MiniBooNE Event Reconstruction and Particle Identification

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Outline

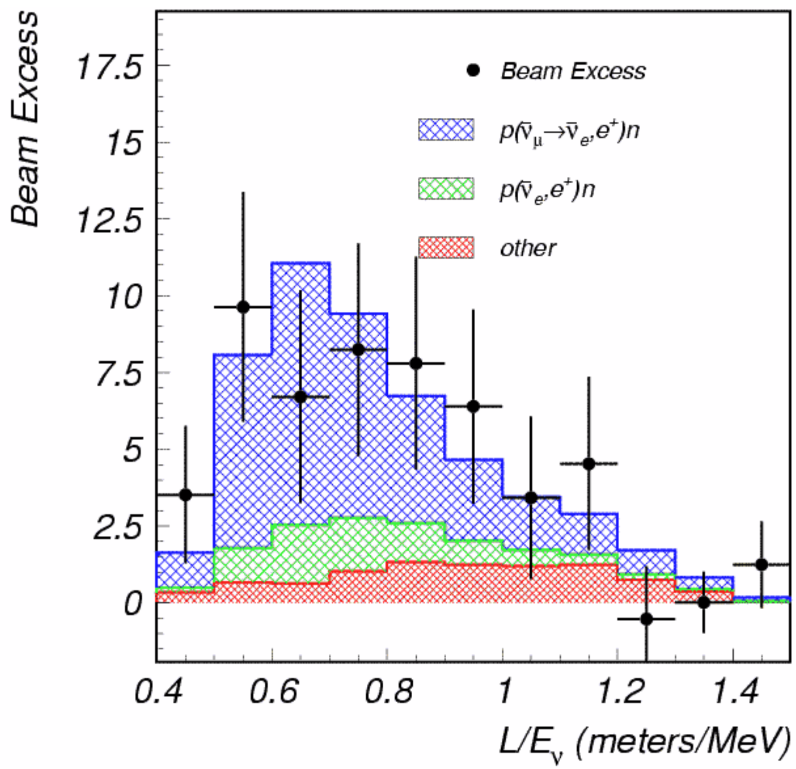
- Physics Motivation
- MiniBooNE Event Types
- Event Reconstruction
- Particle Identification
- Summary

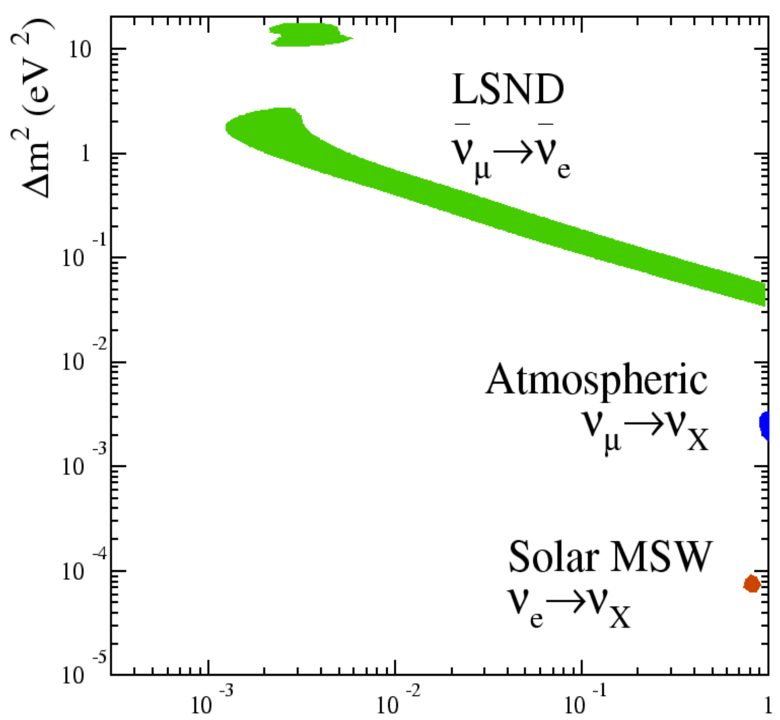
Physics Motivation

➔ LSND observed a positive signal, but not confirmed.

$$P(\bar{\nu}_\mu \to \bar{\nu}_e) = \sin^2(2\theta)\sin^2(\frac{1.27\,L\Delta m^2}{E}) = (0.264 \pm 0.067 \pm 0.045)\%$$

➔ The MiniBooNE is designed to confirm or refute LSND oscillation result at $\Delta m^2 \sim 1.0\ eV^2$.





