Analysis techniques of neutrino cross section measurements in MiniBooNE

outline

1. Introduction
2. Overview of MiniBooNE cross section measurement
3. Neutrino cross section measurement
4. Conclusion

Teppei Katori for the MiniBooNE collaboration
Massachusetts Institute of Technology
PPD neutrino seminar, Fermilab, November 5, 2010

1. Introduction

2. Overview of MiniBooNE cross section measurement

3. Neutrino cross section measurement

4. Conclusion

1. Introduction

Purpose of this talk

- This talk is prepared to students who want to measure neutrino cross sections for their thesis.

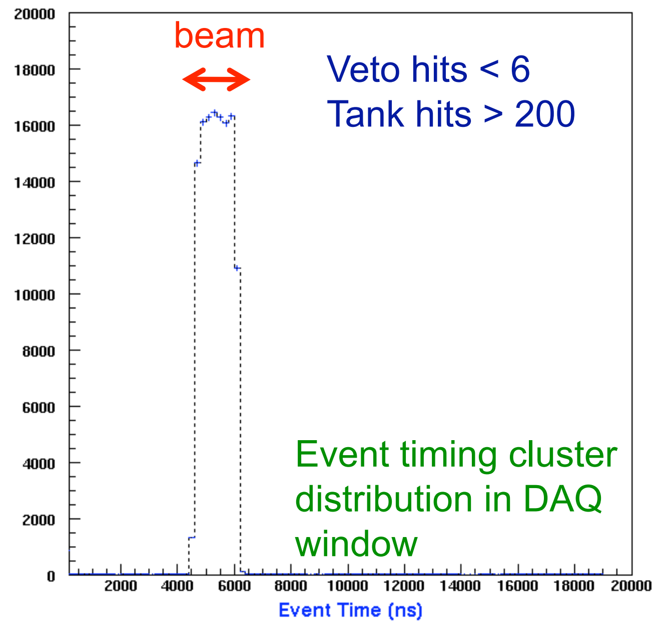
- It especially focuses on the measurement of absolute flux-integrated differential cross sections which is one of the most important quantities to contribute to this field.

- MiniBooNE developed a number of techniques necessary to measure these, and the talk covers technical aspects from the CCQE, NCEL, NCπ^o, CCπ^+ and CCπ^o absolute differential cross section measurements.

1. Introduction

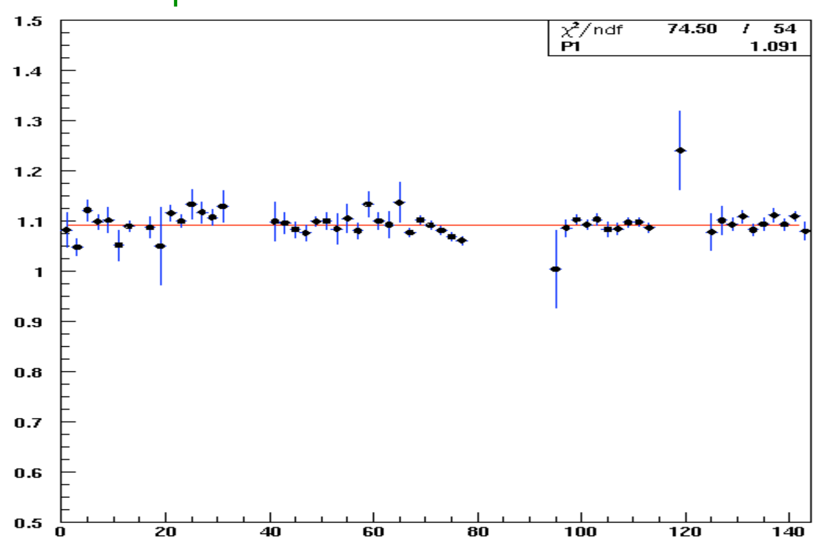
Introduction of MiniBooNE

- MiniBooNE is ~O(1GeV) accelerator neutrino experiment at Fermilab.
- Primary goal of MiniBooNE is to find small ν_e (anti-ν_e) in ν_μ (anti-ν_μ) beam.
- MiniBooNE is spherical (12m diameter, 10 meter fiducial) Cherenkov detector with mineral oil (CH_2) target.
- CC Neutrino candidate is isolated by veto hits<6 and tank hits>200.
- roughly 1 neutrino candidate recorded per minute for 5E16 proton per hour (neutrino mode).



Tepp

Event per 1E15POT vs Week



1. Introduction

Goal of neutrino cross section experiment

- Goal is to measure model independent absolute flux-integrated differential cross section. This is what theorists want to study there models. Model dependent parameters, such as axial mass M_A or coherent fraction of pion production are not very interesting.

Absolute flux-integrated differential cross section

- cross section should be interaction or nuclear model independent
- detector efficiency is corrected, cross section is always detector model dependent!
- flux prediction should be independent of neutrino interaction measurement.
- The cross section is absolute scale, believe your normalization!
- result is desirable in differential cross section, not just total cross section
- result is desirable if cross section is function of measured variable, not reconstructed variable

Formula of flux-integrated differential cross section

- you see so many times in this talk

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i (\Phi T) \Delta x_i}$$

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by Teppei Katori

2. Overview of MiniBooNE xs measurement

MiniBooNE collaboration, PRD81(2010)092005

CCQE
PRD81(2010)092005
FERMILAB-THESIS-2008-64
Teppei, katori@fnal.gov

$$\nu_\mu + n \rightarrow p + \mu^-$$

$$(\nu_\mu + {}^{12}C \rightarrow X + \mu^-)$$

Largest sample (~40%) in MiniBooNE
- it is crucial to test all analysis tools in MiniBooNE by this channel

Same CCQE model is used for ν_eCCQE measurement (=oscillation measurement)
- Since ν_μ-ν_e oscillation is measured by CCQE interaction, CCQE interaction model must be very correct. Data driven correction is performed for CCQE model, and effective M_A and Pauli blocking parameter κ are introduced. They shouldn't affect cross section measurement!

ν_μCCQE for ν_μ-flux measurement to constraint ν_e from μ-decay
- ν_e from μ-decay is the largest beam ν_e background. But muons which give ν_e and ν_μ are tightly related in pion kinematic space, so ν_μCCQE measurement. allows to constrain ν_e-flux error from μ-decay.

It is crucial to measure CCQE!

by Denis Perevalov

2. Overview of MiniBooNE xs measurement

MiniBooNE collaboration, arXiv:1007.4730

NCEL
arXiv:1007.4730
FERMILAB-THESIS-2009-47
Denis, denis@fnal.gov

$$\nu_\mu + p \rightarrow \nu_\mu + p$$

$$\nu_\mu + n \rightarrow \nu_\mu + n$$

NCEL measurement and Δs

- It is always intriguing that NCEL is sensitive with isoscalar term of nucleon form factor, i.e., strange quark contribution, especially strange quark spin contribution to nucleon called "Δs"

$$\int_0^1 dx \Delta s(x) \equiv \Delta s \equiv G_A^s(Q^2 = 0)$$

NCEL to constrain optical model of MiniBooNE

- The largest error of MiniBooNE oscillation analysis is the light propagation model in the oil, called "optical model". NCEL is the unique tool to test scintillation model, and NCEL is used to understand scintillation light from the oil.

It is crucial to measure NCEL!

by Colin Anderson

2. Overview of MiniBooNE xs measurement

MiniBooNE collaboration, PRD81(2010)013005

NCπ^o
PRD81(2010)013005
Thesis in preparation
Colin, ancolin@gmail.com

$$\nu_\mu + N \rightarrow \nu_\mu + \Delta^o \rightarrow \nu_\mu + N + \pi^o$$
$$\nu_\mu + A \rightarrow \nu_\mu + A + \pi^o$$

NCπ^o as a background of ν_e appearance oscillation experiment

- It is well known NCπ^o is single most important largest critical background of ν_e-appearance experiment, such as MiniBooNE. Data driven correction is performed to NCπ^o model, to give a better prediction for NCπ^o when we lose one gamma ray

It is crucial to measure NCπ^o!

$$\nu_\mu \xrightarrow{\text{oscillation}} \nu_e + n \rightarrow p + e \rightarrow e-\text{like} \quad (\text{signal})$$
$$\nu_\mu + N \rightarrow \nu_\mu + N + \pi^o \rightarrow \gamma + \cancel{\gamma} \rightarrow e-\text{like} \quad (\nu_\mu \text{background})$$

by Mike Wilking

2. Overview of MiniBooNE xs measurement

MiniBooNE collaboration,
paper in preparation

CCπ^+
Paper in preparation
FERMILAB-THESIS-2009-27
Mike, wilking@fnal.gov

$$\nu_\mu + p(n) \rightarrow \mu + \Delta^{+(+)} \rightarrow \mu + p(n) + \pi^+$$
$$\nu_\mu + A \rightarrow \mu + A + \pi^+$$

CCπ^+ event as a background of ν_μCCQE measurement
- CCπ^+ event without pion is the intrinsic background for ν_μCCQE in MiniBooNE or ν_μ-disappearance measurement in Super-K. It is critical to understand this channel for future oscillation experiment.

CCπ^+ as a highest purity channel in MiniBooNE
- CCπ^+ is very unique, because simple timing cut select highest purity channel ~90% purity CCπ^+ in MiniBooNE. This high pure data is used for CCQE, CCπ^o, and antiCCQE measurement to improve background prediction.

CCπ^+ as a ν-contamination monitor
- There is no anti-ν induced CCπ^- event in MiniBooNE (π^- is absorbed before decay to μ), on the other hand, ν induced CCπ^+ is can be identified easily. So CCπ^+ is a unique tool to measure neutrino contamination in antineutrino beam.

It is crucial to measure CCπ^+!

by Bob Nelson

MiniBooNE collaboration,
arXiv:1010.3264

2. Overview of MiniBooNE xs measurement

CCπ^o
arXiv:1010.3264
FERMILAB-THESIS-2010-09
Bob, rhn@caltech.edu

$$\nu_\mu + n \rightarrow \mu + \Delta^+ \rightarrow \mu + p + \pi^o$$

CCπ^o is unique pion production channel
- There is no coherent pion production by CCπ^o, therefore this channel is may be the key to understand mystery of coherent production by neutrino interaction.

Normalization is higher!
MiniBooNE measured higher cross section than the typical models for all channels. The largest normalization mismatching is observed in this channel (~60%).

It is crucial to measure CCπ^o!

2. Overview of MiniBooNE xs measurement

Channels not covered by this talk

CC inclusive (by Martin Tzasov)
- Insensitive of detail of FSI

AntiCCQE (by Joe Grange)
- Additional test for CCQE model made in ν-mode
- Critical for CP measurement
- Data driven correction to improve wrong sign fraction

AntiNCEL (by Ranjan Dharmapalan)
- Further test of QE model
- New way to measure Δs?

$CC\pi^+$/CCQE ratio measurement (by Steven Linden)
- Free from normalization problem
- First place to use new signal definition by MiniBooNE

2. Overview of MiniBooNE xs measurement

Channels MiniBooNE don't try to measure (so far)

The measurement of these channels may be important for future precise oscillation experiment…

$NC\pi^+$
- the largest error for $NC\pi^o$ measurement
- other resonance only pion production channel

Multi π production channels
- large error for $CC\pi^o$ measurement

etc…

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3. Neutrino cross section measurement

Absolute flux-integrated differential cross section formula

i :true index
j : reconstructed index

Integrated flux (Φ) is removed, so it is called flux-integrated differential cross section. If flux is corrected bin-by-bin (Φ_i), it is called flux-unfolded total cross section

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

- U_{ij} :unsmearing matrix
- b_j :predicted background
- d_j :data vector
- Δx_i :bin width
- ε_i :efficiency
- T :integrated target number
- Φ :integrated ν-flux

3.1 Signal definition
3.2 Background removing
3.3 Unsmearing
3.4 Efficiency correction
3.5 Flux correction
3.6 Target number correction
3.7 Binning
3.8 Systematic errors
3.8 Data format

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3.1 Signal definition

Event reconstruction and cuts to select events

- You have good reconstruction and all cuts to select your data sample, congratulations, you are ready to measure cross sections!

