T2K Near Detector Fit - Exclusive Behind the Scenes Materials

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T2K

Introduction

I am working on the oscillation analysis in T2K.

In oscillation analysis we perform fit/fits using near detector data and far detector data.

Analysis is still ongoing however main part of my work is mostly finished.

Those results will be shown at **Neutrino 2022** conference.

Main aim of this talk is to present tools that are used in the T2K analysis, and to convince you that we know what we are doing ☺

Outline

- T2K experiment
- Cross Section Model and parameters used in the fit
- ND280 selections for data/MC comparison used in the fit
  - New photon and proton selection
- Markov Chain Monte Carlo
  - What is it
  - How T2K uses it
- Reweighting
- Impact of ND280 Fit

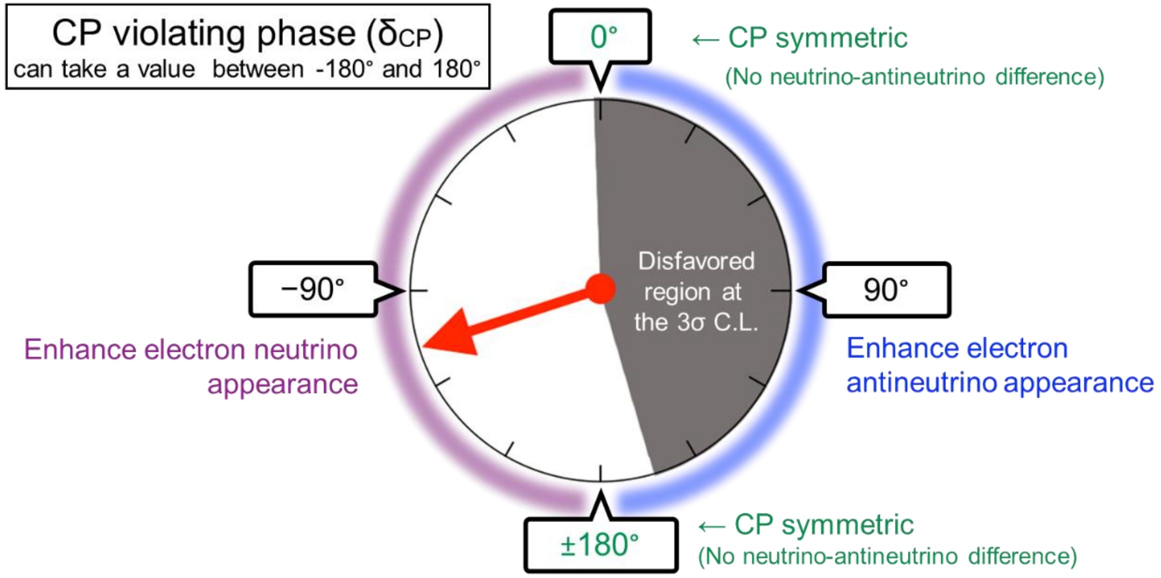
T2K

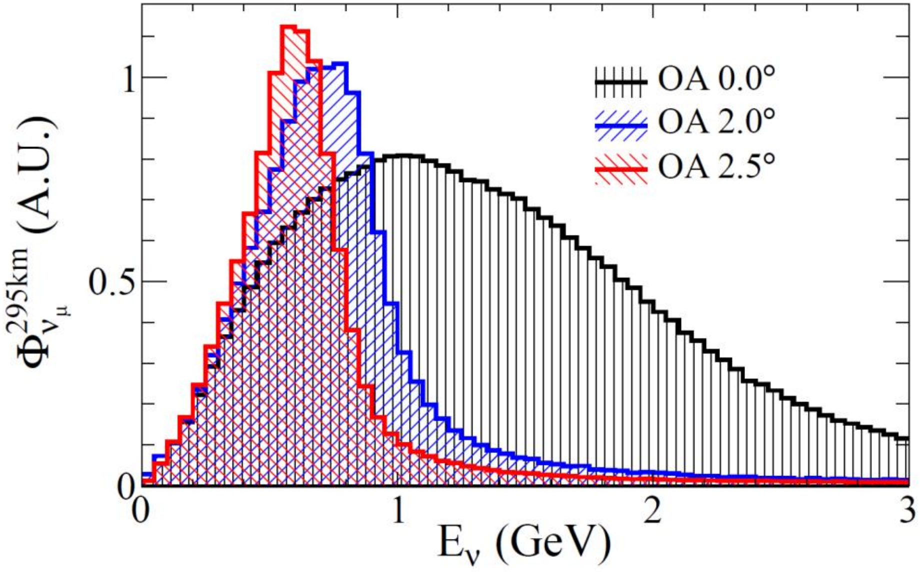
T2K

T2K is long baseline experiment studying neutrino oscillation.

T2K is studying neutrino and antineutrino oscillations to determine δ_{CP}. Latest results suggest nearly maximal CP violation.

T2K uses off-axis technique to have much narrower beam spectrum.