MiniBooNE Flux

8 GeV protons on Be target gives:

$p + Be \rightarrow \pi^+ , K^+ , K^0_L$

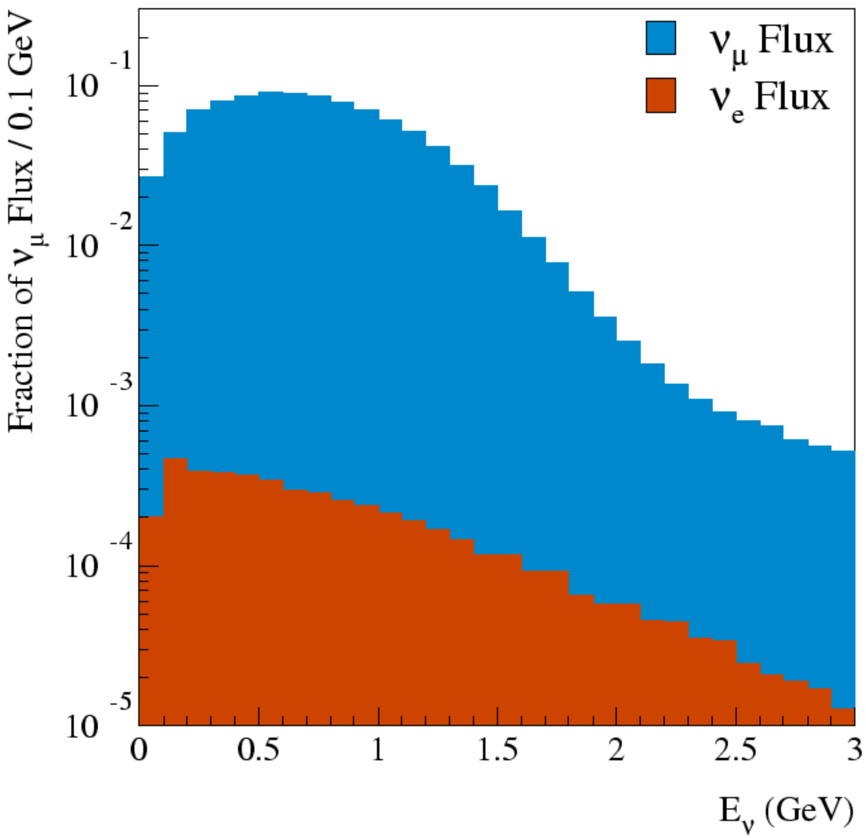
ν_μ from:

$\pi^+ \rightarrow \mu^+ \nu_\mu \quad K^+ \rightarrow \mu^+ \nu_\mu \quad K^0_L \rightarrow \pi^- \mu^+ \nu_\mu$

Intrinsic ν_e from:

$\mu^+ \rightarrow e^+ \nu_e \bar{\nu}_\mu \; K^+ \rightarrow \pi^0 e^+ \nu_e \; K^0_L \rightarrow \pi^- e^+ \nu_e$

The intrinsic ν_e is ~0.5% of the neutrino Flux, it's one of major backgrounds for $\nu_\mu \rightarrow \nu_e$ search.



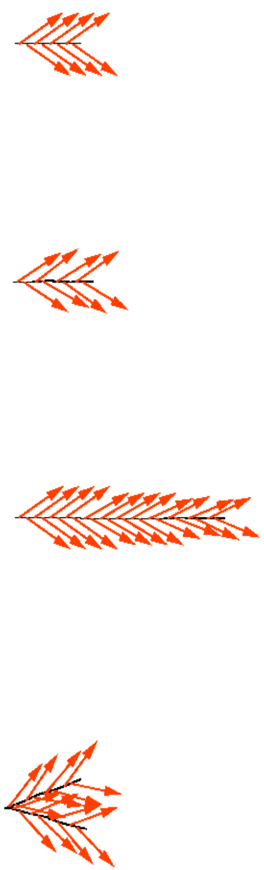
$$P(\nu_\mu \rightarrow \nu_e) = \sin^2(2\theta)\sin^2\left(\frac{1.27 L \Delta m^2}{E}\right)$$