NCEL | $NC\pi^o$ | $CC\pi^+$ | $CC\pi^o$

How to define signal channel? effective cross section definition

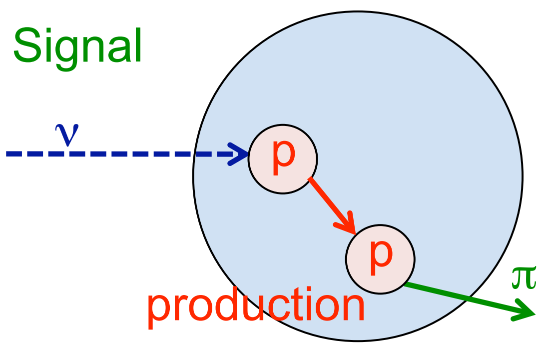
- For example, $NC\pi^o$ event is defined as NC interaction with one π^o exiting nuclei and no other mesons. This definition implies following 2 crucial points,

i. This definition includes π^o production by final state interactions (FSIs).

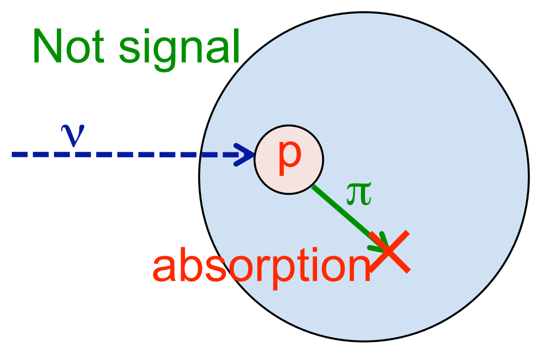
ii. This definition excludes $NC\pi^o$ interaction when π^o is lost by FSIs.

This is the necessary definition for the theorists to understand final state interactions (FSIs) without biases. Don't rely on the definition given by your interaction generator. "Signal" needs to be added to signal MC, and "Not signal" needs to be removed from signal MC. By this definition, FSI of pion is not your error, for example, error of nuclear pion absorption shouldn't be added to final error, but detector pion absorption is part of final error.

Signal



Not signal



3.1 Signal definition

How to define signal channel? initial interaction cross section definition **CCQE**

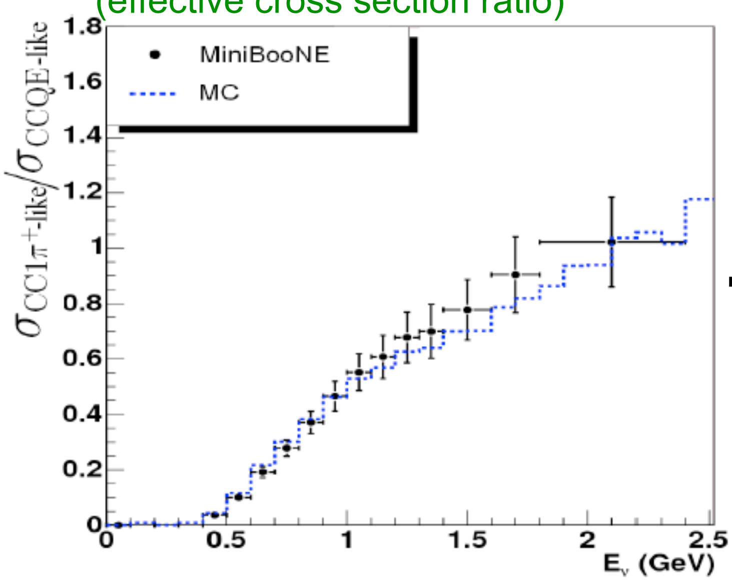
- This is definitely simpler, true distribution is what your interaction generator says “signal”. You can use this if signal channel is not very sensitive with FSI (i.e., CCQE).
- Some theorists cannot perform the MC simulation for FSI, so initial interaction cross section is also useful even though it is model dependent most of case.

CCQE NCEL $CC\pi^+/CCQE$

How to present signal channel? effective and initial interaction cross section definition

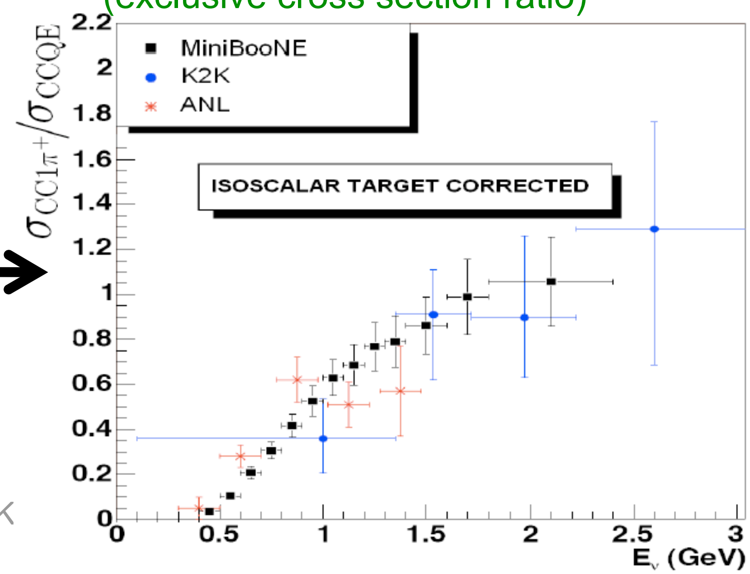
- Old data is published only in initial nucleon definition, so this definition is also useful to compare with old data. You are welcome to publish data in 2 ways, e.g., MiniBooNE $CC\pi^+$/CCQE ratio result.

$CC\pi^+$like/CCQElike cross section ratio (effective cross section ratio)



→

$CC\pi^+$/CCQE cross section ratio (exclusive cross section ratio)



3.1 Signal definition

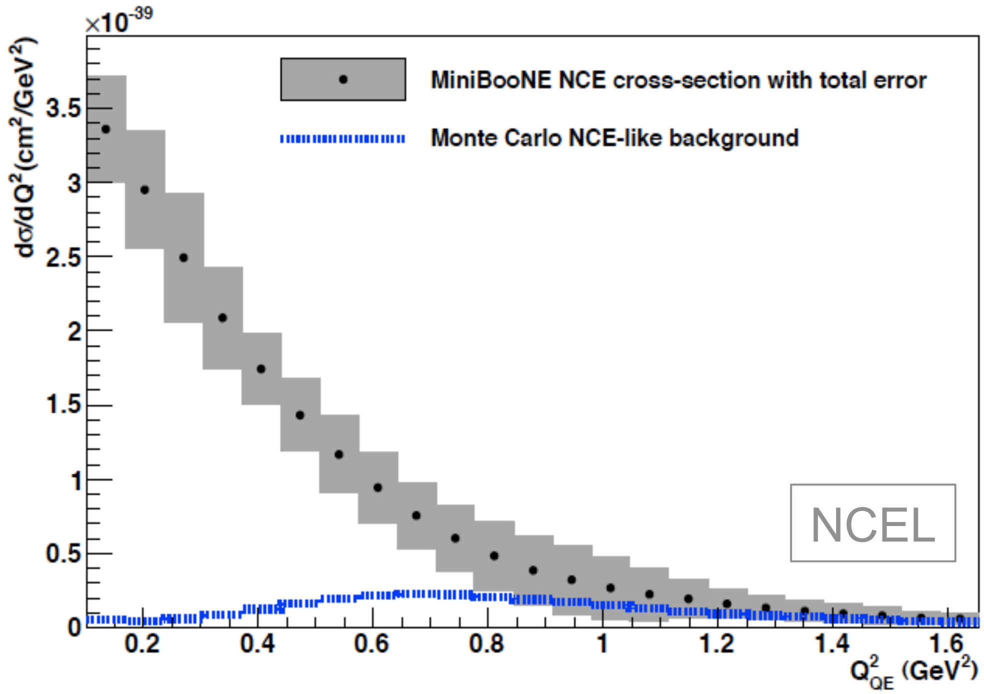
NCEL | NCπ° | CCπ+ | CCπ°

How to define signal channel? mixed target definition

- Don't separate anything which requires interaction MC! The effective cross section measurements often need mixed target definition, too.

(ex) Flux-integrated NCEL (ν-N) differential cross section on CH_2

- NCEL differential cross section is interpreted ν+N, which means sum of ν+p (carbon), ν+p (hydrogen), and ν+n (carbon). Efficiency of each channel is provided so that people can separate them if they want. $NC\pi^+$ background is subtracted based on MC (model dependent), but subtracted amount is also published so that you can recover, if you don't like this subtraction method.



These are all important to theorists to compare their models with your data. Their models include all effects in nuclei so you don't need to correct any effects in nuclei. However, all effect outside of nuclei, i.e. detector effect, have to be removed!

3.1 Signal definition

Function of measured variables

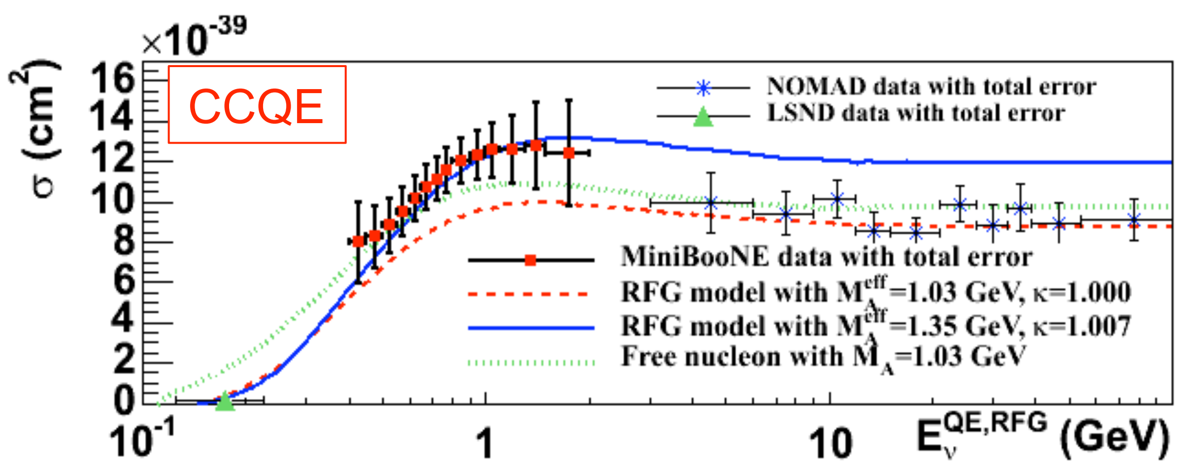
CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

- It is desired to present differential cross section of measured quantities, such as muon energy, pion angle, etc, because they are not biased by reconstruction. However, theorists usually need flux-table to compare with your data. Most of differential cross section measured by MiniBooNE are first time in history.

Function of reconstructed variables

CCQE | NCπ^o | CCπ^+ | CCπ^o

- It is possible to measure the cross section for Q^2 or E_ν, but it is very tricky how to define them in true distribution. However, flux-unfolded total cross section ($\sigma[E_\nu]$) is the only way to compare neutrino cross section from different experiments with different neutrino beams, so it is interesting to measure cross section in function of E_ν. All these are important for unfolding problem (later).