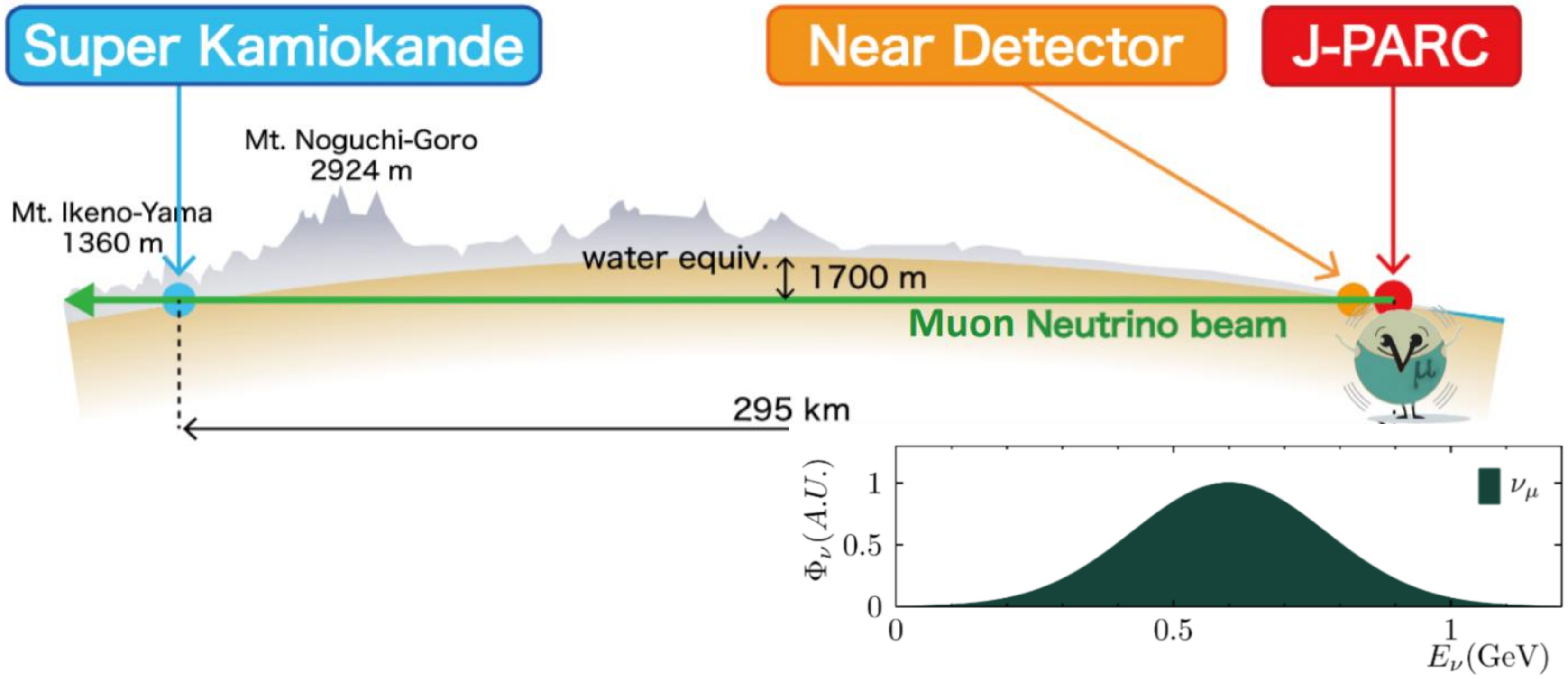




Tokai to Kamioka (T2K) experiment

T2K is located in Japan

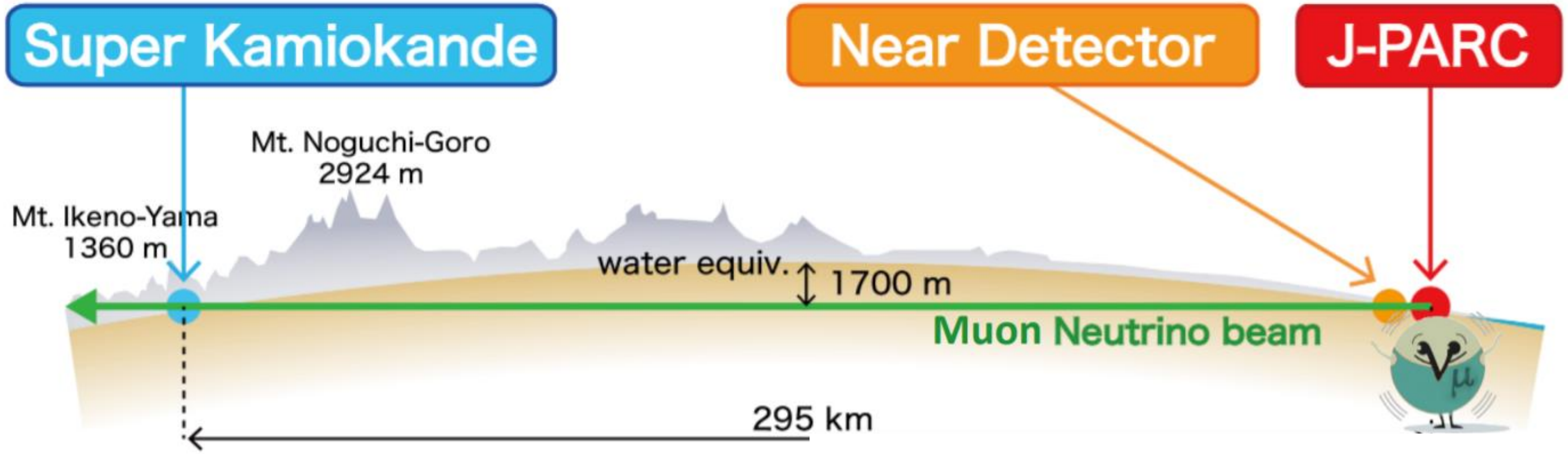
- We create mostly muon neutrinos at J-PARC.

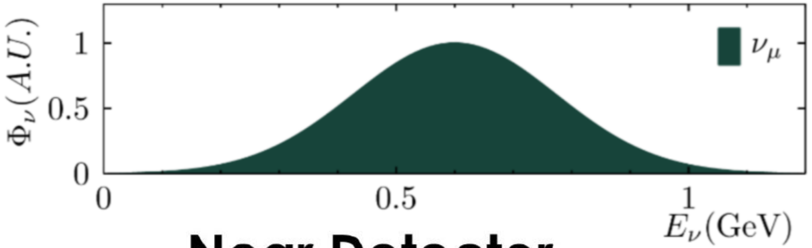


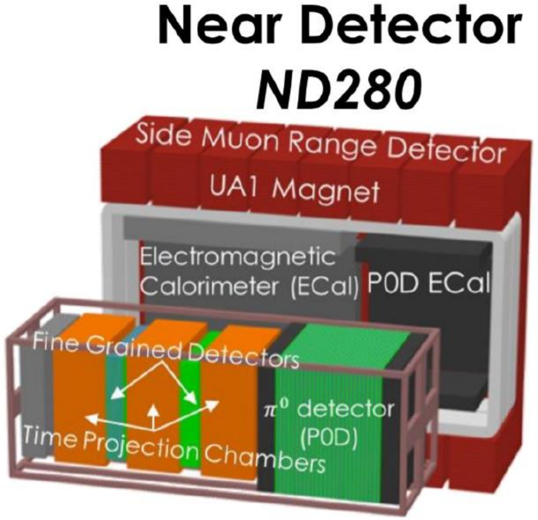
T2K experiment

T2K is located in Japan

- We create mostly muon neutrinos at J-PARC.
- We measure neutrinos with Near Detector.