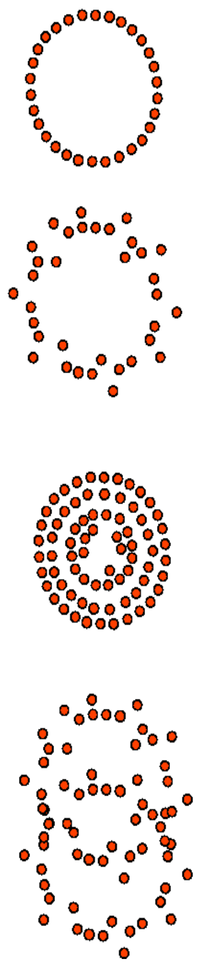
L(m), E(MeV), $\Delta m^2(eV^2)$

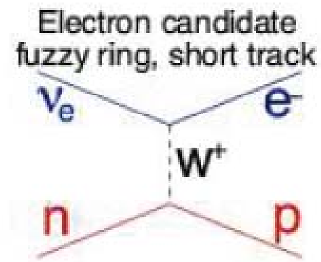
Event Topology

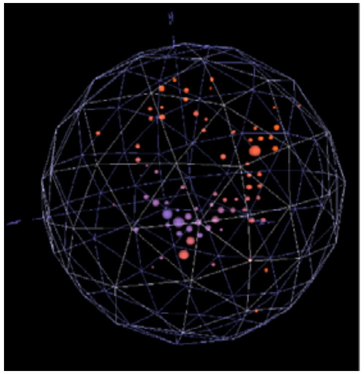
Cerenkov Light...

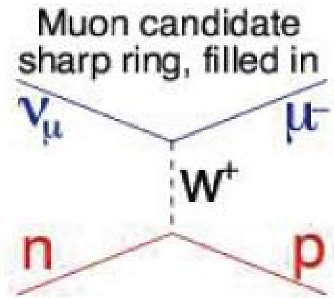
From side		Ring	
short track, no multiple scattering			Sharp Ring
electrons: short track, mult. scat., brems.			Fuzzy Ring
muons: long track, slows down			Sharp Outer Ring with Fuzzy Inner Region
neutral pions: 2 electron-like tracks			Two Fuzzy Rings