3.1 Signal definition

3.2 Background removing

3.3 Unsmearing

3.4 Efficiency correction

3.5 Flux correction

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3.9 Data format

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

U_{ij} :unsmearing matrix

b_j :predicted background

d_j :data vector

Δx_i :bin width

ε_i :efficiency

T :integrated target number

Φ :integrated ν-flux

3.2 Background removing process

CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

Background subtraction is favored

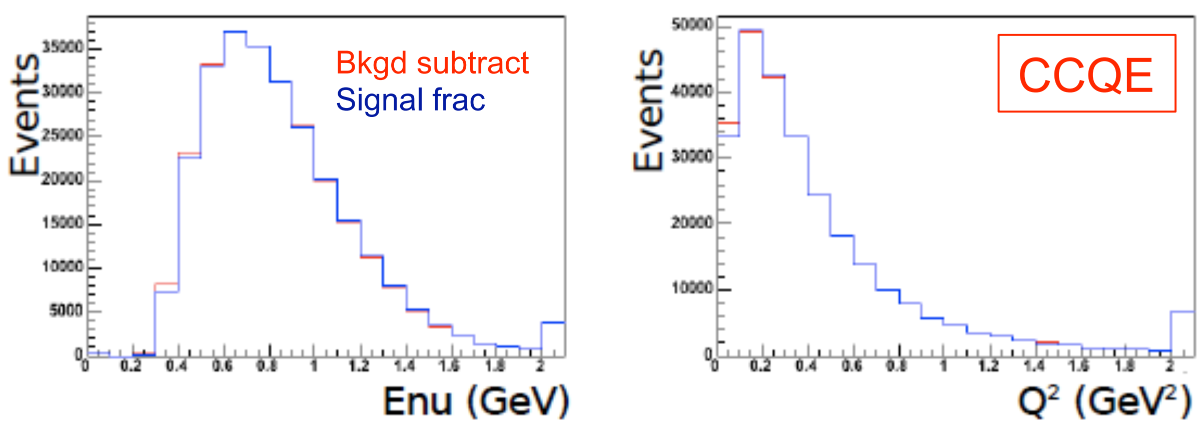
- Background can be removed by 2 methods. Background subtraction is favored because this is independent from signal MC. Signal fraction is used in some case (for example, background subtraction makes negative event rate in some bin).

$$d_i - b_i \qquad\qquad d_i \times \frac{s_i}{s_i + b_i}$$

Signal fraction is sensitive to your signal prediction, we want to avoid that. The difference of these 2 methods are only important where background is large. If background is small in everywhere (i.e., CCπ^+), they make no difference.

For example, CCQE difference is only large at lowQ^2, where background is ~30%

Background subtraction vs Signal fraction



3.2 Background removing process

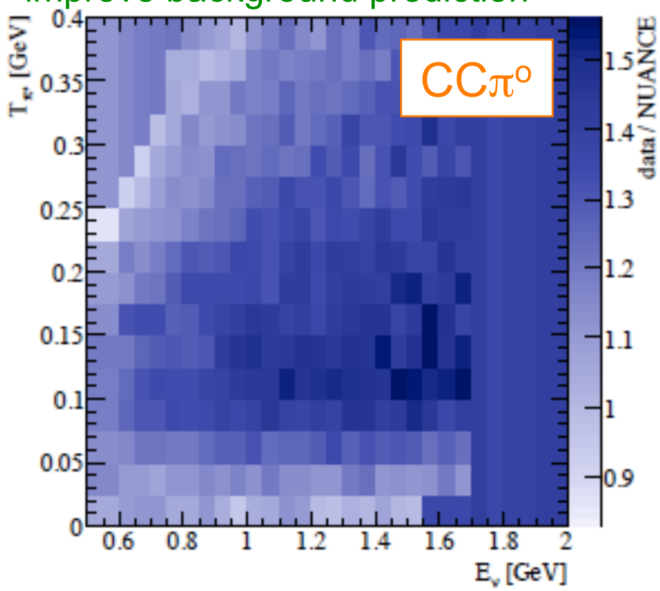
Cross section error CCQE NCEL NCπ^o CCπ^+ CCπ^o

- In general, background cross section error is the only cross section error applying to your final cross section sample

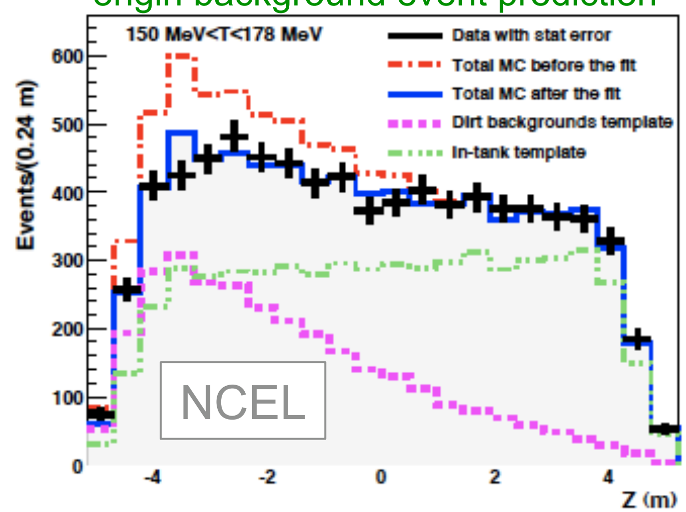
Data driven background correction CCQE NCEL CCπ^o

- We can minimize model dependency of background relying on external measurement or in situ measurement. For example, CCQE and CCπ^o used high CCπ^+ sample to improve their background prediction. NCEL used dirt event sample to improve dirt origin event prediction.

data-MC ratio of CCπ^+ cross section to improve background prediction



Dirt enhanced sample to improve origin background event prediction



3.1 Signal definition

3.2 Background removing

3.3 Unsmearing

U_{ij} :unsmearing matrix

b_j :predicted background

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3.4 Efficiency correction

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3.3 Unsmearing

Unfolding

- The process removing the detector effects, mainly smearing and detector cut, is called unfolding. It is often easier to think by separating unfolding process to 2 parts, unsmearing and efficiency correction. We focus on unsmearing here.

Detector error

CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

- Unfolding is the place you assign detector error. By definition, many systematic variations are canceled. So even you assign other errors, such as cross section error and flux error, they are safely canceled.

3.3 Unsmearing

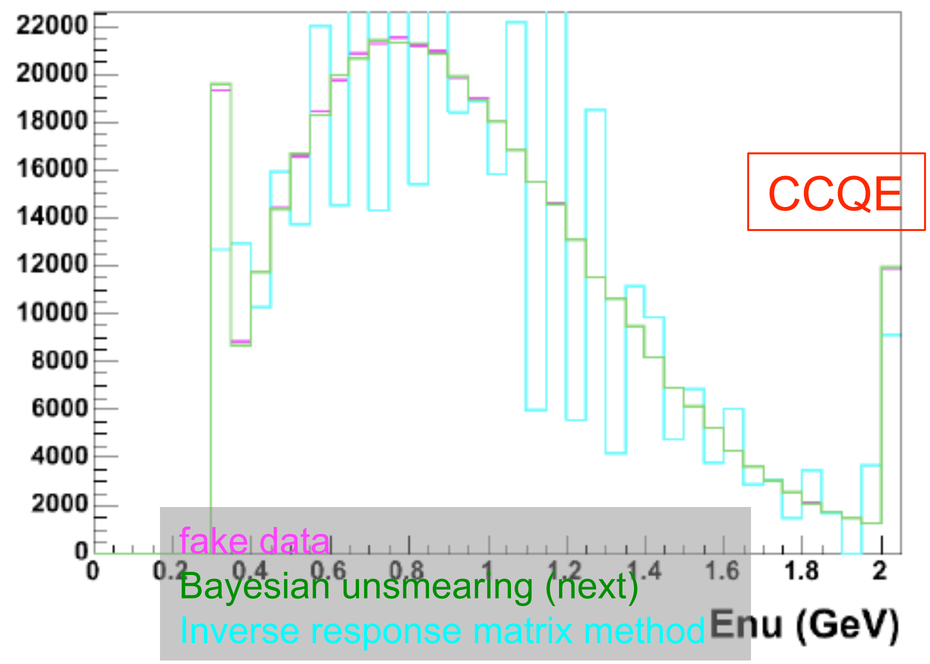
Inverse response matrix method

None

Inverse response matrix method is the bias-free unfolding method, but this method doesn't work for anybody. Typically, it makes rapid oscillated solution (Gibb's phenomenon). Say, response matrix R gives the smearing and detector cut of true distribution α to measured distribution β in MC, it's inverse can be used to unfold data b to true distribution a

$$\beta_i = R_{ij}\alpha_j \rightarrow a_j = (R)^{-1}_{ji} b_i$$

Inverse response matrix is very sensitive with MC statistics. It doesn't work for sparse matrix, it cannot handle large bin number, it cannot deal histogram with zero even bins. But all these are features for differential cross section!



Höcker, Kartvelishvili
NIM.A372(1996)469

3.3 Unsmearing

Tikhonov regularization method

NCπ^o

- The regularization term from the prior knowledge of distribution (e.g., how smooth is) can stabilize inverse response matrix. The bias is introduced through the linear operator L.

$$\beta_i = R_{ij}\alpha_j \rightarrow a_j = (R)^{-1}_{ji} b_i \rightarrow (Ra-b)^T V(b)^{-1}(Ra-b) + \tau(La)^T(La)$$

Regularization parameter τ should be chosen with care (there is some procedure to find τ).
- too small τ doesn't regulate matrix inversion
- too large τ too much smoothes out response matrix R

Solution is,

$$a = [R + \tau V(R^T)^{-1}(L^T L)] \cdot b = U' \cdot b$$

Since unsmearing doesn't change normalization, Langrange multiplier is applied to keep normalization.

$$\sum_j a_j = \sum_i b_i$$

Then, solution under constraint is,

$$a = U' \cdot b + \left[\sum_i [(I - U') \cdot b]_i \right] \cdot s \qquad s_i = \frac{\sum_j [U'VR^{-1}]_{ij}}{\sum_{jk} [U'VR^{-1}]_{jk}}$$

D'Agostini, NIM.A362(1995)487

3.3 Unsmearing

CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

Iterative Bayesian method

- Unsmearing is based on the Bayesian statistics, so the bias is introduced from MC knowledge and it is model dependent

Efficiency ε is defined by true distribution after cut μ to true distribution before cut α.
M-matrix gives transformation from measured distribution to true distribution after cut. It give the true distribution after cut μ on projection on one axis.

$$\varepsilon_i = \frac{\mu_i}{\alpha_i} \qquad \sum_{j=1}^{n} M_{ij} = \mu_i = \varepsilon_i \alpha_i$$

Now, define U-matrix by normalizing M-matrix with other axis,

$$U_{ij}^{0th} = \frac{M_{ij}}{\sum_{k=1}^{n} M_{kj}}$$

So, background subtracted data d^{0th} can be unsmeared and efficiency corrected to obtain unfolded cross section d^{1th}

$$d_i^{1st} = \frac{1}{\varepsilon_i} \sum_{j=1}^{n} U_{ij}^{0th} d_j^{0th}$$

D'Agostini, NIM.A362(1995)487

3.3 Unsmearing

CCQE | NCEL | $NC\pi^o$ | $CC\pi^+$ | $CC\pi^o$

Iterative Bayesian method

- Unsmearing is based on the Bayesian statistics, so the bias is introduced from MC knowledge and it is model dependent
- If initial guess μ (=prior probability of Bayesian statistics) is not so close from the nature, we can improve U-matrix by assuming d^{1th} is close the the nature

$$\omega_i^{1st} = \frac{d_i^{1st}}{\alpha_i} \qquad U_{ij}^{1st} = \frac{\omega_i^{1st} M_{ij}}{\sum_{k=1}^{n} (\omega_k^{1st} M_{kj})} \qquad d_i^{2nd} = \frac{1}{\varepsilon_i} \sum_{j=1}^{n} U_{ij}^{1st} d_j^{0th}$$

- This iteration process usually converge <5 times. 0^{th} iteration is not bad at all.
- Signal model dependence will become systematic error, this is done by varying M-matrix by changing systematics. So signal cross error is part of final error.
- This method also fails if M-matrix is highly non-diagonal.
- 0^{th} and 1^{st} iteration difference of data is also included as systematic error.

