The MaCh3 Bayesian Oscillation Analysis framework of the T2K experiment









Tokai-to-Kamioka (T2K) experiment

- Tokai-to-Kamioka (T2K) is a long-baseline accelerator neutrino experiment.
 Physics goals:
- Precise measurement of PMNS neutrino flavour oscillation parameters: θ_{23} and Δm^2_{32} .
- Test of Charge-Parity-symmetry conservation through the PMNS parameter δ_{CP}
- Test of the 3-flavour oscillation model.









Sensitivity to neutrino flavour oscillation parameters



- Muon (anti)neutrino disappearance:
 - Location of dip determined by Δm²₃₂
 - Depth of the dip given by $sin^2(2\theta_{23})$
- Electron (anti)neutrino appearance:
 - Leading term depends on sin²(θ₂₃), sin²(θ₁₃) and
 Δm²₃₂
 - Sub-leading δ_{CP} dependence
 - Matter effects give some dependence on mass hierarchy
- With the 295 km baseline the first oscillation maximum is at 0.6 GeV, a 2.5° off-axis neutrino beam flux can be focused to this energy



ed 280m graphite target

detectors.

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Far Detector (Super-Kamiokande): v beam after flavour oscillations

- The (anti-)neutrino beam is sampled at the **Far Detector:** single ring: μ^{\pm} and e^{\pm} -like Cherenkov rings corresponding mainly to ν_{μ} and ν_{e} CC0 π and CC1 π interactions, and multiring selection: ν_{μ} CC1 π sample.
- Event samples used from both neutrino-mode and anti-neutrino mode beams.







Neutrino Interactions at T2K



- Cannot separately measure $P(v_{\mu} \rightarrow v_{x})(E_{\nu}), \sigma(E_{\nu}), \phi_{\nu}(E_{\nu})$
- Cannot directly measure E_v^{true}, cannot separately resolve interaction modes
- Need a model-based analysis to infer parameters and relate reconstructed quantities to true quantities





T2K joint oscillation fit overview

Model-based analysis: statistical likelihood approach evaluates the compatibility between the observed data and MC predictions from a combined neutrino beam flux + interaction cross-section + detector + flavour oscillation model

T2K pi





Evaluating the Bayes-theorem with MaCh3

- The MaCh3 analysis performs statistical inference using the Bayes-theorem.
- Likelihood term is
 - Likelihood ratio assuming Poisson statistics (Baker, Cousins 1984)
 - Terms for ND MC statistical fluctuation (Barlow, Beeston 1993)
- Priors terms are
 - Physics parameters or model constraints: multivariate "Gaussian" terms acting either in the model parameter space or in the observable final-state kinematic bins
- Prior constraints: ND fit, external data, detector systematics, etc.

Bayes-theorem:



Joint posterior probability dist:

$$P(D|\vec{\theta})P(\vec{\theta}) = \prod \mathcal{L}_{\text{Total}} = \prod \left(\mathcal{L}_{\text{Bins}} \times \mathcal{L}_{\text{Systematics}}\right)$$

$$-2 \log \mathcal{L}_{\text{Total}} = -2 \log \mathcal{L}_{\text{Stat}} - 2 \log \mathcal{L}_{\text{Sys}}$$

$$= 2 \sum_{i}^{\text{Nbins}} N_{i}^{\text{MC}}(\vec{f}, \vec{x}, \vec{d}) - N_{i}^{\text{data}} + N_{i}^{\text{data}} \ln \left(\frac{N_{i}^{\text{data}}}{N_{i}^{\text{MC}}(\vec{f}, \vec{x}, \vec{d})}\right) + \frac{(\beta_{i} - 1)^{2}}{2\sigma_{\beta_{i}}^{2}}$$

$$+ \sum_{i}^{E_{\nu} bins} \sum_{j}^{E_{\nu} bins} \Delta \vec{f}_{i} \left(V_{f}^{-1}\right)_{i,j} \Delta \vec{f}_{j}$$

$$+ \sum_{i}^{\sum_{j}} \sum_{j}^{\sum_{j}} \Delta \vec{x}_{i} \left(V_{x}^{-1}\right)_{i,j} \Delta \vec{x}_{j}$$

$$+ \sum_{i}^{\text{detbins detbins}} \sum_{j}^{\sum_{j}} \Delta \vec{d}_{i} \left(V_{d}^{-1}\right)_{i,j} \Delta \vec{d}_{j}$$