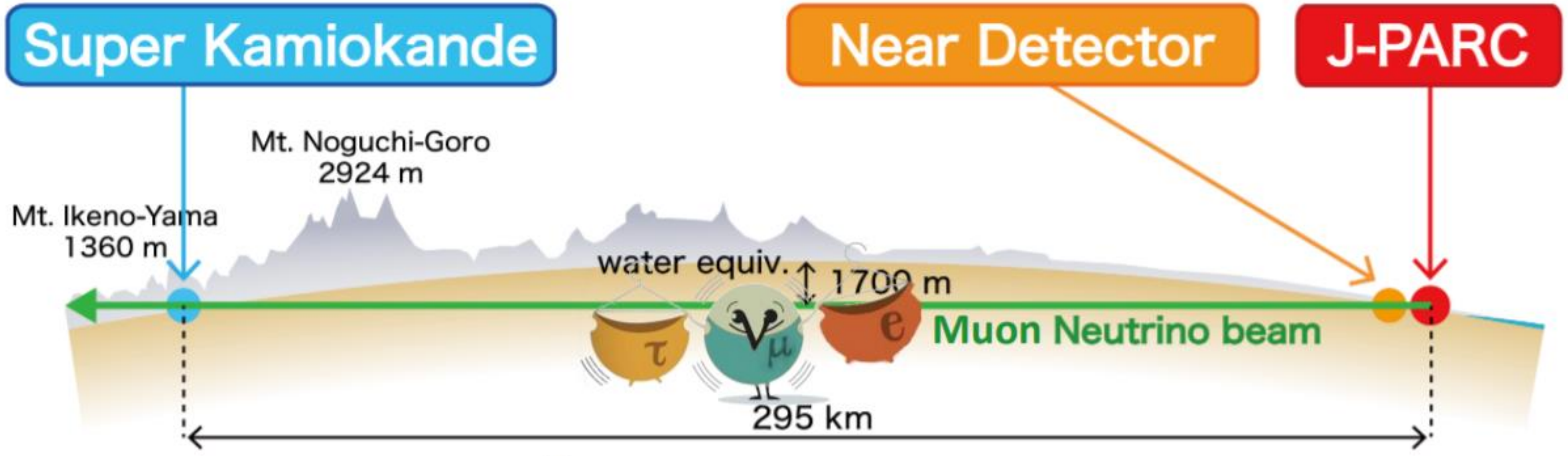


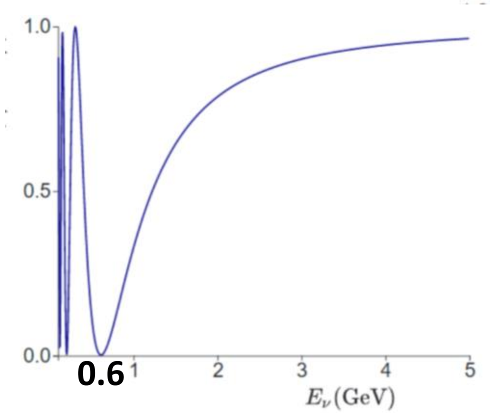


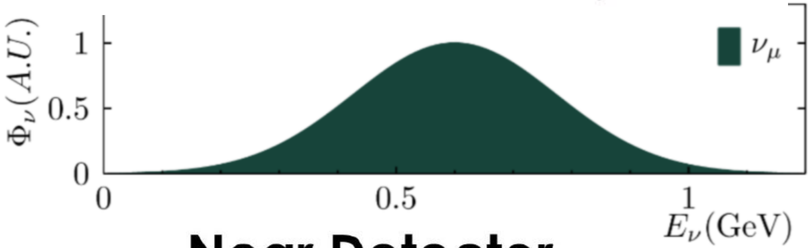
T2K experiment

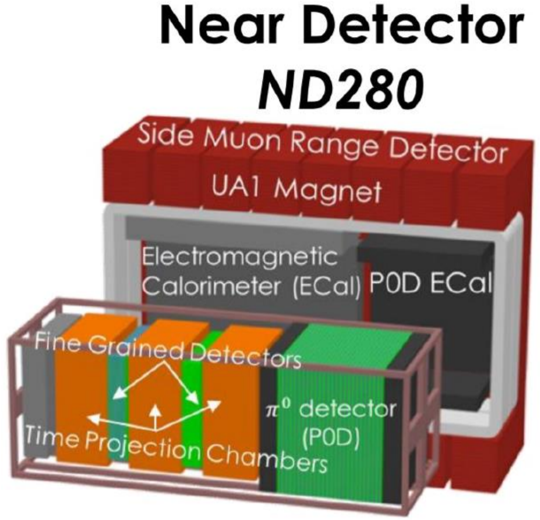
T2K is located in Japan

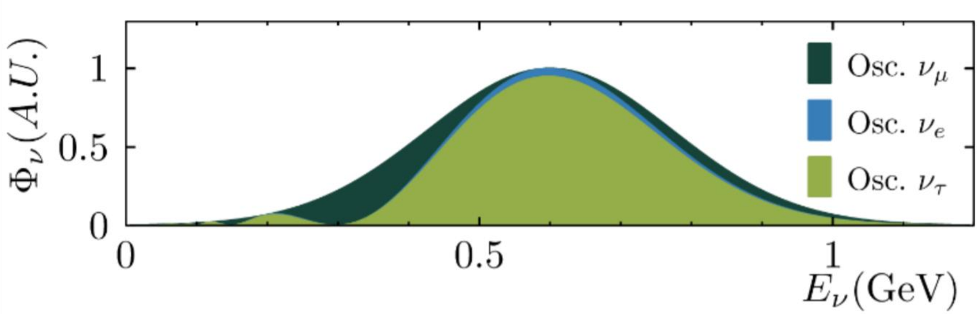
- We create mostly muon neutrinos at J-PARC.
- We measure neutrinos with Near Detector.
- Neutrinos oscillate.