D'Agostini, NIM.A362(1995)487

3.3 Unsmearing

CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

Iterative Bayesian method

- It is based on Bayes theorem

$$M_{ij} = P(\text{recon}_j \mid \text{true}_i)P(\text{true}_i)$$

$$P(\text{true}_i \mid \text{recon}_j) = \frac{P(\text{recon}_j \mid \text{true}_i)P(\text{true}_i)}{\sum_k P(\text{recon}_j \mid \text{true}_k)P(\text{true}_k)} = \frac{M_{ij}}{\sum_k M_{kj}} = U_{ij}^{0\text{th}}$$

$$d_i^{1\text{st}} = \frac{1}{\varepsilon_i}\sum_{j=1}^{n} U_{ij}^{0\text{th}} d_j^{0\text{th}}$$

D'Agostini,
NIM.A362(1995)487

3.3 Unsmearing

How to construct M-matrix, measured variables

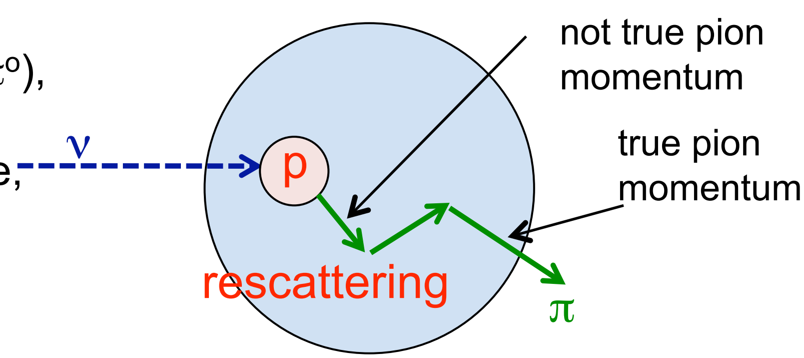
- It is desired to present differential cross section with function of measured quantities, such as muon energy, pion angle, etc, because they are not biased by reconstruction.

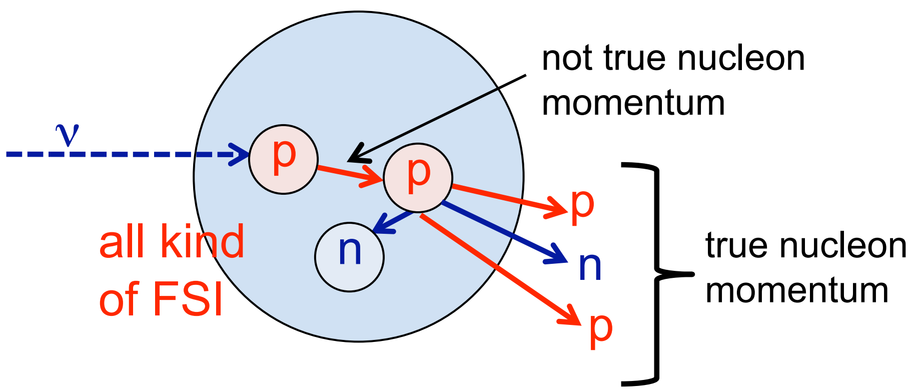
i. It is straightforward if you measure initial nucleon cross section. True kinematics is the true information for M-matrix.

CCQE

NCπ^o CCπ^+ CCπ^o

ii. If you measure effective cross section (e.g., CCπ^o), your "true" kinematics is not MC says "true". You need to defined true kinematics from final state, i.e., particle exiting the nuclei.





NCEL

iii."true" momentum is defined by sum of all outgoing nucleons, because that is the observables.

D'Agostini, NIM.A362(1995)487

3.3 Unsmearing

How to construct M-matrix, reconstructed variables

- The definition of true kinematics is tricky, because you have choice.

i. True Q^2 is defined by reconstructed Q^2 from true kinematics CCQE NCEL

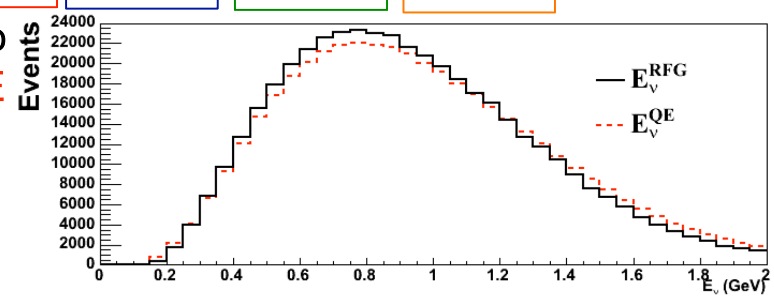
For example, CCQE, true Q^2 is defined "reconstructed Q^2 from true muon energy and angle", and we call it "Q^2_{QE}" to remind people this is reconstructed under QE assumption.

ii True Q^2 is defined by true Q^2 in MC $CC\pi^+$ $CC\pi^o$

This may be useful to compare with old data, only presented by this way

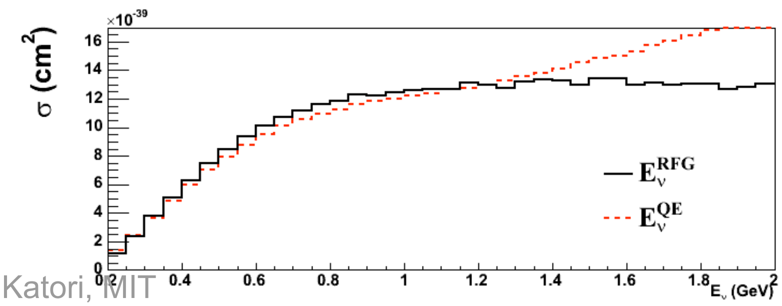
iii True E_ν is defined by true E_ν in MC CCQE $NC\pi^o$ $CC\pi^+$ $CC\pi^o$

For example, CCQE, E_ν is called "$E_\nu^{QE,RFG}$" to remind people this is reconstructed under QE assumption then unfolded by assuming RFG model.



Flux-unfolded total cross section

- it is important to unfold under RFG, otherwise reconstruction bias deviate cross section at the tail significantly.



Cowan,
"Statistical Data Analysis"

3.3 Unsmearing

Bias of unsmearing NCπ^o

- There is no perfect unfolding, unfolding method can be different depending on your distribution. Biases may be one of criteria.

i. Inverse response matrix method:
No bias, but it only works for very few bin histogram

$$B^{Inverse} = 0$$

ii. Tikhonov regularization
Bias is introduced from linear function and regularization parameter. It also require fair amount of statistics.

$$B^{Tikhonov} = \sum_i \left[U' \cdot (Ra - b)\right]_i$$

iii. Iterative Bayesian method
Bias is introduced from prior knowledge of MC (model dependent). It works for any distribution.

$$B^{Bayesian} = \sum_i \left[M \cdot (Ra - b)\right]_i$$

iv. No unsmearing

$$B^{NoUnsmear} = \sum_i \left[(U - I) \cdot b\right]_i$$

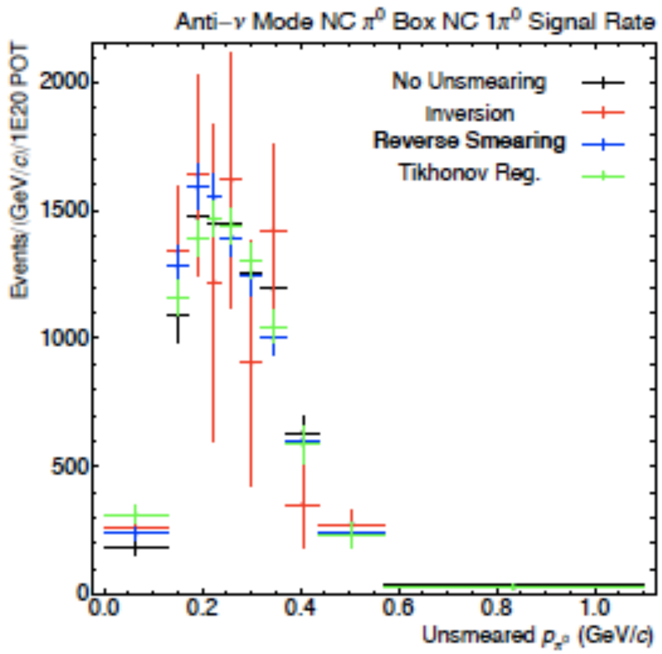
For example, NCπ^o, 3 different unfolding methods are used depending on the distribution.
$P_p(\nu)$: Tikhonov regularization
$\cos\theta_\pi(\nu)$: Iterative Bayesian
$P_p(\text{anti-}\nu)$: Iterative Bayesian
$\cos\theta_\pi(\text{anti}\nu)$: No unsmearing

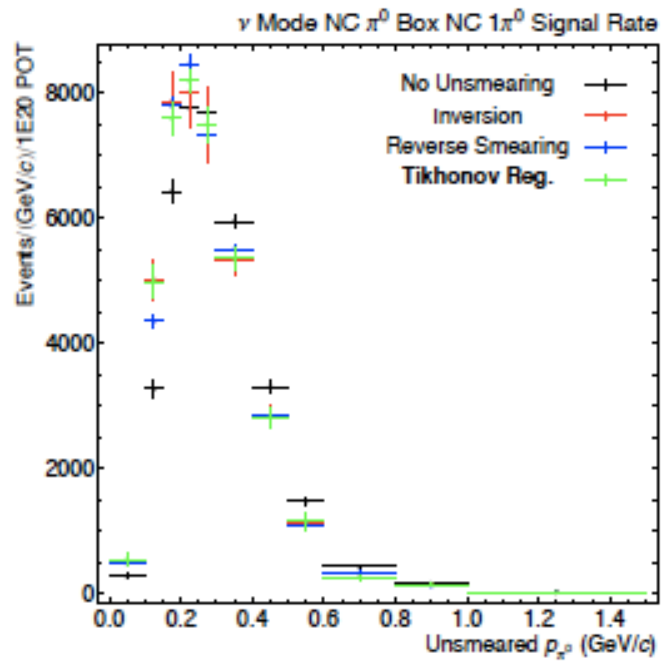
Cowan,
"Statistical Data Analysis"

3.3 Unsmearing

Bias of unsmearing NCπ^o

- There is no perfect unfolding, unfolding method can be different depending on your distribution. Biases may be one of criteria.





For example, NCπ^o, 3 different unfolding methods are used depending on the distribution.

$P_p(\nu)$: Tikhonov regularization
$\cos\theta_\pi(\nu)$: Iterative Bayesian
$P_p(\text{anti-}\nu)$: Iterative Bayesian
$\cos\theta_\pi(\text{anti}\nu)$: No unsmearing

3.1 Signal definition

3.2 Background removing

3.3 Unsmearing

3.4 Efficiency correction

3.5 Flux correction

3.6 Target number correction

3.7 Binning

3.8 Systematic errors

3.9 Data format

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

U_{ij} :unsmearing matrix

b_j :predicted background

d_j :data vector

Δx_i :bin width

ε_i :efficiency

T :integrated target number

Φ :integrated ν-flux

3.4 Efficiency correction

CCQE NCEL NCπ^o CCπ^+ CCπ^o

Looks straightforward, no?

