Unfolding: the neutrino experiment experience

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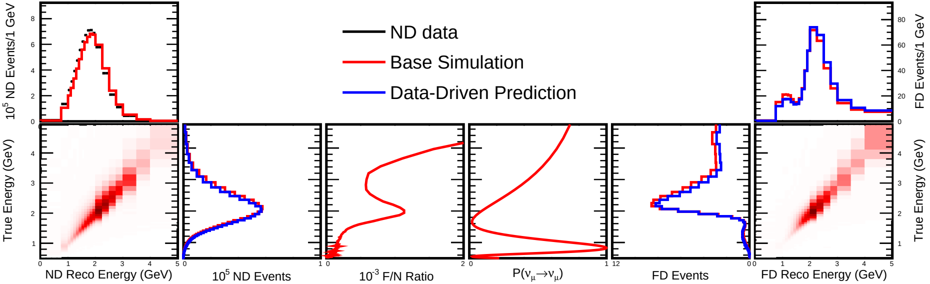
Introduction

- Who am I?
  - MINOS, T2K, Minerva, DUNE; Neutrino-nucleus interaction measurement and fitting
- Which neutrino experiments use/don't use unfolding and why?
- What have we done in the past?
- What are we doing now?
- What are we likely to do in the future?

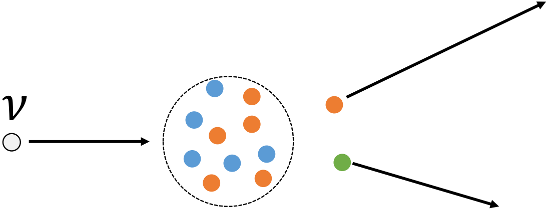
Oscillation analyses don't (explicitly) use unfolding

- Measuring small number of parameters in a "well-known" model.
- But maybe future experiments will want to map out $P(\nu_\alpha \to \nu_\beta)$, say
- Implicit unfolding in "beam matrix" methods



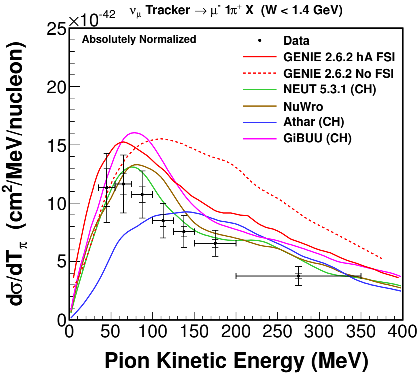
NOvA, J. Wolcott, NuInt18

Unfolding *is* widely used in neutrino interaction analyses

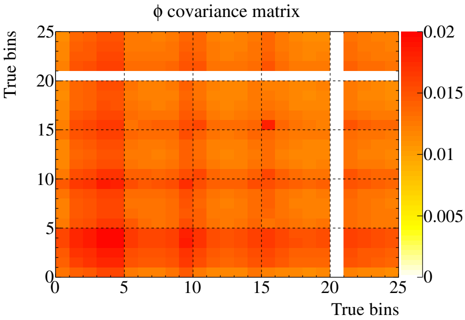


- Approximate "effective" models used at each stage
- Want to measure identity and kinematics of final-state particles
- Renewed interest because of importance to oscillation analyses

Some common features of neutrino interaction measurements



MINERνA, Phys. Rev. D92, 092008 (2015)

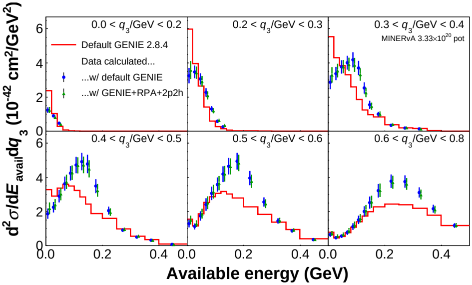


T2K, Phys Rev D 87, 092003

- Measure flux-integrated distributions of kinematic variables to distinguish widely-varying models
- Often systematics-limited
- Largest systematic often flux: strong positive correlations

What we've done in the past: D'Agostini, mostly

- O(1) iteration of D'Agostini on background-subtracted data
- "Unfolding error": 2nd iteration minus first
- Choice of N_{it}: warp MC to look like data. Iterate until bin contents "close" to truth
- Unfold using different models; add to systematic error



MINERνA, Phys. Rev. Lett. 116, 071802 (2016)