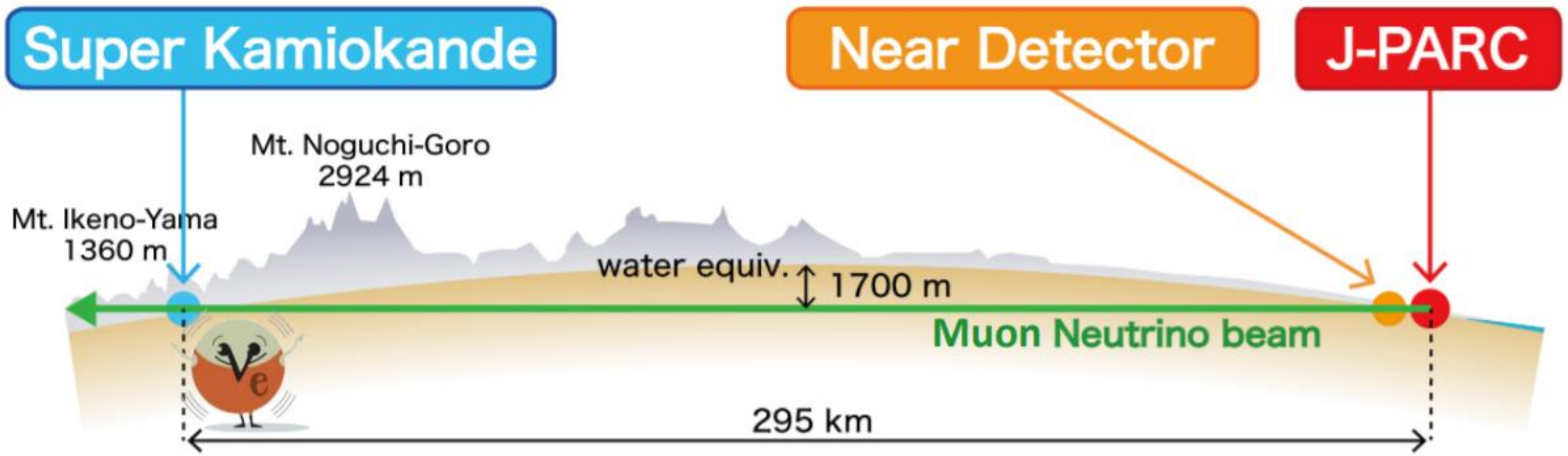


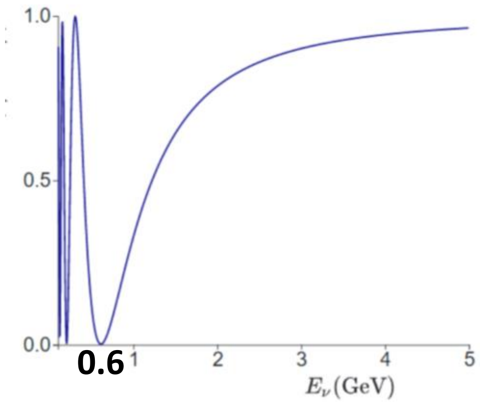


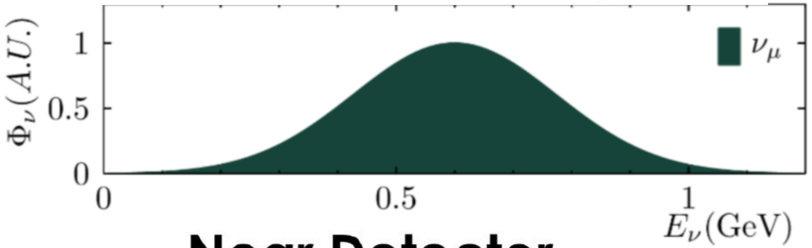
T2K experiment

T2K is located in Japan

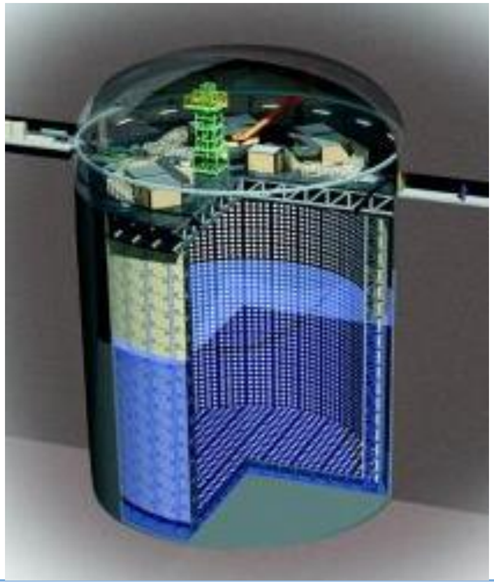
- We create mostly muon neutrinos at J-PARC.
- We measure neutrinos with Near Detector.
- Neutrinos oscillate.
- Neutrinos are measured in Far Detector

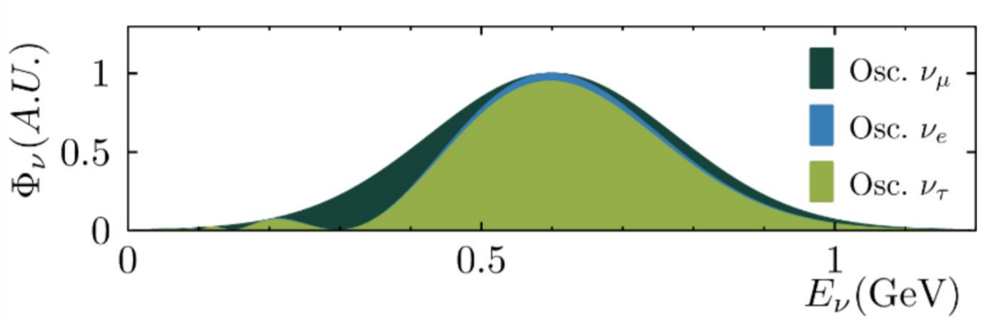




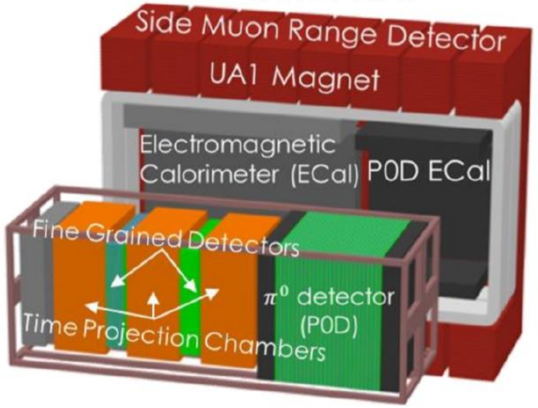


Far Detector
Super Kamiokande





Near Detector
ND280



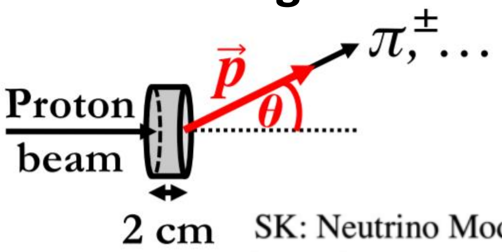
Flux Model

Primary interactions of protons in target simulated with **FLUKA**, propagation through horns and decay volume with GEANT3

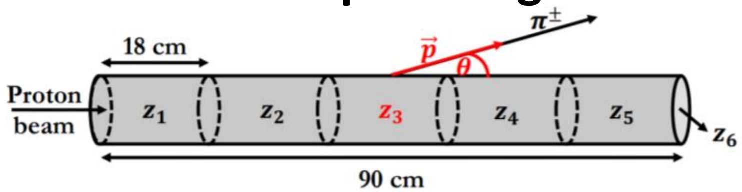
To make flux prediction less model dependent T2K uses **NA61/SHINE** replica target data to tune flux model.

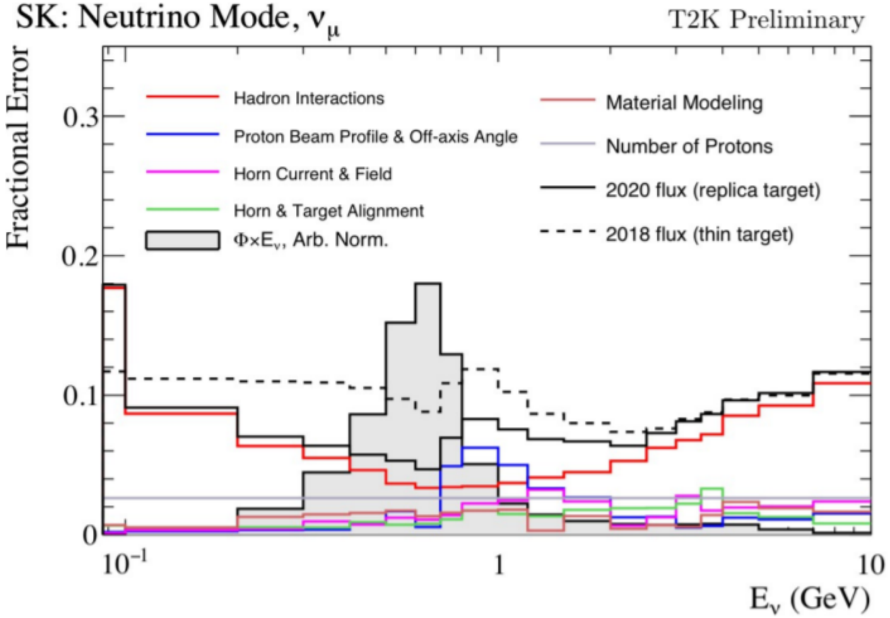
Flux uncertainties reduced from 8% (thin) to 5% (replica) in flux peak.