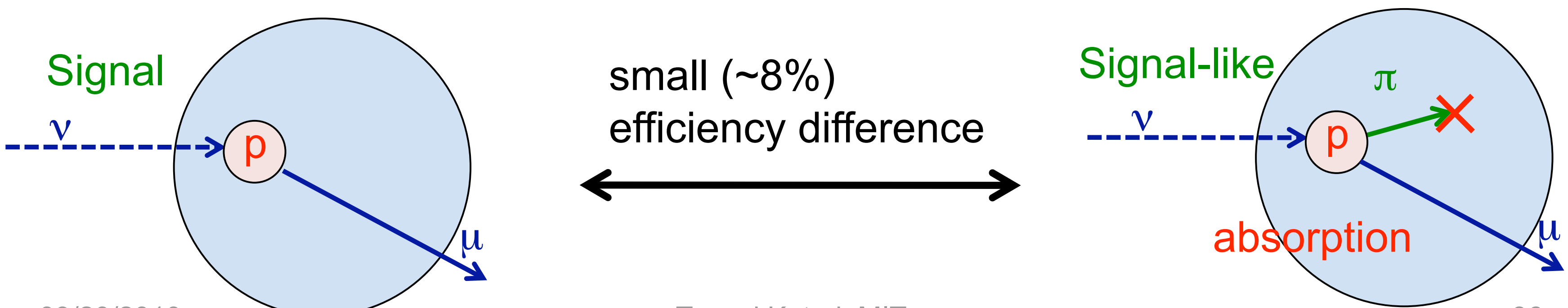
- Unsmearing and efficiency correction are call unfolding problem, again, they are not separated problem. But we separate them because most of us use iterative Bayesian method.
- The efficiency is defined true distribution after cut μ divided by before cut α. Because of ratio, ε is insensitive with many systematic variations common for numerator and denominator such as flux error and cross section error. The detector error is important.

$$\varepsilon_i = \frac{\mu_i}{\alpha_i} = \frac{N_i(\mathrm{AfterCut})}{N_i(\mathrm{BeforeCut})}$$

CCQE NCEL NCπ^o CCπ^+ CCπ^o

Efficiency of effective cross section

- NCπ^o, CCπ^+, CCπ^o are always effective cross section measurement, CCQE and NCEL provide unfolded background distribution so that people can recover effective CCQE, NCEL cross section. By definition, efficiency is assumed same for signal (e.g., CCQE) and signal-like (e.g., CCπ^+ with π-absorption), but this is not completely true.



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3.5 Flux correction

Integral region of flux

- Flux is integrated and removed. There is a big difference how to introduce flux error.

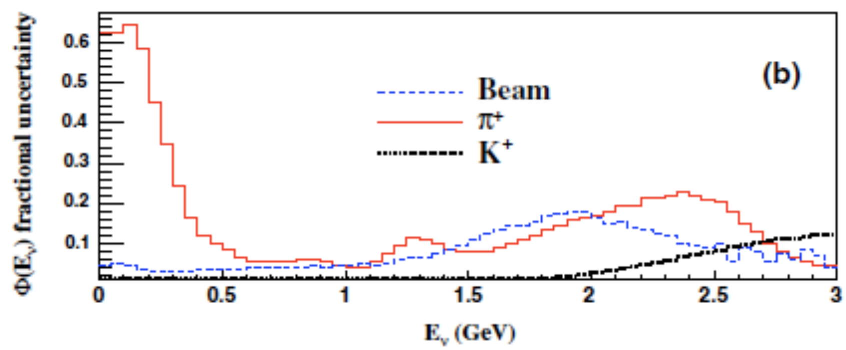
i. Flux is integrated in all spectrum region and it's variation is the flux error. This choice gives rather large flux error (e.g., ~12% for NCπ^o).

NCπ^o

ii. Cutoff for flux integration

CCπ^o

Flux is integrated in [0.5-2.0] GeV, and error is variation of that. In this way, you can avoid flux variation at low energy which don't contribute to the channel. Error is smaller, ~7%.



iii. Flux is integrated all region, but flux error is calculated separately
Flux variation is calculated by variation of numerator of efficiency term.
In this way, flux variation is automatically limited within the region relevant to cross section measurement. Both normalization and shape flux error are taken into account.
Error is smaller, ~8%.

CCQE NCEL

$$\varepsilon_i^s = \frac{\mu_i^s}{\alpha_i}$$

3.5 Flux correction

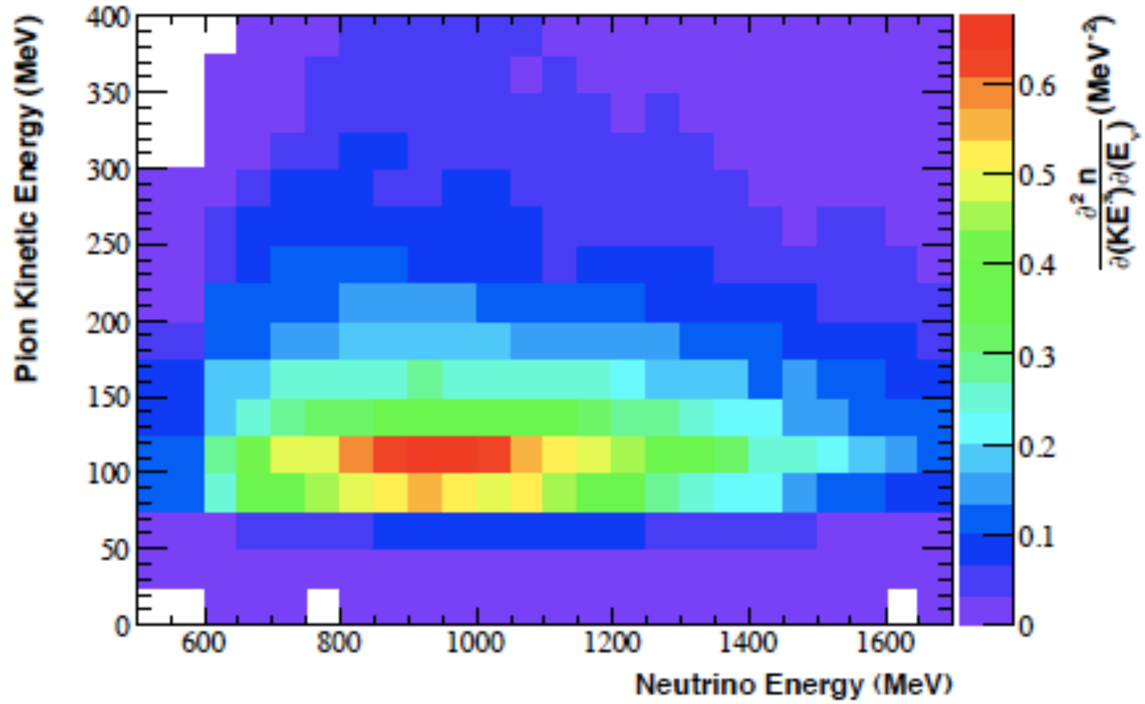
Integral region of flux

- Flux is integrated and removed. There is a big difference how to introduce flux error.

iv. cross sections are function of neutrino energy $CC\pi^+$

In this way, integrated flux in E_ν bin is unfolded in each bin of measured variables (e.g., pion kinetic energy), then flux error only relevant E_ν region apply to measured variables. This minimizes flux error at many region.

Pion kinetic energy- neutrino energy 2-dimentional cross section



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Δx_i :bin width

ε_i :efficiency

Φ :integrated ν-flux

T :integrated target number

3.6 Target number correction

Don't use all volume! CCQE | NCπ^o | CCπ^+ | CCπ^o

- Usually, you generate interaction at all places, because unwanted events are removed by cut anyway. However, target number correction try to recover all events. So MC should be generated in the region within the region you can trust.

i. MiniBooNE is ~600cm radius sphere.
ii. MC is generated within 550cm sphere.
iii. The fiducial cut is 500cm sphere.

In this way, we can guarantee cross section is calculated in the region where we believe uniform.

Event created outside of fiducial cut, but reconstructed in fiducial cut and vice versa

- this type of event is taken care automatically by efficiency correction.

If reconstruction is completely wrong, even though MC and data agree?

- In general, data-MC agreement is not enough for absolute cross section measurement. The systematic effect of misreconstruction should be taken care by detector error in efficiency.

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d_j :data vector

Δx_i :bin width

ε_i :efficiency

T :integrated target number

Φ :integrated ν-flux

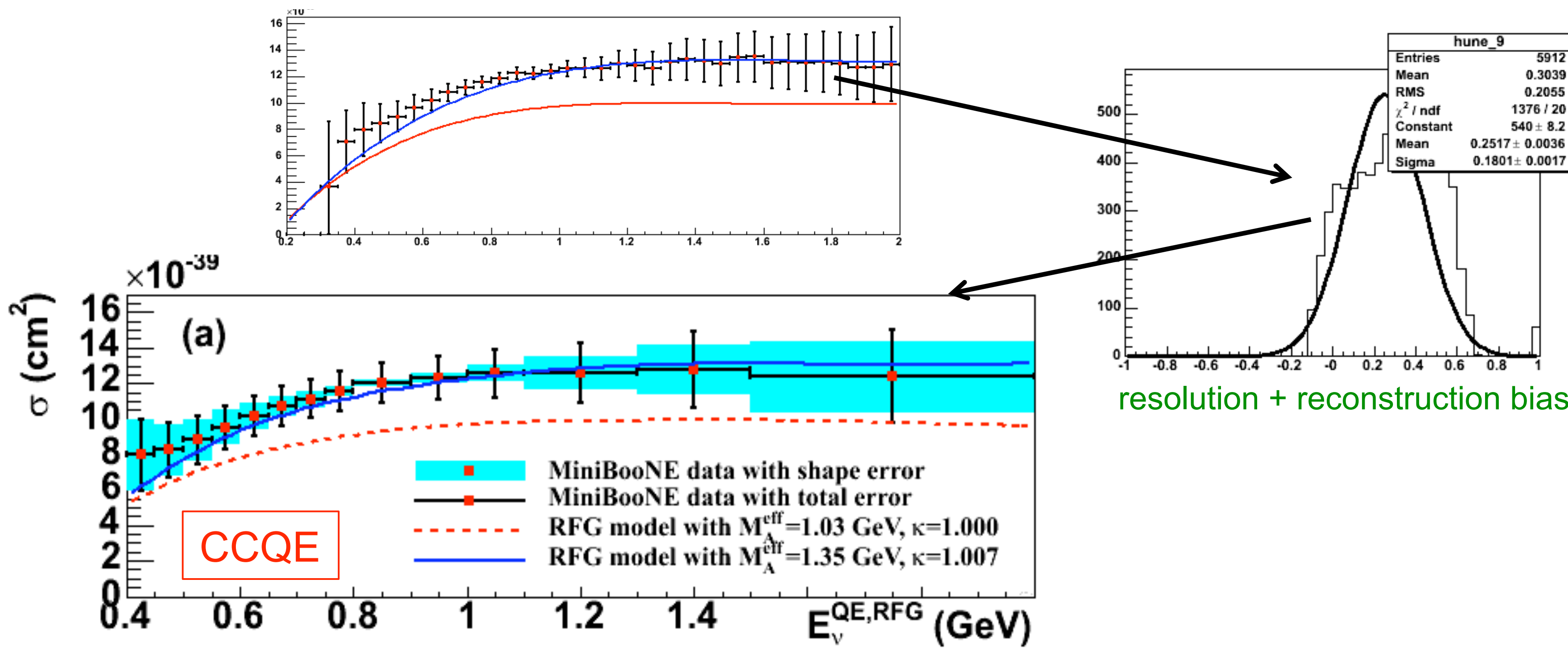
3.7 Binning of data

Bin width takes into account statistics NCπ^o CCπ^+ CCπ^o

- High statistic region is finer, low statistics is coarser binning…

Bin width takes into account reconstruction biases CCQE

- Unsmearing depends on Q^2_{QE} or $Q^2_{QE,RFG}$ in true axis (this difference is not covered by unfolding error). To take account this, bin width is increased where reconstruction bias is large. Those region also has large systematic error, so finer binning doesn't make sense anyway. You can always merge bins later, so it's better to have finer bins as long as statistics allow.