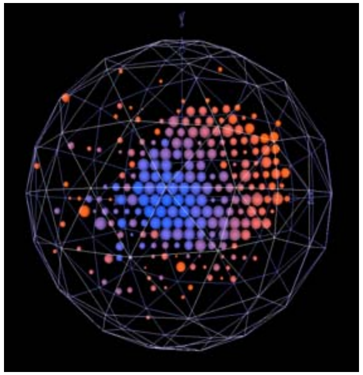


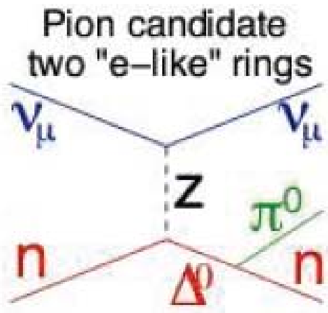


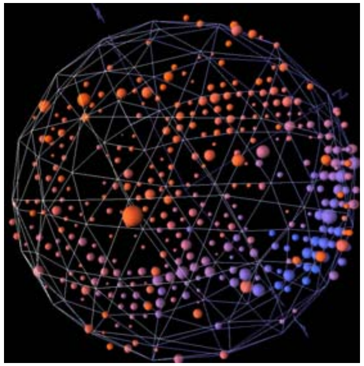








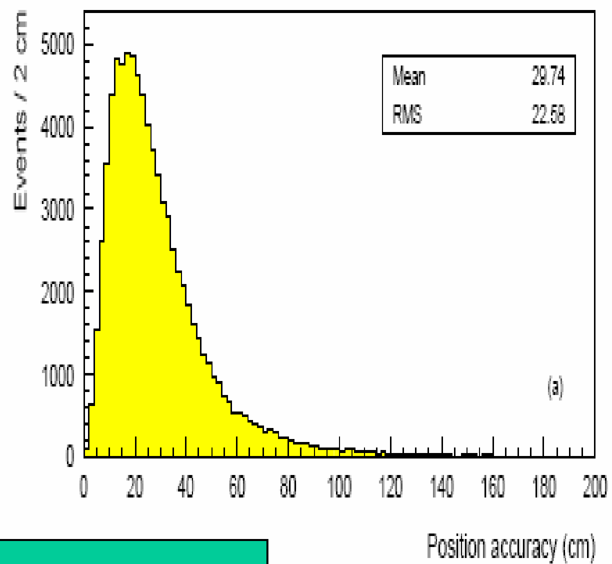


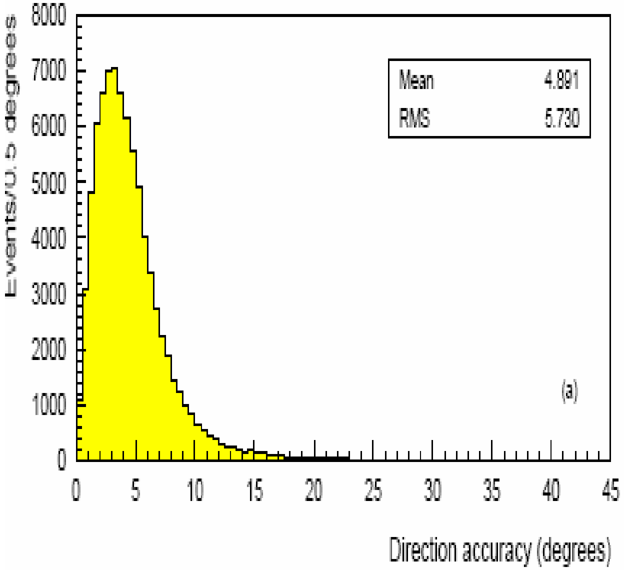


Event Reconstruction

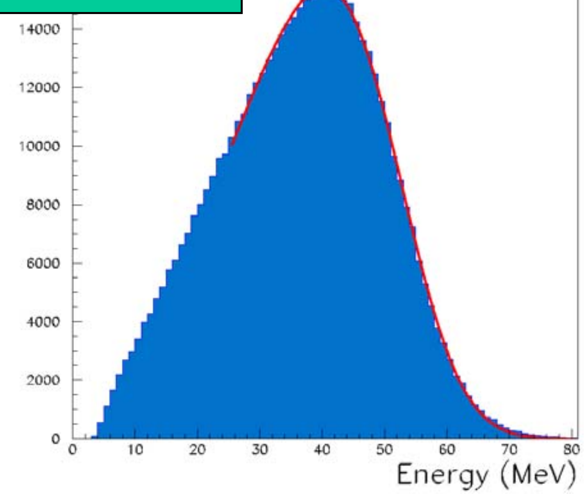
- To reconstruct event position, direction, time, energy and invariant mass etc.
- Cerenkov light – prompt, directional
- Scintillation light – delayed, isotropic
- Using time likelihood and charge likelihood method to determine the optimal event parameters.
- Two parallel reconstruction packages
  - S-Fitter is based on a simple, point-like light source model;
  - P-Fitter differs from S-Fitter by using more 0^{th} approximation tries, adding e/μ tracks with longitudinally varying light source term, wavelength-dependent light propagation and detection, non-point-like PMTs and photon scattering, fluorescence and reflection.