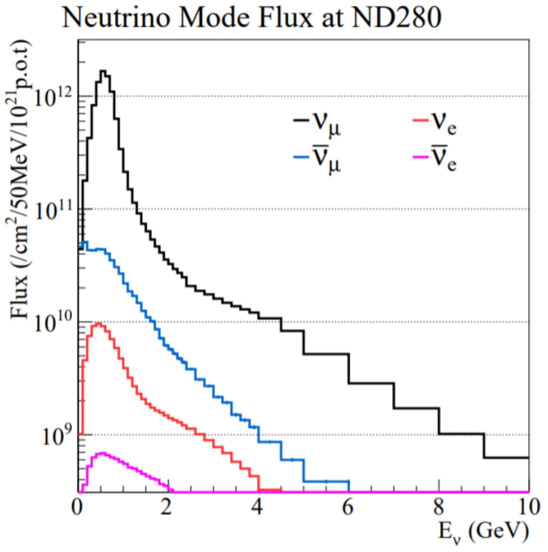
Thin target

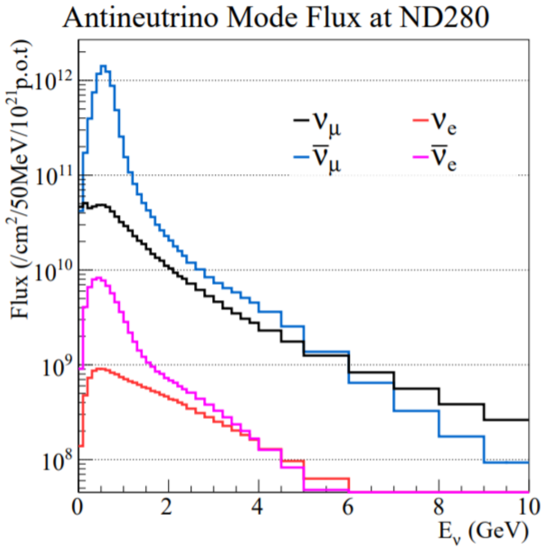


Replica target









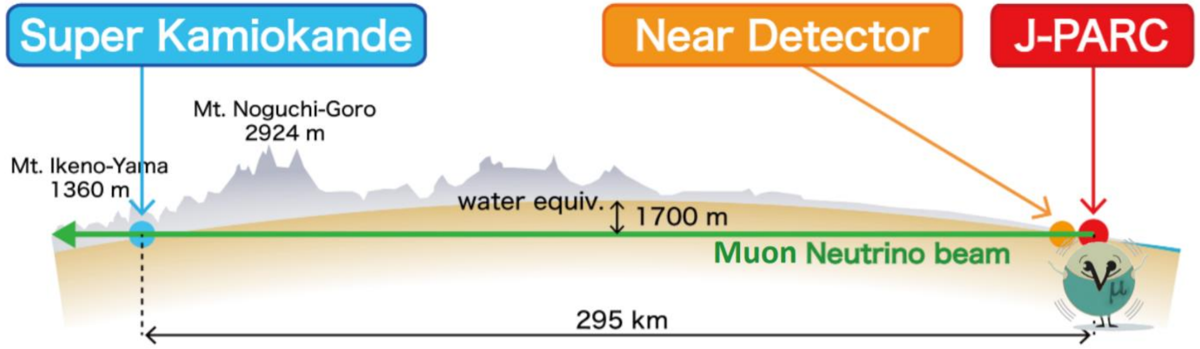
In antineutrino mode, there is higher fraction of wrong sign component than in neutrino mode.

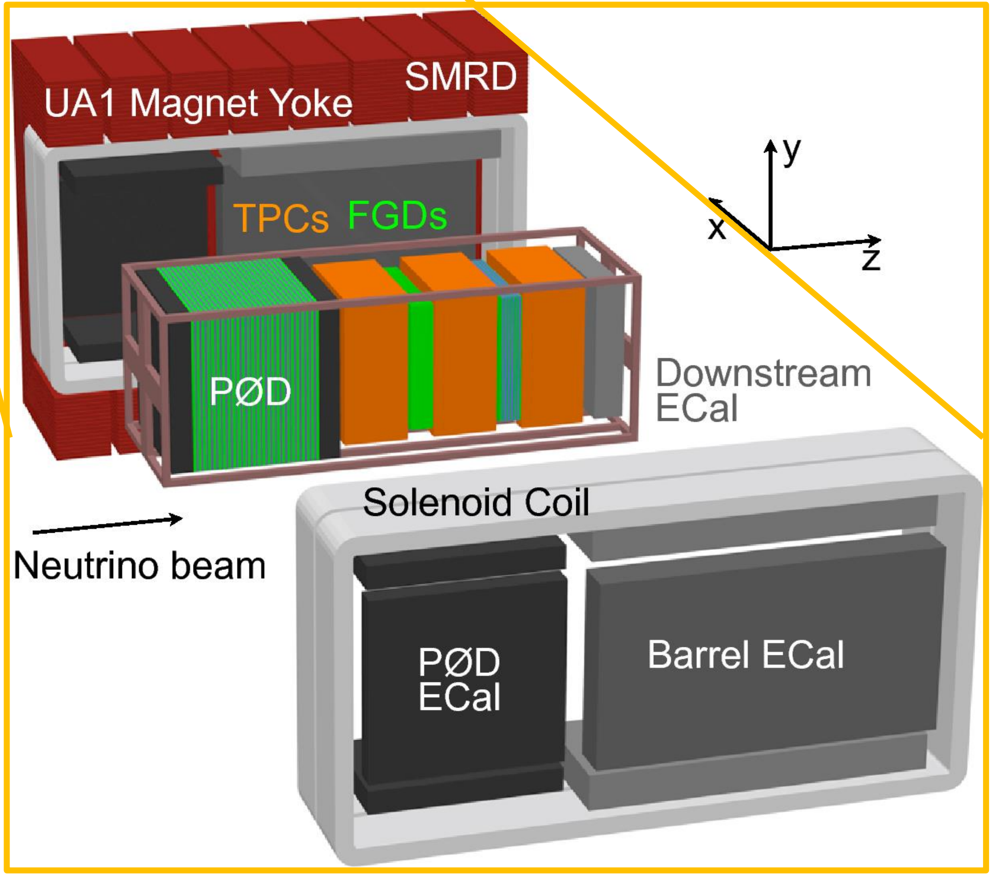
Why Near Detector

$$N(E_\nu^{rec}) = \Phi_{SK}^{exp}(E_\nu^{true}) \times \boxed{\sigma(E_\nu^{true})} \times P_{osc}(E_\nu^{true})$$

Number of expected events in SK depends on neutrino **flux** and **cross-section** and **oscillations**.

ND280 measures neutrinos before oscillations, this means we can constrain **cross-section** without worrying about oscillations.