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ε_i :efficiency

T :integrated target number

Φ :integrated ν-flux

3.8 Systematic errors

Systematic error is calculated from the difference of systmetics varied cross section result and central value cross section result.

$$E_{ij}=\left[\left(\frac{d\sigma}{dx}\right)_i-\left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j-\left(\frac{d\sigma^s}{dx}\right)_j\right]$$

4 parts are related with systematic error. Don't vary all of them with all systematics! You need to think about the effect of each term

3.8.1 background
3.8.2 U-matrix
3.8.3 Efficiency
3.8.4 Flux term
3.8.5 Target number

$$\left(\frac{d\sigma}{dx}\right)_i=\frac{\sum_j U_{ij}(d_j-b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

U_{ij} :unsmearing matrix

b_j :predicted background

d_j :data vector

Δx_i :bin width

ε_i :efficiency

T :integrated target number

Φ :integrated ν-flux

3.8.1 Background variation

Systematic error is calculated from the difference of systmetics varied cross section result and central value cross section result.

$$E_{ij}=\left[\left(\frac{d\sigma}{dx}\right)_i-\left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j-\left(\frac{d\sigma^s}{dx}\right)_j\right]$$

4 parts are related with systematic error. Don't vary all of them with all systematics! You need to think about the effect of each term

3.8.1 background
3.8.2 U-matrix
3.8.3 Efficiency
3.8.4 Flux term
3.8.5 Target number

background variation

$$\left(\frac{d\sigma}{dx}\right)_i=\frac{\sum_j U_{ij}(d_j-b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

Basically, cross section error is only applied here. We only care background cross section model, not signal! Don't add flux error! Background variation by flux is first order approximation canceled.

3.8.2 Unsmearing matrix variation

Systematic error is calculated from the difference of systmetics varied cross section result and central value cross section result.

$$E_{ij} = \left[\left(\frac{d\sigma}{dx}\right)_i - \left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j - \left(\frac{d\sigma^s}{dx}\right)_j\right]$$

4 parts are related with systematic error. Don't vary all of them with all systematics! You need to think about the effect of each term

3.8.1 background
3.8.2 U-matrix
3.8.3 Efficiency
3.8.4 Flux term
3.8.5 Target number

Unsmearing matrix variation

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

In fact, signal cross section error is here, because of Bayesian prior probability error. Detector error is applied here, too. Flux error is applied here, too. Since this is normalized, only shape part of flux error is automatically taken into account.

3.8.3 Efficiency variation

Systematic error is calculated from the difference of systmetics varied cross section result and central value cross section result.

$$E_{ij} = \left[\left(\frac{d\sigma}{dx}\right)_i - \left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j - \left(\frac{d\sigma^s}{dx}\right)_j\right]$$

4 parts are related with systematic error. Don't vary all of them with all systematics! You need to think about the effect of each term

Detector error is here. This term is insensitive with flux error and cross error anyway due to ratio.

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i (\Phi T) \Delta x_i}$$

Efficiency variation

3.8.4 Integrated flux factor

Systematic error is calculated from the difference of systmetics varied cross section result and central value cross section result.

$$E_{ij} = \left[\left(\frac{d\sigma}{dx}\right)_i - \left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j - \left(\frac{d\sigma^s}{dx}\right)_j\right]$$

4 parts are related with systematic error. Don't vary all of them with all systematics! You need to think about the effect of each term

Flux normalization error is here. You need to tweak to remove flux variation irrelevant for cross section measurement.

Flux shape error is neglected by Φ variation. Varying the numerator of efficiency is reasonable way to take account both effect.

$$\varepsilon_i^s = \frac{\mu_i^s}{\alpha_i}$$

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i(\Phi T)\Delta x_i}$$

Integrated flux variation

3.8.5 Target number and other overall normalization error

Systematic error is calculated from the difference of systmetics varied cross section result and central value cross section result.

$$E_{ij} = \left[\left(\frac{d\sigma}{dx}\right)_i - \left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j - \left(\frac{d\sigma^s}{dx}\right)_j\right]$$

4 parts are related with systematic error. Don't vary all of them with all systematics! You need to think about the effect of each term

3.8.1 background
3.8.2 U-matrix
3.8.3 Efficiency
3.8.4 Flux term
3.8.5 Target number

Error of target number (e.g., MiniBooNE, Avogadro number, density of oil, chemical composition) is purely normalization and you can add by quadrature for your final sample (no need to vary in MC). Same is true for total POT error.

$$\left(\frac{d\sigma}{dx}\right)_i = \frac{\sum_j U_{ij}(d_j - b_j)}{\varepsilon_i (\Phi T) \Delta x_i}$$

Total target number

3.8.6 Systematic error matrix construction, Unisim and Multisim

Unisim

The error matrix can be made by changing one of systematics and calculate differential cross section ($d\sigma^s/dx$), then take a difference with differential cross section calculated with central value MC ($d\sigma/dx$).

$$E_{ij}=\left[\left(\frac{d\sigma}{dx}\right)_i-\left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j-\left(\frac{d\sigma^s}{dx}\right)_j\right]$$

Multisim

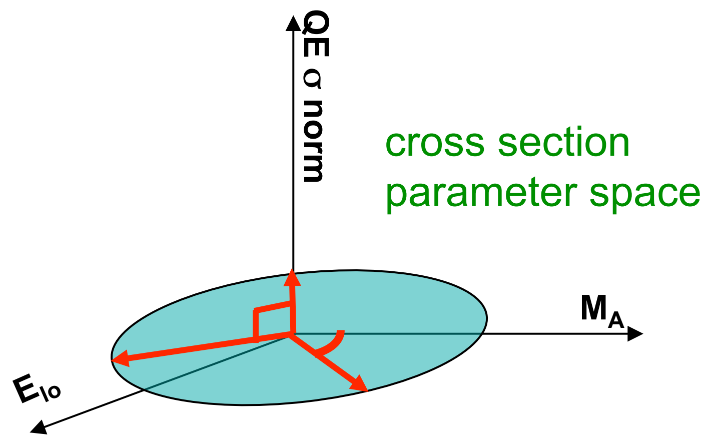
If there is a correlation between systematics (input error matrix), it should propagate correctly. In this case, number of $d\sigma^s/dx$ with different set of systematics drawn from input error matrix make many error matrices. Then, we take average of them to construct output error matrix.

$$E_{ij}=\frac{1}{M}\sum_s\left[\left(\frac{d\sigma}{dx}\right)_i-\left(\frac{d\sigma^s}{dx}\right)_i\right]\left[\left(\frac{d\sigma}{dx}\right)_j-\left(\frac{d\sigma^s}{dx}\right)_j\right]$$

3.8.6 Multisim

ex) cross section uncertainties

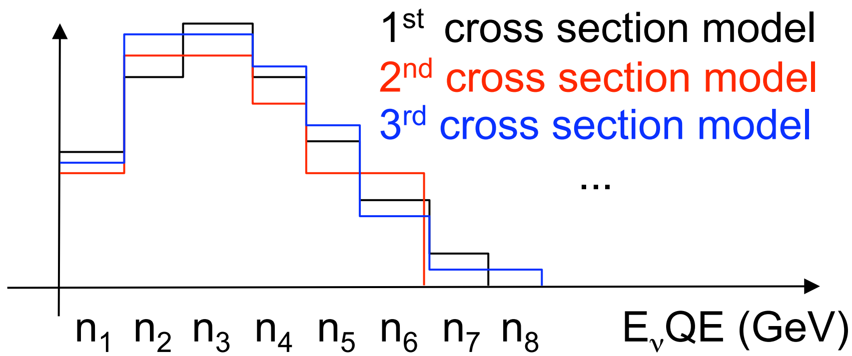
M_AQE	6%	correlated
E_{lo}sf	2%	
QE σ norm	10%	uncorrelated



Input cross section error matrix

$$M_{input}(xs) = \begin{pmatrix} var(M_A) & cov(M_A, E_{lo}) & 0 \\ cov(M_A, E_{lo}) & var(E_{lo}) & 0 \\ 0 & 0 & var(\sigma - norm) \end{pmatrix}$$

cross section error for E_νQE



repeat this exercise many times to create smooth error matrix for E_νQE

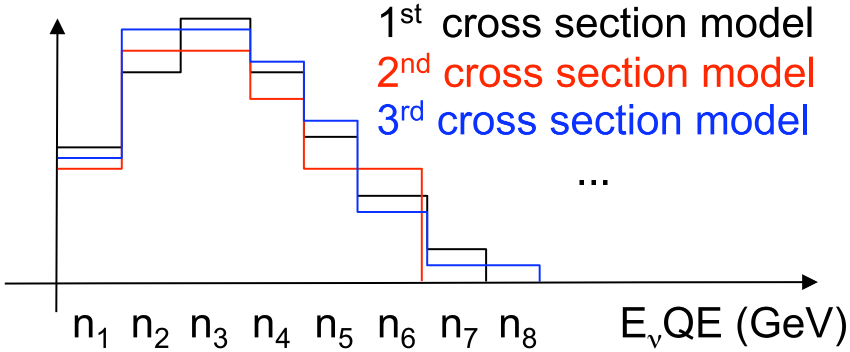
3.8.6 Multisim

Output cross section error matrix for $E_\nu QE$

$$[M_{output}(xs)]_{ij} \approx \frac{1}{S}\sum_{k}^{S}\left(N_i^k(xs)-N_i^{MC}\right)\left(N_j^k(xs)-N_j^{MC}\right)$$

$$M_{output}(xs)=\begin{pmatrix} var(n_1) & cov(n_1,n_2) & cov(n_1,n_3) & \cdots \\ cov(n_1,n_2) & var(n_2) & cov(n_2,n_3) & \cdots \\ cov(n_1,n_3) & cov(n_2,n_3) & var(n_3) & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

cross section error for $E_\nu QE$



3.8.7 Statistical errors

Statistical error propagation NCπ^o CCπ^o

Due to unfolding, there is data statistical error on off-diagonal term of error matrix. The diagonal statistical error can be propagated through Jacobian. It is weakened, and smoothly migrate to off diagonal. MC statistics can be transferred by similar way if it is large.

$$V_{ij}\left[\frac{d\sigma}{dx}\right] = V_{ij}\left[\frac{\sum U(d-b)}{\varepsilon(\Phi T)\Delta x}\right] = \left(\frac{\partial\left[\frac{\sum U(d-b)}{\varepsilon(\Phi T)\Delta x}\right]}{\partial d}\right)_{ki} V_{km}[d]\left(\frac{\partial\left[\frac{\sum U(d-b)}{\varepsilon(\Phi T)\Delta x}\right]}{\partial d}\right)_{mj}$$

Statistical error through Multisim NCEL

Fake data set is made by applying fluctuation on data within data statistics. Then statistics multisim output error matrix is made from fake data set.

Statisical error through detector error CCQE CCπ^+

Detector error multisim MC set is made with data statistics, so the multisim output error matrix can posses statistical error, too. In this way, data statistics is added through unfolding variation.

