

Istituto Nazionale di Fisica Nucleare

SHOW WITH THE WITH TH

Università degli Studi di Padova

Accelerating Neutrino Physics Analysis with GPU Parallelization

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Model

- Reactor model
- Backgrounds model
- Covariances
- SNIPER
- Detector response

Cost function

- χ² (Pearson, Neyman, combined)
- Likelihood (binned, extended)

Fitter

- Minuit
- Markov Chains MC
- Nested sampling







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Results

- Best fit values
- Posteriors

- Correlations
 - Model selection 4

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Results

Data processing

Event selection

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Energy reconstruction













Unbinned likelihood calculation
Poisson term

$$f \\ \mathcal{L}(\theta) = P(N_{evts}|\theta) \cdot \prod_{i}^{N_{evts}} P(E_{i}, \bar{r}_{i}, t_{i}|\theta)$$
Reconstructed energy E_{rec}
 $P_{rec}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = f_{rec}(E_{i}, \bar{r}_{i}, t_{i}|\theta)$
Reconstructed energy E_{vis}
 $P_{vis}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = \int f_{vis}(E_{vis}, \bar{r}_{i}, t_{i}|\theta) \cdot G(E_{vis}, E_{i}) \cdot dE_{vis}$

Unbinned likelihood calculation
Poisson term

$$\int_{\mathcal{L}} (\theta) = P(N_{evts}|\theta) \cdot \prod_{i}^{N_{evts}} P(E_{i}, \bar{r}_{i}, t_{i}|\theta)$$
Reconstructed energy E_{rec}
 $P_{rec}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = f_{rec}(E_{i}, \bar{r}_{i}, t_{i}|\theta)$
Reconstructed energy E_{vis}
 $P_{vis}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = \int_{f_{vis}(E_{vis}, \bar{r}_{i}, t_{i}|\theta) \cdot G(E_{vis}, E_{i}) \cdot dE_{vis}$
 $P_{dep}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = \int_{f_{dep}} (nl(E_{dep}), \bar{r}_{i}, t_{i}|\theta) \cdot G(nl(E_{dep}), E_{i}) \cdot dE_{vis}$

Unbinned likelihood calculation
Poisson term

$$f(\theta) = P(N_{evts}|\theta) \cdot \prod_{i}^{N_{evts}} P(E_{i}, \bar{r}_{i}, t_{i}|\theta)$$
Reconstructed energy E_{rec} $P_{rec}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = f_{rec}(E_{i}, \bar{r}_{i}, t_{i}|\theta)$
Reconstructed energy E_{vis} $P_{vis}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = \int f_{vis}(E_{vis}, \bar{r}_{i}, t_{i}|\theta) \cdot G(E_{vis}, E_{i}) \cdot dE_{vis}$
Schullator nonlinearity of
Deposited energy E_{vis} $P_{\overline{v}}(E_{i}, \bar{r}_{i}, t_{i}|\theta) = \int f_{dep}(nl(E_{dep}), \bar{r}_{i}, t_{i}|\theta) \cdot G(nl(xs(E_{\overline{v}})), E_{i}) \cdot dE_{vis}$

Our model

Detector response:

- IBD cross section (w/ recoil) (fixed)
- Energy resolution
- Liquid scintillator nonlinearity





Neutrino oscillations:

Signal components:

PDFs (fixed)

Normalizations





Constrained with prior at 0.5%

Constrained with DayaBay prior

Constrained with prior at 5%

Unbinned likelihood numerical computation

In theory:

$$\mathcal{L}(\theta) \cong \prod_{i}^{N_{evts}} \int P(E_{vis}) \cdot G(E_{vis}, E_i) \cdot dE_{vis}$$

Unbinned likelihood numerical computation

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$$\mathcal{L}(\theta) \cong \prod_{i}^{N_{evts}} \int P(E_{vis}) \cdot G(E_{vis}, E_i) \cdot dE_{vis}$$