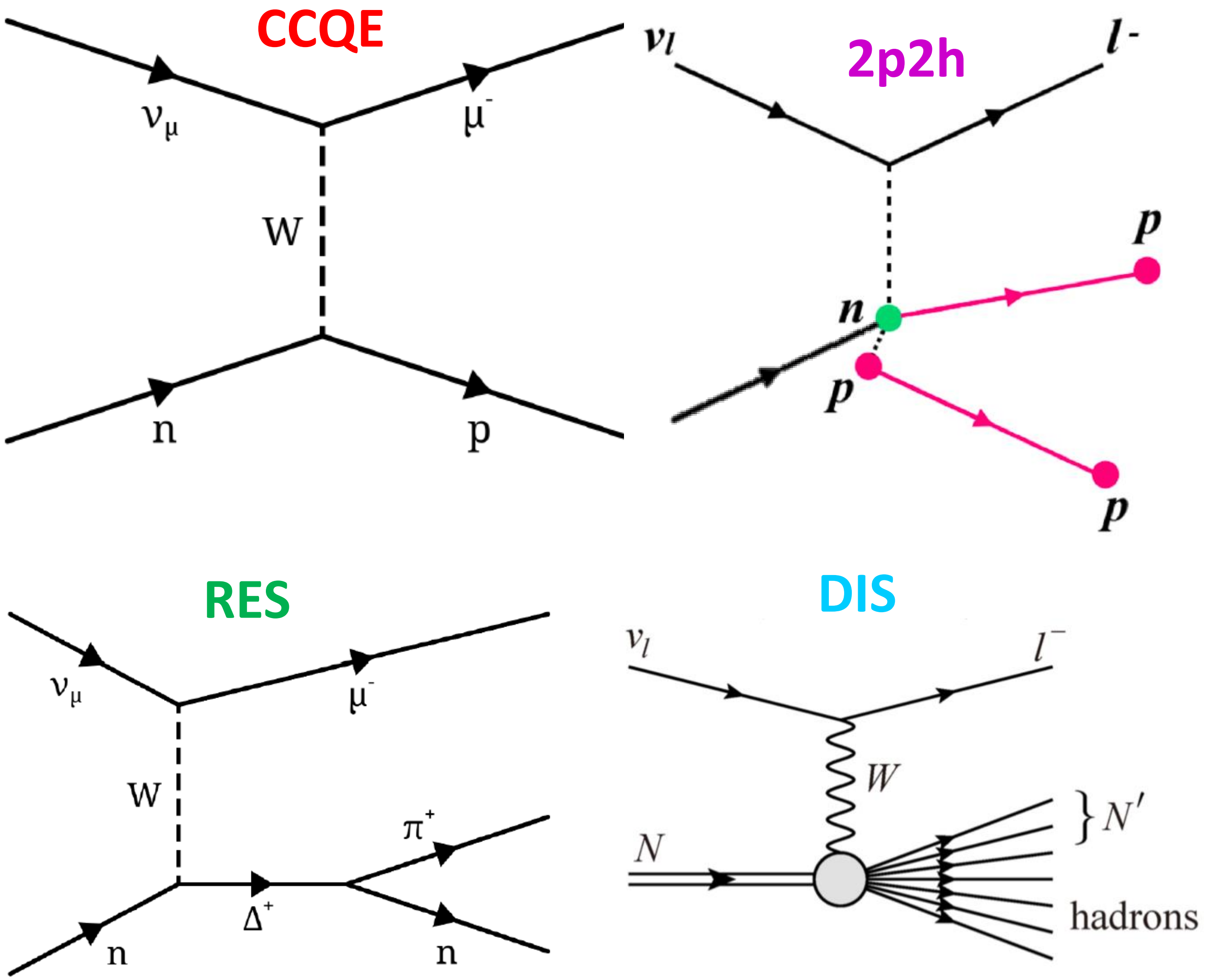
Neutrino Interactions

Neutrino can undergo different interactions, most important are:

- CCQE – two body process.
- 2p2h – on correlated nucleon pair.
- RES – delta resonance production.
- DIS – parton level interaction.

Each interaction is simulated using different model.

Our cross-section models are described by many parameters. Each parameter has prior value with an error which can be changed (constrained) using the ND fit.



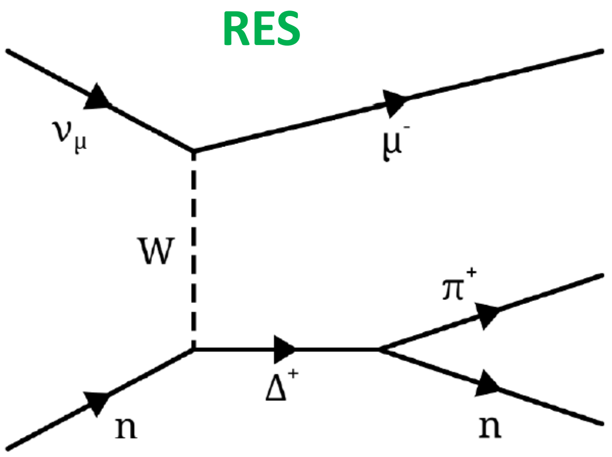
FSI

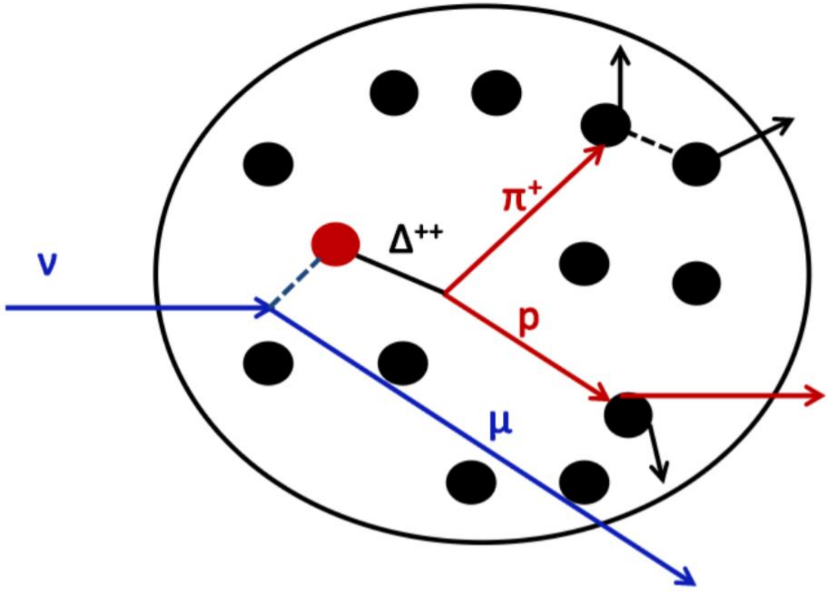
Final State Interactions – interactions that secondary particles can undergo inside nucleus.

For example, pion produced in **RES** can be absorbed. Pion can also change its charge or eject nucleon.

Proton can eject neutron or another proton.

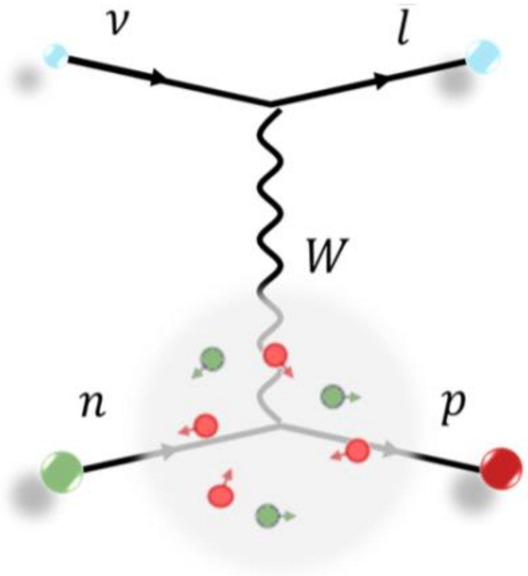
FSI can highly alter what we see in experiments, this can result in wrong evaluation of cross-section for given interactions.