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3.9 Data format

CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

Tables on MiniBooNE data release website
- In MiniBooNE, all cross section tables, as well as flux table, are released in website
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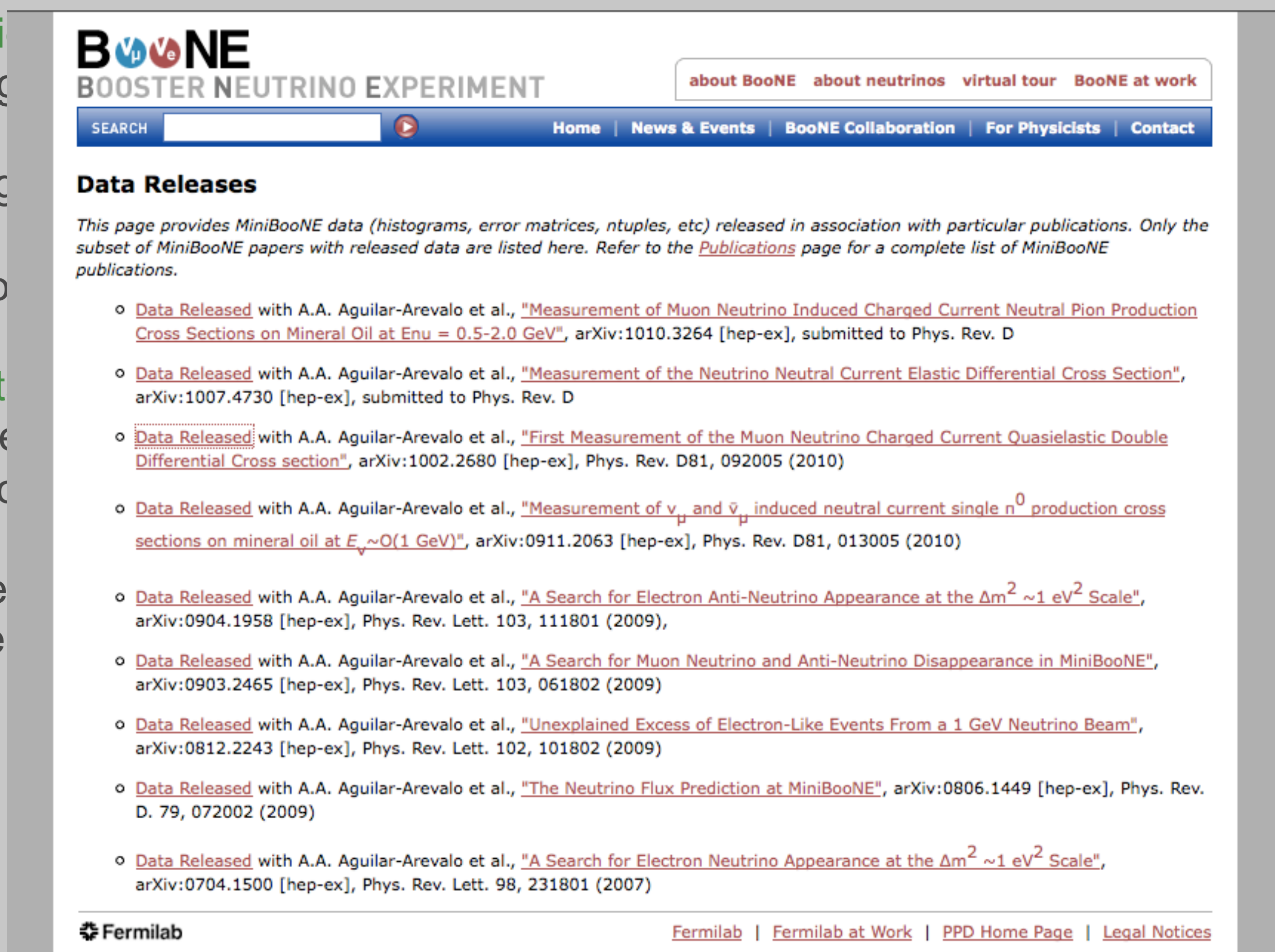
Cross secti
- Flux-integ
- Flux integ
- Flux-unfo

Additional t
- signal-like
cross sectic
- response
observed e

CCπ^+ CCπ^o
Cπ^o
clusive
QE NCEL
EL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Data Releases

This page provides MiniBooNE data (histograms, error matrices, ntuples, etc) released in association with particular publications. Only the subset of MiniBooNE papers with released data are listed here. Refer to the Publications page for a complete list of MiniBooNE publications.

- Data Released with A.A. Aguilar-Arevalo et al., "Measurement of Muon Neutrino Induced Charged Current Neutral Pion Production Cross Sections on Mineral Oil at Enu = 0.5-2.0 GeV", arXiv:1010.3264 [hep-ex], submitted to Phys. Rev. D
- Data Released with A.A. Aguilar-Arevalo et al., "Measurement of the Neutrino Neutral Current Elastic Differential Cross Section", arXiv:1007.4730 [hep-ex], submitted to Phys. Rev. D
- Data Released with A.A. Aguilar-Arevalo et al., "First Measurement of the Muon Neutrino Charged Current Quasielastic Double Differential Cross section", arXiv:1002.2680 [hep-ex], Phys. Rev. D81, 092005 (2010)
- Data Released with A.A. Aguilar-Arevalo et al., "Measurement of ν_μ and $\bar{\nu}_\mu$ induced neutral current single π^0 production cross sections on mineral oil at E_ν~O(1 GeV)", arXiv:0911.2063 [hep-ex], Phys. Rev. D81, 013005 (2010)
- Data Released with A.A. Aguilar-Arevalo et al., "A Search for Electron Anti-Neutrino Appearance at the Δm^2 ~1 eV^2 Scale", arXiv:0904.1958 [hep-ex], Phys. Rev. Lett. 103, 111801 (2009),
- Data Released with A.A. Aguilar-Arevalo et al., "A Search for Muon Neutrino and Anti-Neutrino Disappearance in MiniBooNE", arXiv:0903.2465 [hep-ex], Phys. Rev. Lett. 103, 061802 (2009)
- Data Released with A.A. Aguilar-Arevalo et al., "Unexplained Excess of Electron-Like Events From a 1 GeV Neutrino Beam", arXiv:0812.2243 [hep-ex], Phys. Rev. Lett. 102, 101802 (2009)
- Data Released with A.A. Aguilar-Arevalo et al., "The Neutrino Flux Prediction at MiniBooNE", arXiv:0806.1449 [hep-ex], Phys. Rev. D. 79, 072002 (2009)
- Data Released with A.A. Aguilar-Arevalo et al., "A Search for Electron Neutrino Appearance at the Δm^2 ~1 eV^2 Scale", arXiv:0704.1500 [hep-ex], Phys. Rev. Lett. 98, 231801 (2007)

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3.9 Data format

CCQE | NCEL | NCπ^o | CCπ^+ | CCπ^o

Tables on MiniBooNE data release website

- In MiniBooNE, all cross section tables, as well as flux table, are released in website

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Data Release for A.A. Aguilar-Arevalo et al., "First Measurement of the Muon Neutrino Charged Current Quasielastic Double Differential Cross section", arXiv:1002:2680 [hep-ex], Phys. Rev. D81, 092005 (2010)

The following MiniBooNE information from the 2010 CCQE cross section paper is made available to the public:

- **ν_μ CCQE cross sections:**
  - **MiniBooNE flux**
    - table of predicted MiniBooNE muon neutrino flux (Table V)
  - **flux-integrated double differential cross section (Figure 13)**
    - 1D array of bin boundaries partitioning the muon kinetic energy (top) and the cosine of the muon scattering angle (bottom)
    - 2D array of the value of the double differential cross section in each bin in units of 10^{-41} cm^2/GeV/nucleon. The muon kinetic energy increases from left to right, and the cosine of the muon scattering angle decreases from top to bottom (Table VI)
    - 2D array of the shape uncertainty of the double differential cross section in each bin in units of 10^{-42} cm^2/GeV/nucleon. The total normalization error is 10.7% (Table VII)
    - 2D array of the predicted CCQE-like background double differential cross section in each bin in units of 10^{-41} cm^2/GeV/nucleon (Table VIII)
  - **flux-integrated single differential cross section in bins of Q^2 (Figure 14)**
    - 1D array of bin boundaries partitioning the reconstructed four momentum transfer, Q^2
    - 1D array of the value of the single differential cross section in each bin in units of cm^2/GeV^2/nucleon (Table IX)
    - 1D array of the shape uncertainty of the single differential cross section in each bin in units of cm^2/GeV^2/nucleon. The total normalization error is 10.7% (Table IX)
    - 1D array of the predicted CCQE-like background single differential cross section in each bin in units of cm^2/GeV^2/nucleon (Table IX)
  - **flux-unfolded cross section as a function of neutrino energy (Figure 15)**
    - 1D array of bin boundaries partitioning the neutrino energy
    - 1D array of the value of the cross section in each bin in units of cm^2/nucleon (Table X)
    - 1D array of the shape uncertainty of the cross section in each bin in units of cm^2/nucleon. The total normalization error is 10.7% (Table X)
    - 1D array of the total uncertainty of the cross section in each bin in units of cm^2/nucleon (Table X)
    - 1D array of the predicted CCQE-like background cross section in each bin in units of cm^2/nucleon (Table X)

3.9 Data format

Tables on MiniBooNE data release website CCQE NCEL NCπ^o CCπ^+ CCπ^o

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Cross section format

- Flux-integrated double differential cross section CCQE CCπ^+
- Flux integrated single differential cross section CCQE NCEL NCπ^o CCπ^+ CCπ^o

190.0	326.5	539.2	901.8	1288	1633	1857	1874	1803	1636	1354	1047	794.0	687.9	494.3	372.5	278.3	227.4
401.9	780.6	1258	1714	2084	2100	2035	1620	1118	783.6	451.9	239.4	116.4	73.07	41.67	36.55	0	0
553.6	981.1	1501	1884	1847	1629	1203	723.8	359.8	156.2	66.90	26.87	1.527	19.50	0	0	0	0
681.9	1222	1546	1738	1365	909.6	526.7	222.8	81.65	35.61	11.36	0.131	0	0	0	0	0	0
765.6	1233	1495	1289	872.2	392.3	157.5	49.23	9.241	1.229	4.162	0	0	0	0	0	0	0
871.9	1279	1301	989.9	469.1	147.4	45.02	12.44	1.012	0	0	0	0	0	0	0	0	0
910.2	1157	1054	628.8	231.0	57.95	10.69	0	0	0	0	0	0	0	0	0	0	0
992.3	1148	850.0	394.4	105.0	16.96	10.93	0	0	0	0	0	0	0	0	0	0	0
1007	970.2	547.9	201.5	36.51	0.844	0	0	0	0	0	0	0	0	0	0	0	0
1003	813.1	404.9	92.93	11.63	0	0	0	0	0	0	0	0	0	0	0	0	0
919.3	686.6	272.3	40.63	2.176	0	0	0	0	0	0	0	0	0	0	0	0	0
891.8	503.3	134.7	10.92	0.071	0	0	0	0	0	0	0	0	0	0	0	0	0
857.5	401.6	79.10	1.947	0	0	0	0	0	0	0	0	0	0	0	0	0	0
778.1	292.1	33.69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
692.3	202.2	17.42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
600.2	135.2	3.624	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
497.6	85.80	0.164	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
418.3	44.84	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
348.7	25.82	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
289.2	15.18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3.9 Data format

Tables on MiniBooNE data release website CCQE NCEL NCπ^o CCπ^+ CCπ^o

- In MiniBooNE, all cross section tables, as well as flux table, are released in website
http://www-boone.fnal.gov/for_physicists/data_release/

Cross section format

- Flux-integrated double differential cross section CCQE CCπ^+

- Flux integrated single differential cross section CCQE NCEL NCπ^o CCπ^+ CCπ^o

- Flux-unfolded total cross section CCQE NCπ^o CCπ^+ CCπ^o

Additional tables

- signal-like background tables are presented, so that people can use either exclusive cross section or effective cross section. CCQE NCEL

- response matrix R is presented so that people can calculate MiniBooNE observed energy spectrum NCEL