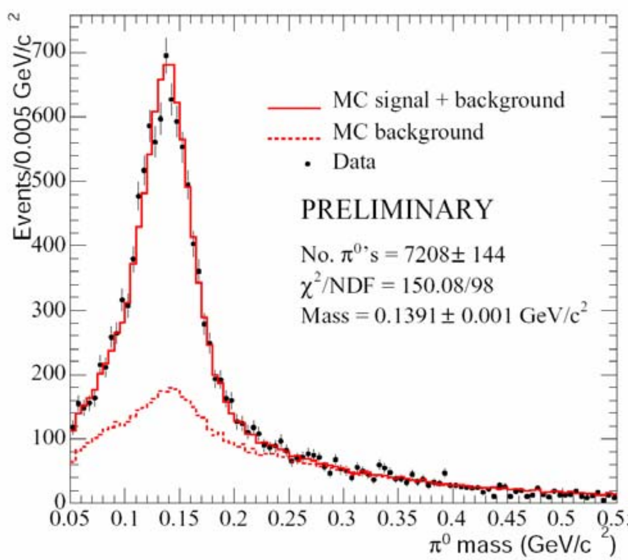
Reconstruction Performance





Michel Electron





Particle Identification

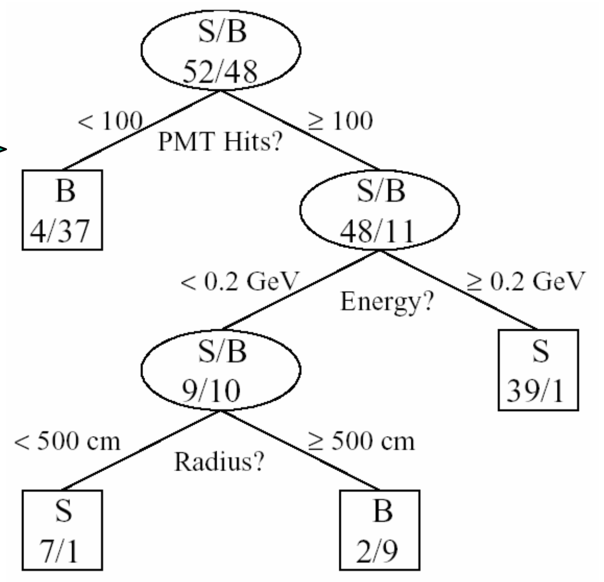
Two complementary and parallel methods:

- Log-likelihood technique:
  - simple to understand, widely used in HEP data analysis but less sensitive
- Boosted Decision Trees:
  - Non-linear combination of input variables
  - Great performance for large number of input variables (about two hundred variables)
  - Powerful and stable by combining many decision trees to make a “majority vote”

Boosted Decision Trees

How to build a decision tree ?

For each node, try to find the best variable and splitting point which gives the best separation based on Gini index.
Gini_node = Weight_total*P*(1-P), P is weighted purity
Criterion = Gini_father – Gini_left_son – Gini_right_son
Variable is selected as splitter by maximizing the criterion.

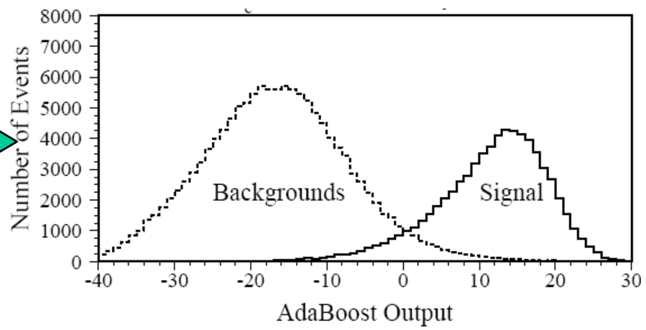


How to boost the decision trees?

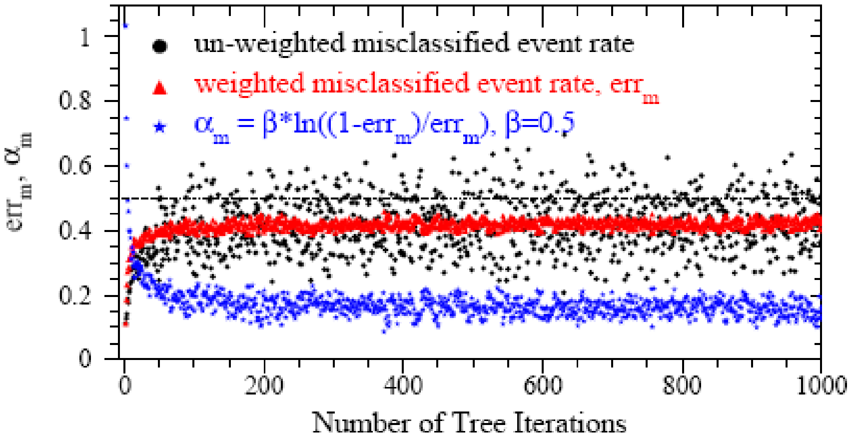
Weights of misclassified events in current tree are increased, the next tree is built using the same events but with new weights, Typically, one may build few hundred to thousand trees.

How to calculate the event score ?

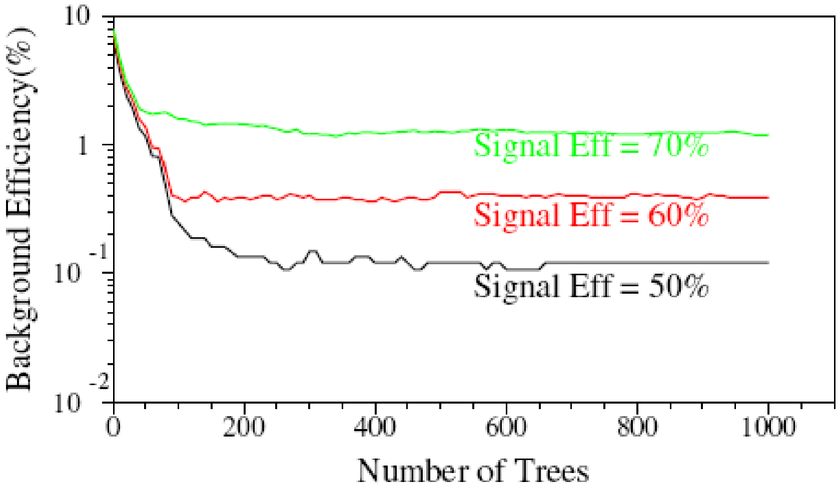
For a given event, if it lands on the signal leaf in one tree, it is given a score of 1, otherwise, -1. The sum (probably weighted) of scores from all trees is the final score of the event.