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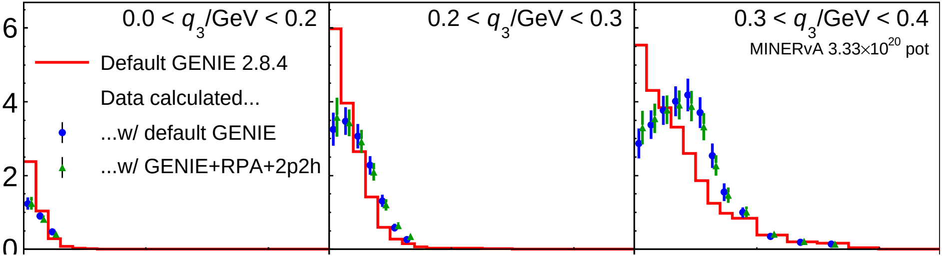


MINERνA, Phys. Rev. Lett. 116, 071802 (2016)

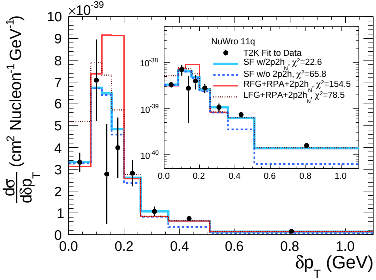
What we've done in the past has some shortcomings

- Background subtraction breaks Poisson assumption in D'Agostini method
- Method of choosing N_{it} is *ad hoc*, doesn't consider stat error

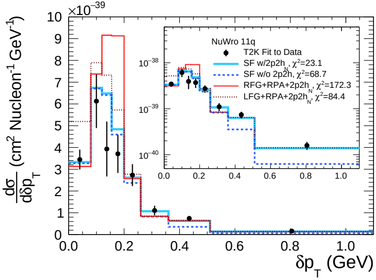
What we're doing now

- Providing unregularized results alongside Tikhonov-regularized ones (T2K)
  - More details in Stephen Dolan's talk

Unregularized



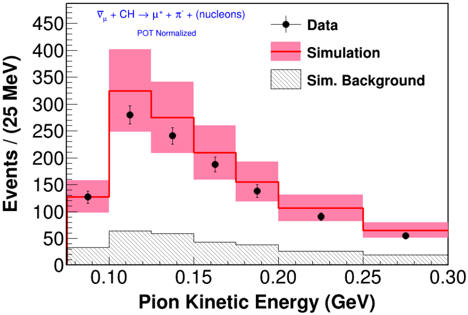
Regularized

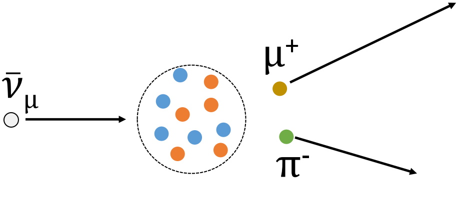


T2K, Phys. Rev. D 98, 032003 (2018)

- More careful checks with covariance matrix chi2 on data-driven warped distributions (Minerva)

MINERνA approach to D'Agostini unfolding: example





Trung Le, Fermilab JETP seminar, Sep 21 2018

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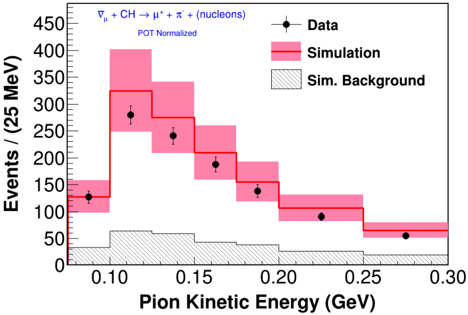

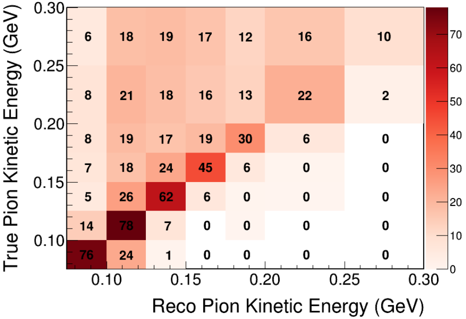

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- "Feed-down" means wider migration matrix than usual. Procedure similar for all variables