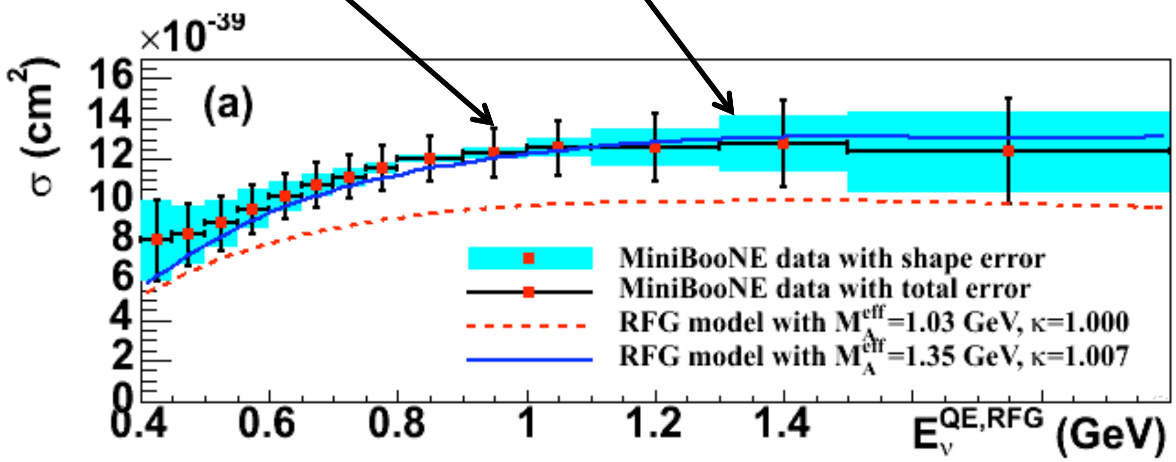
3.9 Data format

Cross section error format

- Complete error matrix of differential cross sections NCπ^o CCπ$^+$ CCπ^o
- Complete error matrix for reconstructed energy spectrum NCEL
- Diagonal term of shape only error matrix and total normalization error. CCQE

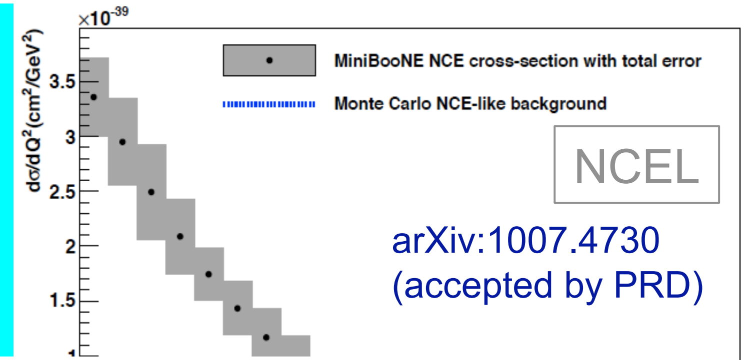
Diagonal term of shape only error matrix has information of covariance of total error matrix, so this is a convenient way to show bin-bin correlation in 1-dimention

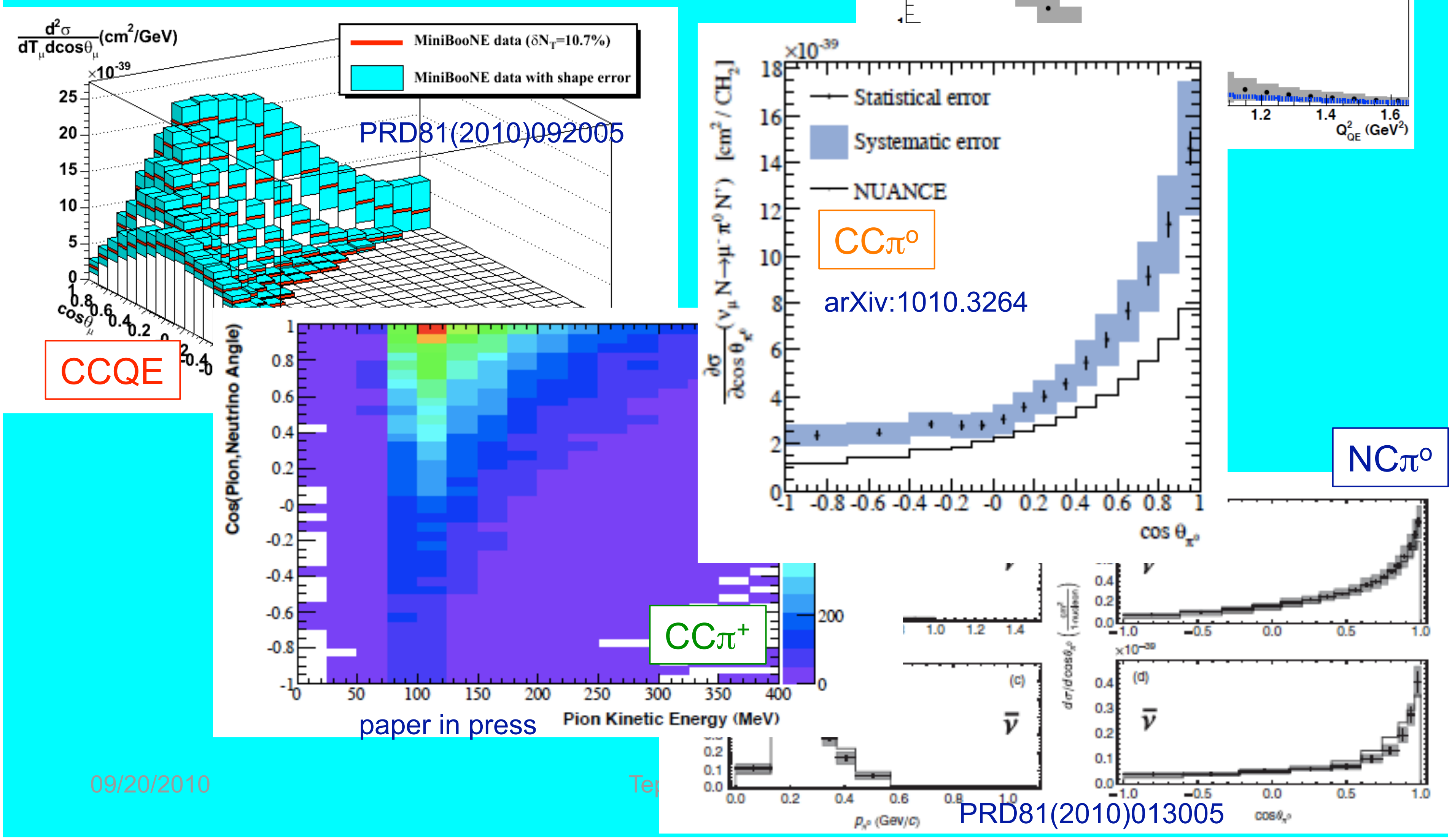
$$\delta V_i^{total} = \sqrt{E_{ii}} \qquad \delta V_i^{shape} = \sqrt{E_{ii} - 2\frac{V_i}{N}\sum_k^n E_{ki} + \frac{V_i^2}{N^2}\sum_{k,m}^n E_{km}}$$



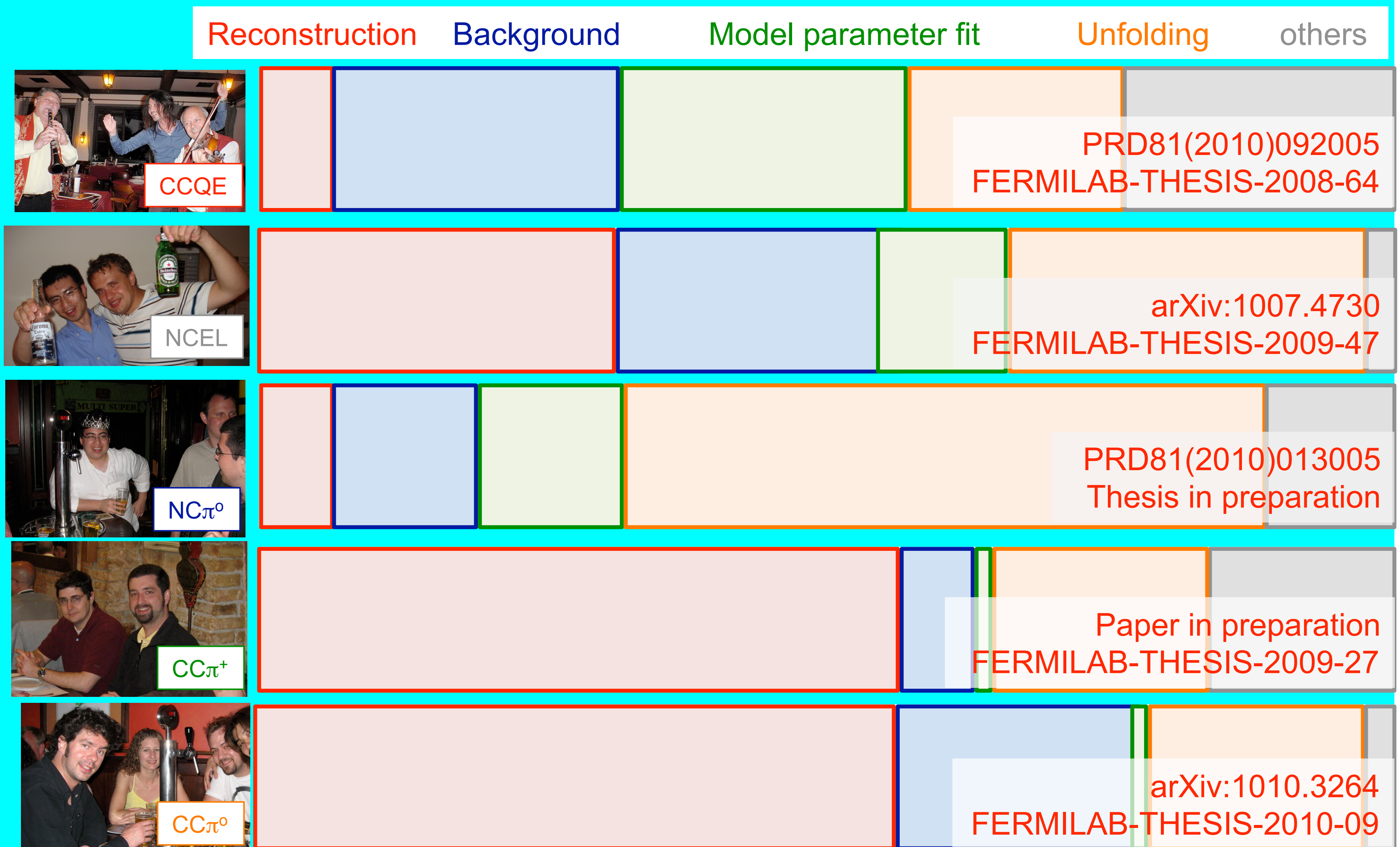
3.9 Data format

MiniBooNE cross section result gallery





3.10 Bar chart of time spent by analyzers



note: Under the assumption everyone spent same amount of time. This is my subjective view!

4. Conclusions

Cross section measurement consist 7 pieces
1. definition of signal
2. background subtraction
3. unsmearing
4. efficiency correction
5. flux correction
6. target number correction
7. binning

Systematic error needs some care, don't add all variations every place!
1. background cross section error
   background term
2. signal cross section error
   unsmearing matrix
3. detector error
   unsmearing matrix, efficiency
4. flux error
   flux term
5. overall normalization error
   target number, POT can be added by quadrature

BooNE collaboration

University of Alabama
Bucknell University
University of Cincinnati
University of Colorado
Columbia University
Embry Riddle Aeronautical University
Fermi National Accelerator Laboratory
Indiana University
University of Florida

Los Alamos National Laboratory
Louisiana State University
Massachusetts Institute of Technology
University of Michigan
Princeton University
Saint Mary's University of Minnesota
Virginia Polytechnic Institute
Yale University

Thank you for your attention!