Performance vs Number of Trees



➔The advantage of using boosted decision trees is that it combines many decision trees, "weak" classifiers, to make a powerful classifier. The performance of boosted decision trees is stable after a few hundred tree iterations.



➔ Boosted decision trees focus on the misclassified events which usually have high weights after hundreds of tree iterations. An individual tree has a very weak discriminating power; the weighted misclassified event rate err_m is about 0.4-0.45.

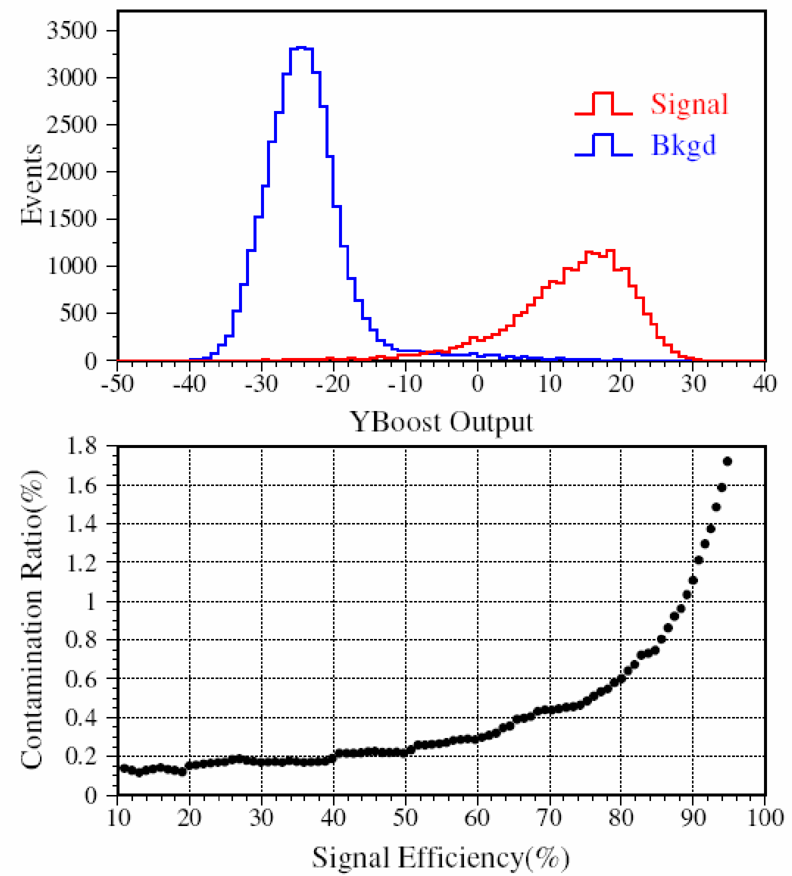
Ref1: H.J.Yang, B.P. Roe, J. Zhu, "Studies of Boosted Decision Trees for MiniBooNE Particle Identification", Physics/0508045, Nucl. Instum. & Meth. A 555(2005) 370-385.

Ref2: B.P. Roe, H.J. Yang, J. Zhu, Y. Liu, I. Stancu, G. McGregor, "Boosted decision trees as an alternative to artificial neural networks for particle identification", physics/0408124, NIMA 543 (2005) 577-584.