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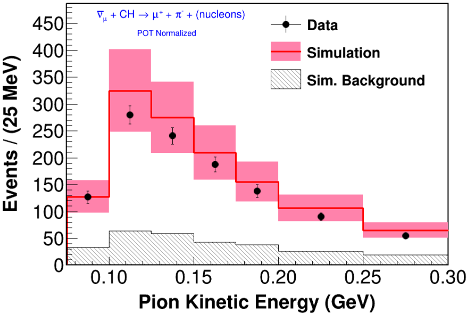

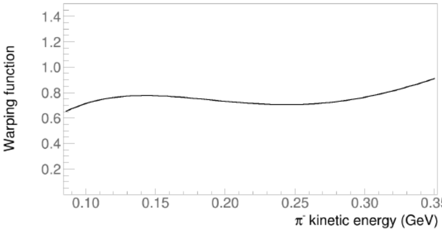

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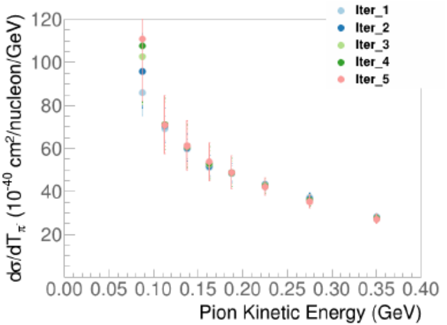
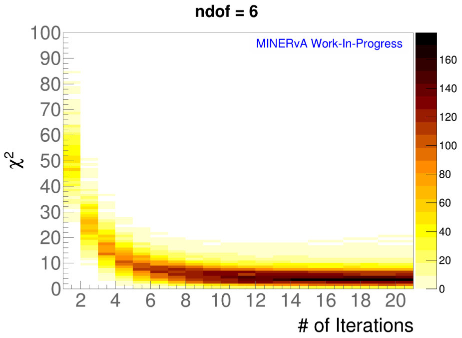
- "Feed-down" means wider migration matrix than usual. Procedure similar for all variables
- Reweight MC to look like data: unfold this warped fake data

Two checks on number of iterations

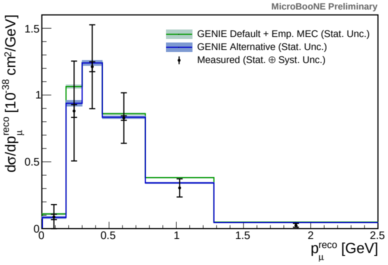
1. When does the unfolded distribution closely approximate the (warped) truth?
2. When is the $\chi^2/\mathrm{dof} \sim 1$, averaged over many Poisson throws?
3. In this case, $\chi^2/\mathrm{dof} \sim 1$ with bins removed





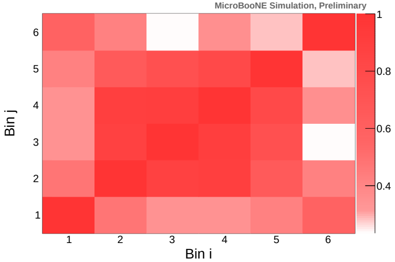
What we might do in the future

- L-curve-alike for D'Agostini unfolding: compare N_{it} result to infinite iterations result. (More details from Stephen Dolan)
- Implement D'Agostini without background subtraction
- Forward folding: provide tools to compare theoretical models directly to reconstructed (smeared) data. Challenges:
  - Publishing systematics
  - Making the response matrix model independent
  - Long-term sustainability (what if the tools are unmaintained?)



MICROBOONE-NOTE-1045-PUB

Fits to strongly-correlated data 1



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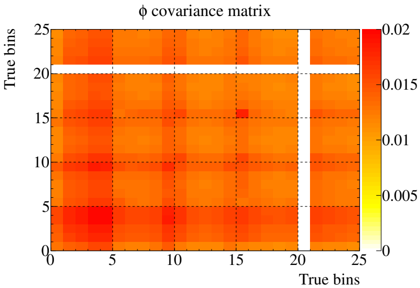
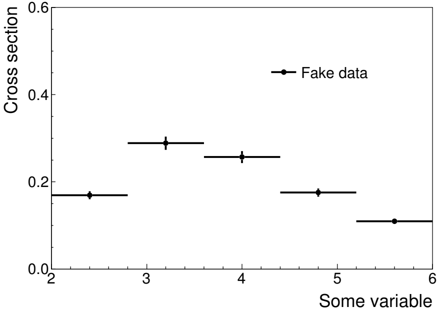
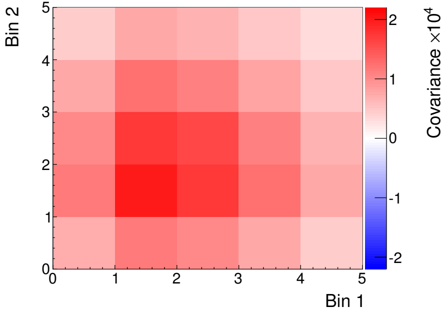


