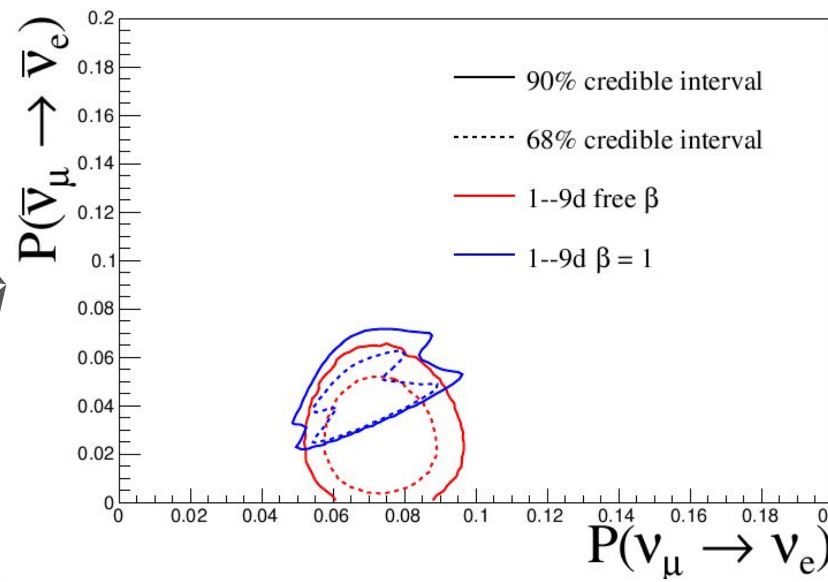
Official T2K Bi-Probability Bayesian Analysis

- Measuring T2K data's compatibility with the PMNS model.
- A way for theorists to compare their novel models against T2K's dataset; both constrained and unconstrained by the PMNS
- Adding a new parameter to oscillation probability to allow the samplers to move unconstrained by the PMNS

Standard T2K PMNS fit

New T2K non-PMNS fit





$$P(\bar{\nu}_\mu \rightarrow \bar{\nu}_e) = \beta \times P_{PMNS}(\bar{\nu}_\mu \rightarrow \bar{\nu}_e)$$
$$P(\nu_\mu \rightarrow \nu_e) = (1/\beta) \times P_{PMNS}(\nu_\mu \rightarrow \nu_e)$$

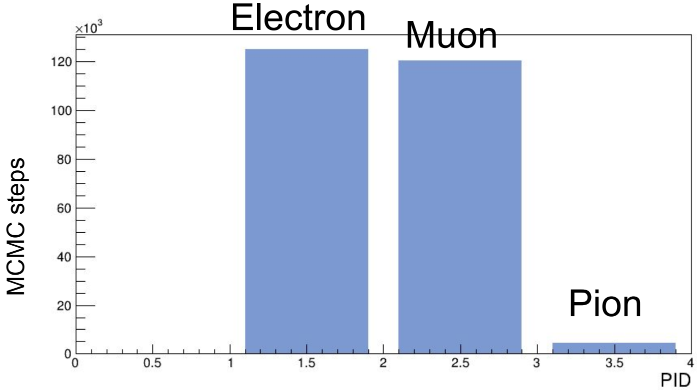
Summary

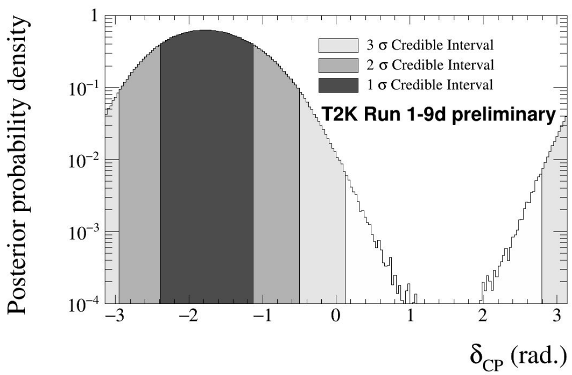
- Reverse-Jump MCMC for neutrino event reconstruction in validation process
- Outstanding issues:
  - MCMC tuning - difficult for fit with unknown dimensionality
  - Analysing/ordering the output where number of dimensions change
  - When do we stop the sampler run?

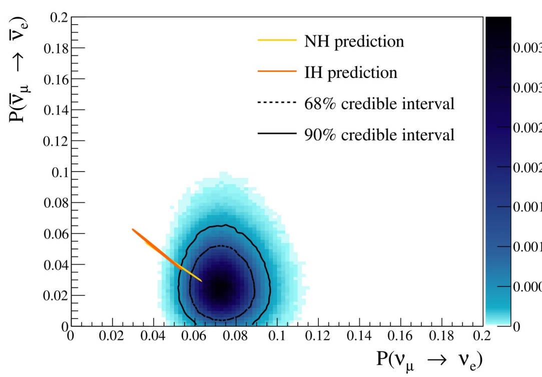
- Bayesian Neutrino Oscillation analysis with T2K's full run 1-9 dataset done

- Bi-Probability plots for non-PMNS-constrained fit compared against PMNS

- More efficient Hamiltonian MCMC for T2K Bayesian Oscillation Analysis implemented, currently being validated and tuned.







Backups

Other bayesian work

Implementing Hamiltonian MCMC for T2K

- 3σ results took ~month to run, using more computing resources than usual
- A faster type of MCMC exploits the Hamiltonian dynamics to propose a new step in a more guided way; possible 2-5x speedup increase!
- Log-Likelihood becomes the potential energy, new arbitrary momentum to evolve parameters' positions
- Method implemented into the analysis, ongoing tuning and validations