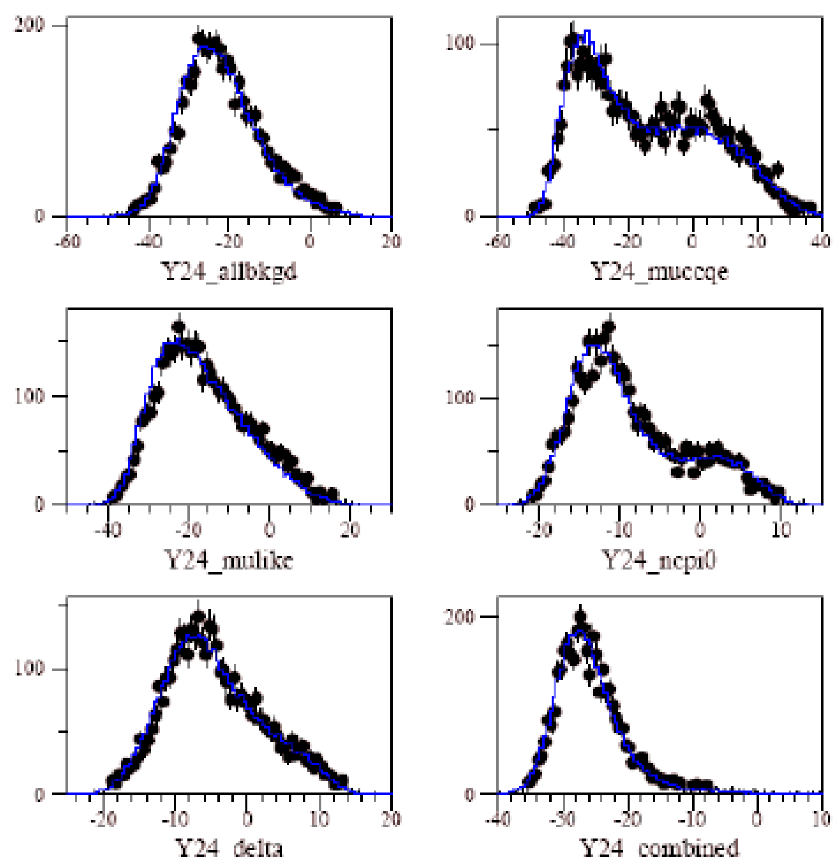
Output of Boosted Decision Trees

Osc ν_e CCQE vs All Background

MC vs ν_μ Data



1subevt,thits>200,vhits<6,R<500 cm,0.1<Efull<1.2 GeV,Y21<-5



Summary

- MiniBooNE Event Reconstruction
  - Position resolution ~ 23 cm
  - Direction resolution ~ 6^{o}
  - Energy resolution ~ 15%
  - Reconstructed π^0 mass resolution ~ 20 MeV/c^2
- MiniBooNE Particle Identification
  - For 0.1% μ eff., ~ 90% electron eff.
  - For 1% π^0 eff., ~ 70% electron eff.
  - For 0.5% all background eff., ~ 80% electron eff.
- MiniBooNE Results are coming soon …

Backup Slides

Light Model

- **Cerenkov light - directional**

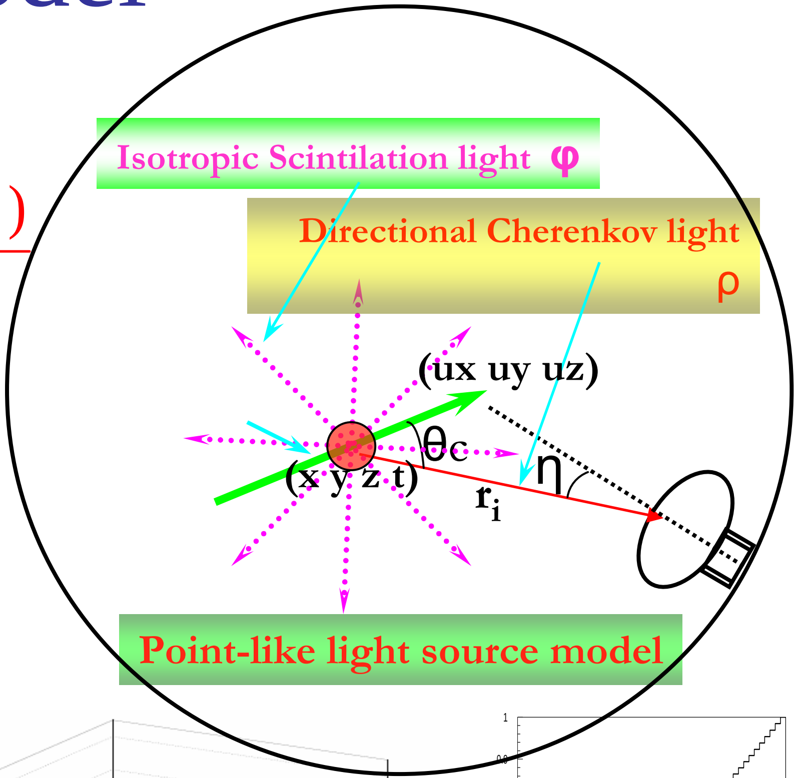
$$\mu_i^{CER} = \rho \varepsilon_i F(\cos\vartheta, E) f(\cos\eta) \frac{\exp(-r_i/\lambda_{CER})}{r_i^2}$$