T2K, Phys Rev D 87, 092003

- Neutrino interaction data strongly positively correlated by flux uncertainties
- Well known that in such cases, the best fit can be well outside the data points
- "Peelle's Pertinent Puzzle" in nuclear physics. Several proposed interpretations/solutions: "International evaluation of neutron cross-section standards", IAEA (2007)

Fits to strongly-correlated data 2





$$C_{ij} = \sum_{\text{universe } k} \left(y_i^{(k)} - y_i^*\right)\left(y_j^{(k)} - y_j^*\right)$$

- "Multi-universe": throw random systematic universes, re-extract result

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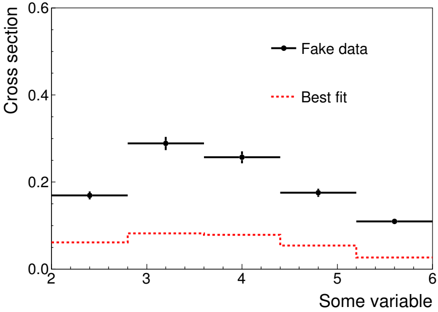

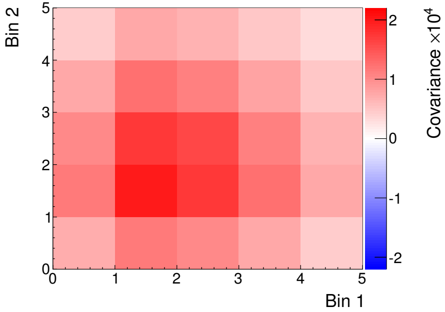

$$\chi^2 = (\mathbf{D} - \mathbf{M})^T \mathbf{C}^{-1} (\mathbf{D} - \mathbf{M})$$

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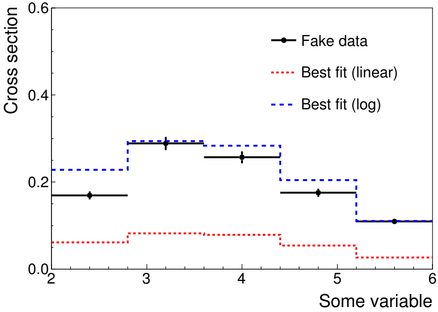

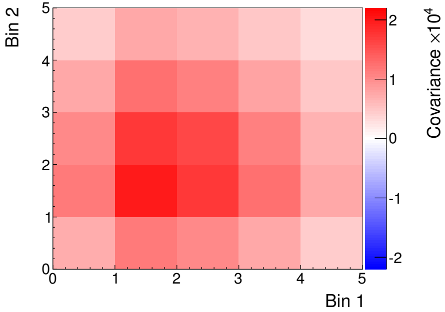

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- "Multi-universe": throw random systematic universes, re-extract result
- Empirically, $y \to \log(y)$, ameliorates the issue, $\Rightarrow$ log-normal uncertainties on $y(?)$

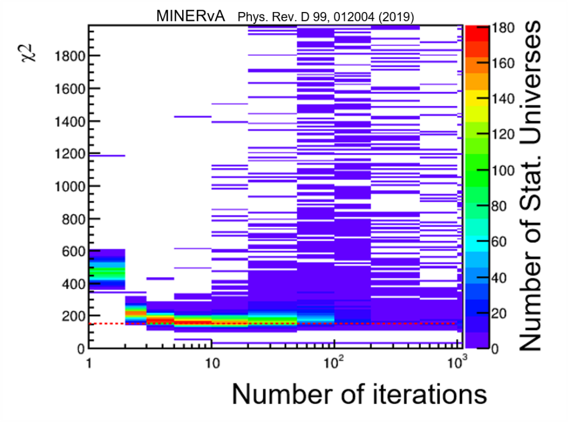
  "Box-Cox transformation for resolving the Peelle's Pertinent Puzzle in curve fitting", Oh and Seo 2004
- Is this the best way to communicate our systematics?