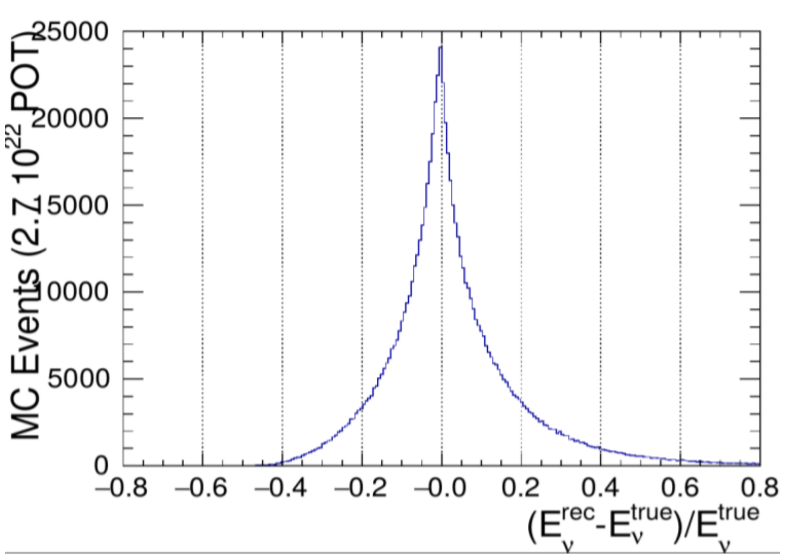




Neutrino interacts with nucleon which isn't stationary. This leads to bias of reconstructed neutrino momentum in T2K.

Hence detailed description of initial state model is important

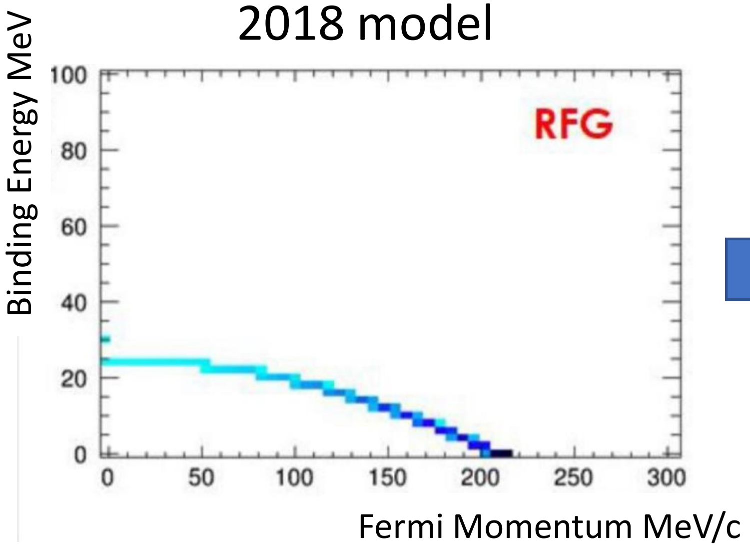




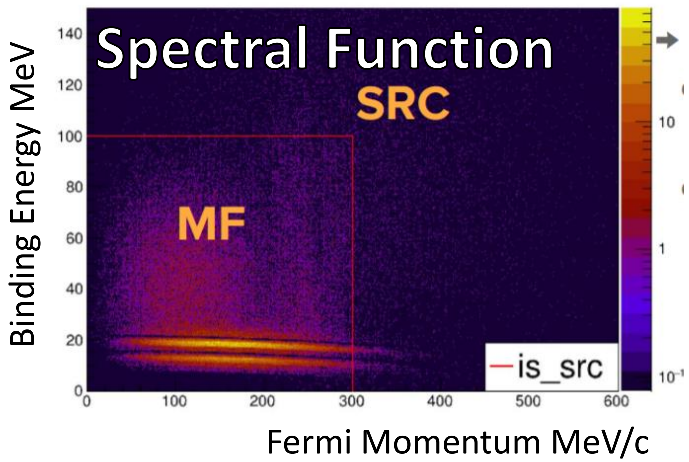
Spectral Function is sophisticated model based on electron scattering data.

Even though Spectral Function was added in 2020, the new analysis significantly improves systematic model related to it.

2018 model



2020 model



Spectral Function: New Parameters

Spectral Function model consist of two parts:

Mean Field - Single nucleon moving in a mean field potential

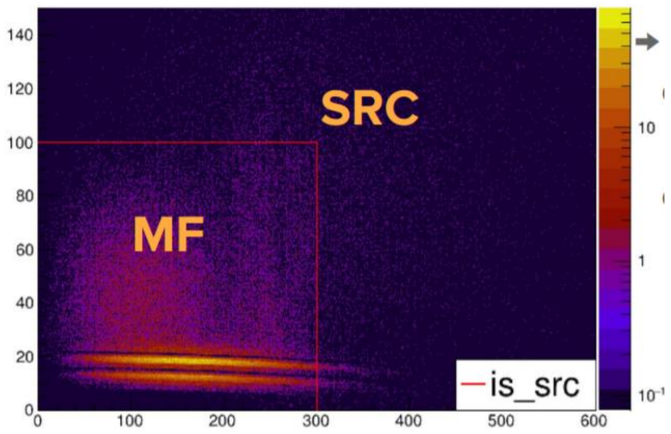
Short Range Correlation - Pairs of strongly-correlated nucleons result in two nucleon in the final state.

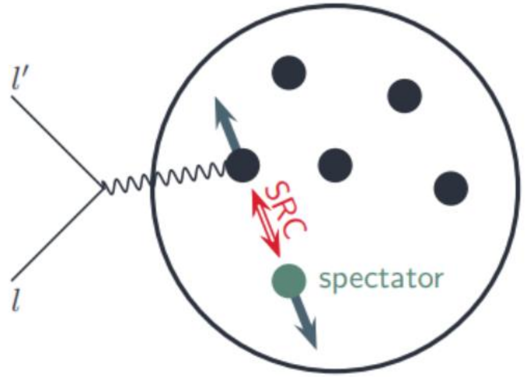
In **the new analysis** we add parameter allowing to modify shell structure.

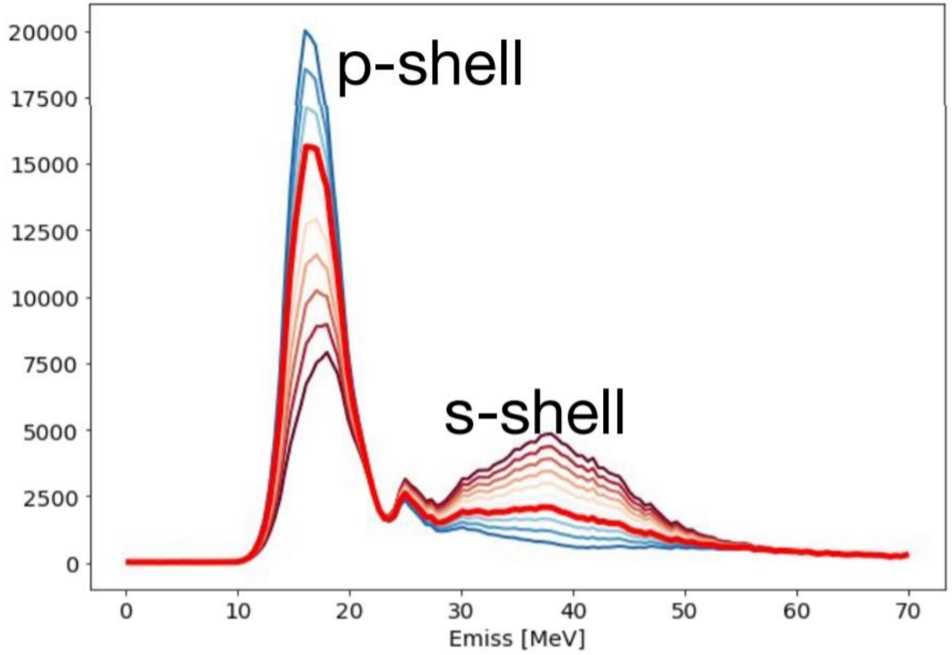
Furthermore, we have parameters allowing to modify fraction of SRC.