In practice:

- $\mathcal{L}(\theta) \rightarrow \log \mathcal{L}(\theta) \quad (\Pi \rightarrow \Sigma)$
- $\int \rightarrow \Sigma$

$$\log \mathcal{L}(\theta) \cong \sum_{i}^{N_{evts}} \log \left(\sum_{j}^{N_{bins}} P(E_j) \cdot G(E_j, E_i) \cdot \Delta E_j \right) = \sum_{i}^{N_{evts}} \log \sum_{j}^{N_{bins}} C_{i,j}$$

Unbinned likelihood numerical computation

In theory: $\mathcal{L}(\theta) \cong \prod_{i}^{N_{evts}} \int P(E_{vis}) \cdot G(E_{vis}, E_i) \cdot dE_{vis}$ $I_{i} = \mathcal{L}(\theta) \rightarrow \log \mathcal{L}(\theta) \quad (\Pi \rightarrow \Sigma)$ $\int \Delta \Sigma$ N_{evts} N_{bins} N_{bins}

$$\log \mathcal{L}(\theta) \cong \sum_{i}^{N_{evts}} \log \left(\sum_{j}^{N_{bins}} P(E_j) \cdot G(E_j, E_i) \cdot \Delta E_j \right) = \sum_{i}^{N_{evts}} \log \sum_{j}^{N_{bins}} C_{i,j}$$

Complexity scales with $N_{evts} \times N_{bins}$!

But the computation of the $C_{i,j}$ is independent \rightarrow "embarrassingly parallel" computation

Implementing parallelization in likelihood calculation

Single-thread $\Delta t = \Delta t_1 + \Delta t_2$ $\log \mathcal{L}(\theta) \cong \sum_{i}^{N_{evts}} \log \sum_{i}^{N_{bins}} C_{i,j}$ 1. **Element calculation** 2. Vector reduction 5,1 N_{bins} 5,3 N_{evts}

Implementing parallelization in likelihood calculation Δt_1 **Multi-thread** Δt_2 Δt N_{threads} $\log \mathcal{L}(\theta) \cong \sum_{i}^{N_{evts}} \log \sum_{i}^{N_{bins}} C_{i,j}$ **Element calculation** 1. 2. Vector reduction 5,1 **N**_{bins} 5,3 N_{evts}

GPU accelerators: taking parallelization to the next level



Performances: call-back time of cost function

Multi-threading implemented in both CPU and GPU!

Multi-threading on **GPU** can achieve **performances x100**

Less time for computations
+ More time for analyses [©]



A case study: Δm_{31}^2 - precision

"What if parameters are different from what we expect? (but we still manage to measure them)" \rightarrow precision loss



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A case study: Δm^2_{31} - precision



Important to maximize number of **selected events**:





Towards the atmospheric mass splitting Δm^2_{31} in JUNO

Vanessa Cerrone, on behalf of the Padova analysis group 29/03/2022 -- JUNO Italia meeting, Roma Tre Università e INFN

A case study: Δm_{31}^2 - accuracy

"What if we fail in fitting/estimating one or more parameter?" \rightarrow possible bias, accuracy loss



A case study: Δm_{31}^2 - accuracy

"What if we fail in fitting/estimating one or more parameter?" \rightarrow possible bias, accuracy loss





Final remarks

- » Unbinned likelihood gives us more freedom in treating space/time-dependent effects:
 - performs comparably to binned likelihood/ χ^2 when no additional info is provided \rightarrow we need to test performances when space/time effects are included
- » In unbinned likelihood computation time scales linearly with the number of events
 - luckily the N_{evts} × N_{bins} computations required are almost fully independent
 → perfect for parallelization
- » **GPUs** are a "no-brainer" when considering **parallelization**
 - Multi-threading implemented in the ORSA fitting framework for both GPU and CPU
 → x100 reduction in computation time
 (e.g., only 10 seconds for an Asimov binned fit with Minuit)