Some outstanding questions

- Can we unfold and quantify bias s.t. it's small enough to not matter?
- How can we adapt unfolding techniques from the literature to work with the multi-universe/multisim method used by Minerva and MicroBooNE?
- Evaluating unfolding bias by comparing to a model "warped like the data": what's the range of validity?
- How do we assign systematic uncertainties to "the unfolding technique" without double-counting?
- How do we deal with PPP? Or, what's the best way to preserve the features of our detailed systematic error estimates in a way that's digestible to users (theorists, other experiments)?

Backup slides

MINERνA ν CC0*pi* χ^2 vs number of iterations



- 4 iterations chosen

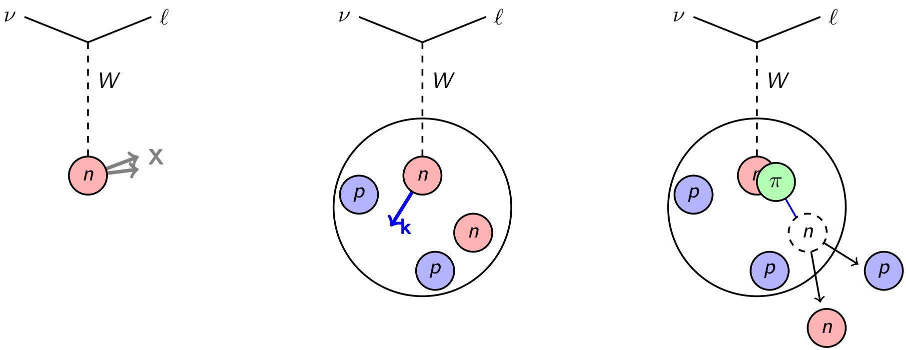
More questions/thoughts

- Probable valuable: “bottom line tests” as in arXiv:1607.07038
- Covariance matrices:
  - How to quote in data releases without numerical issues?
  - How to approximate when large?
  - How to make sure we have enough multisim throws?

Some personal opinions

- Field is strongly "visual": we're always going to want something to look at to assess results
  - ⇒ Unfolding will probably always be with us
- Tikhonov-regularized fits offer some clear advantages over iterative techniques
- Always show full data in reco space (in as many dimensions as the cross section). Not always done!
- Bias-variance tradeoff is a useful frame for thinking about unfolding. Links discussion to the literature. Makes clear pros and cons

Unfolding *is* widely used in neutrino interaction analyses



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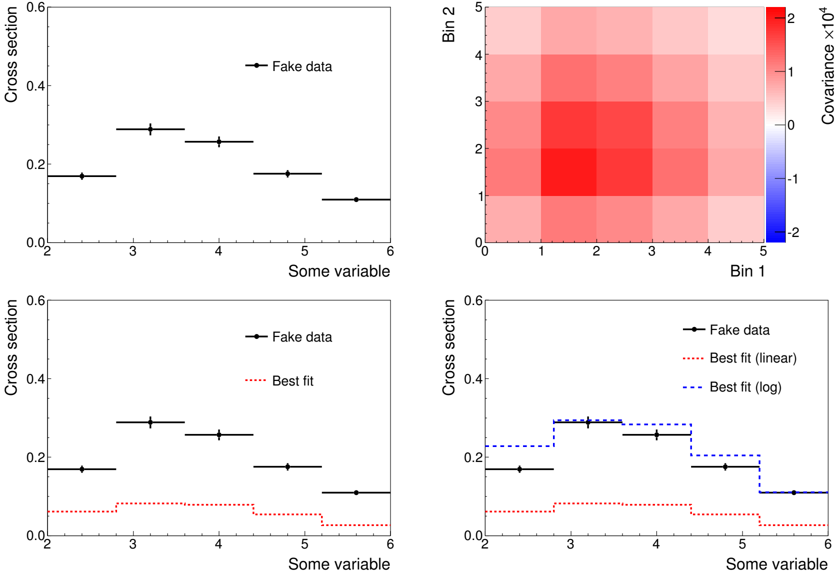

Cross section
Fake data
Some variable
Bin 2
Bin 1
Covariance ×10^4
Best fit
Best fit (linear)
Best fit (log)