- **Scintillation light - isotopic**

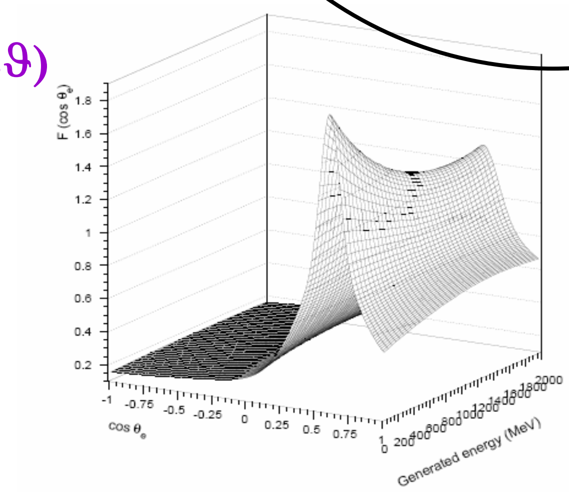
$$\mu_i^{SCI} = \varphi \varepsilon_i f(\cos\eta) \frac{\exp(-r_i/\lambda_{sci})}{r_i^2}$$

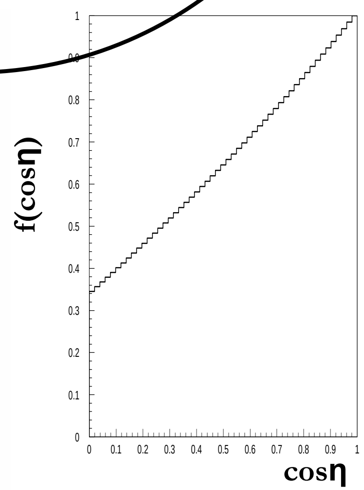
- **Predicted charge**

$$\mu_i = \mu_i^{CER} + \mu_i^{SCI}$$



1. Cerenkov angular distribution - $F(\cos\vartheta)$
2. PMT angular response – $f(\cos\eta)$
3. Cerenkov attenuation length – λcer
4. Scintillation attenuation length – λsci
5. Relative quantum efficiency - ε_i
6. Cerenkov light strength - ρ
7. Scintillation light strength - φ





Light Model

1. **Corrected time** $t_{corr}^{(i)} = t_i - t_0 - \frac{r_i}{c_n}$

2. **Cerenkov light $t_{corr}^{(i)}$ distribution**

$$T_{cer}(t_{corr}) = \frac{1}{\sqrt{2\pi}\sigma(\mu_c,E)}\exp\left\{\frac{-1}{2\sigma^2(\mu_c,E)}[t_{corr}-t_0(\mu_c,E)]^2\right.$$

3. **Scintillation light $t_{corr}^{(i)}$ distribution**

$$T_{sci}(t_{corr}) = \frac{1}{2\tau(\mu_s,E)}\exp\left[\frac{\sigma^2(\mu_s,E)}{2\tau^2(\mu_s,E)} - \frac{t_{corr}-t_0(\mu_s,E)}{\tau(\mu_s,E)}\right]$$
$$\times \quad \exp\left[\frac{\sigma(\mu_s,E)}{\sqrt{2}\tau(\mu_s,E)} - \frac{t_{corr}-t_0(\mu_s,E)}{\sqrt{2}\tau(\mu_s,E)}\right]$$

4. **Input: Cerenkov light – t_0^{cer}, σ^{cer}**
   Scintillation light – t_0^{sci}, σ^{sci}, τ^{sci}

5. **Total negative log time likelihood**

$$L(t_{corr}^{(i)}) = -\log\left(\frac{\mu_c}{\mu_c+\mu_s}T_{cer}(t_{corr}^{(i)},\mu_c) + \frac{\mu_s}{\mu_c+\mu_s}T_{sci}(t_{corr}^{(i)},\mu_s)\right)$$