The MaCh3 T2K joint (log) posterior



f: flux, x: cross section, d/skd: detectors, o: oscillation parameters ND: Near Detector, SK: Super-Kamiokande Far Detector





MCMC exploration of the parameter space

- Joint oscillation fit uses multiple event samples simultaneously from the Near (22) and Far Detector (6): large number of parameters (>800).
- Using Markov Chain Monte Carlo (MCMC) sampling from the joint probability distribution.
- MaCh3 uses the **Metropolis-Hastings** (MH) algorithm to perform the random sampling.
- Starting from random initial parameter values; after convergence the MC sequence approximates the joint posterior.







Metropolis-Hastings algorithm

- Metropolis-Hastings quasi-randomly walk in the parameter space, proposing new values to explore a distribution.
- A proposal function (Gaussian) suggests a step, which is taken based on the acceptance probability:

 $\alpha(\vec{x}_n, \vec{y}_n) = \min\left(1, \frac{P(\vec{y}_n | D)}{P(\vec{x}_n | D)}\right)$

- Generate random number between
 0-1 and accept the steps if *α* is greater!
- Always accept a step if probability is ward Atkin higher. Sometimes accept step at probability is lower.



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Markov Chain Monte Carlo diagnostics

- Aim: MCMC converges to the stationary target distribution, explores parameter space well.
- Control: step-size tuning. Small steps: poor parameter space exploration, highly correlated steps.
 Too large steps: leaving high-probability areas too quickly, poor exploration.
- Diagnostic tools:
 - Monitoring acceptance probability (literature probability: 0.234, Brooks et al. CRC Press, 2011)

 $r_{k} = \frac{\sum_{i=1}^{N-k} (Y_{i} - \bar{Y}) (Y_{i+k} - \bar{Y})}{\sum_{i=1}^{N} (Y_{i} - \bar{Y})^{2}}$

- Autocorrelation function r_k after lag k for a parameter Y_i at step i:
- Typically aiming for auto-correlations less than 0.2 after a lag 10 000.
- Between-chains and within-chain variance convergence test: R-test (Gelman and Rubin, Statist. Sci. 7, 457 (1992)) - starting to being used in MaCh3.



MaCh3 Joint posterior distribution

- Running each MCMC gives an N-dimensional posterior distribution (N ~ 800): ROOT TTree.
- In practice running multiple chain in parallel and use "hadd" of ROOT to combine chains.
- Simultaneously evaluating Normal and Inverted mass hierarchies by randomly "flipping" the sign of <u>Am²32.</u>
- Marginalise out into 1D or 2D posterior distributions (Systematic or Oscillation parameters).
 - Can also marginalize over both mass hierarchies.
- Credible intervals/regions over any parameters are constructed using Highest Posterior Density (HPD).







Posterior-predictive checks, model comparison

- Goodness-of-fit test can be performed using Bayesian approach:
 - For each draw from the joint Posterior distribution a MC prediction and fake data set is generated.
 - MC prediction is compared to fake dataset and to real dataset by calculating a test statistics.
 - Fraction of throws for which data fits the MC prediction better gives the p-value:
 - $\chi^2(y_{fake}|\theta) \ge \chi^2(y_{data}|\theta)$
- Model comparison: Bayes-factor
 - Ratio of the marginal likelihoods of two hypotheses, or ratio of posterior probabilities for equal priors.
 - Ratio of number of steps in one hypothesis compared to other (e.g. Mass hierarchy).





Summary and outlook

Summary:

- T2K have been successfully performing oscillation fits using frequentist and Bayesian approaches: groups cross-check oscillation fit results.
- The MaCh3 Bayesian approach is used for the joint ND+FD fits in Oscillation Analysis.
- Many diagnostic tools used to check reliability of the results.
- T2K Nature results 2020: <u>https://www.nature.com/articles/s41586-020-2177-0</u>

Outlook:

- MaCh3 is now developed to be an experiment-independent neutrino analysis tool, and is being used by new groups:
 - T2K+SK (accelerator + atmospheric)
 - T2K+NOvA (accelerator combination)
 - DUNE, HyperK, etc. (future Long-Baseline neutrino experiments)
- New challenges for oscillation analyses and for neutrino physics.