This means having nucleon information in the ND is even more important.

NEUT







Pauli Blocking

Spectral Function is good model physically motivated; however, it overestimates event rate at low Q2.

This may be not a problem of Spectral Function itself but effects which are not modeled in SF.

Last year to solve this problem T2K used ad-hoc Q2 dependent normalization parameters.

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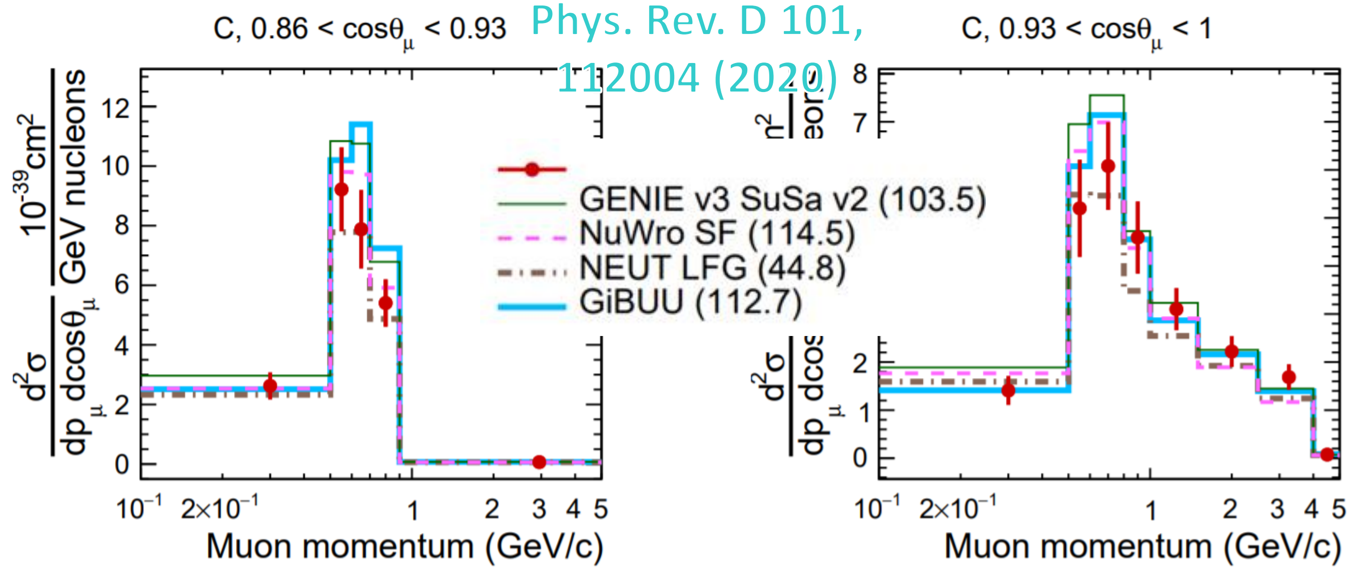
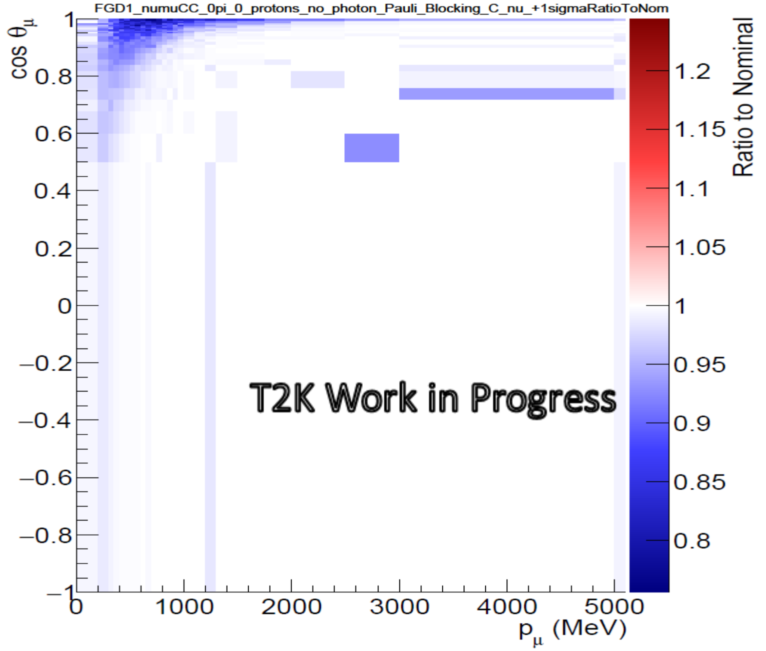
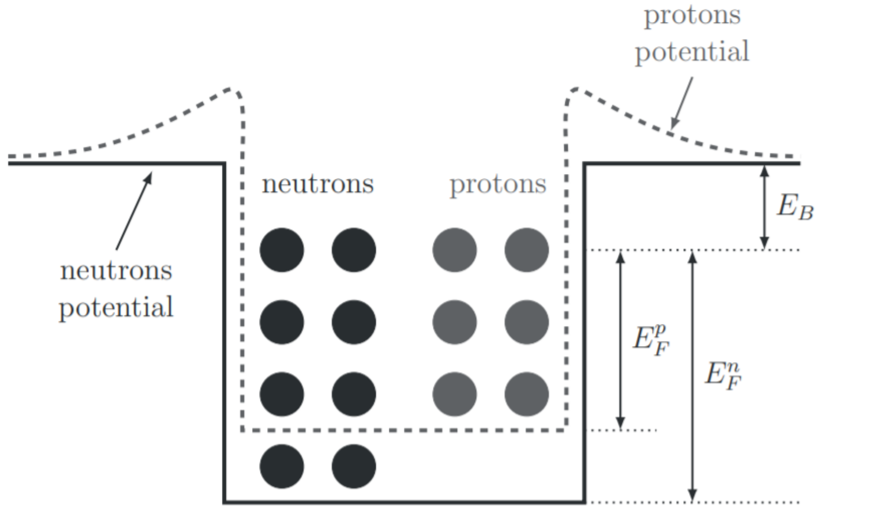


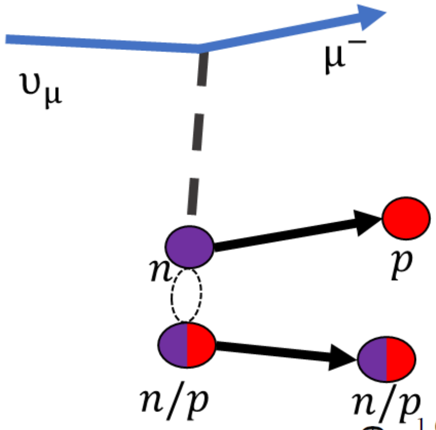




This year T2K introduces Pauli Blocking parameters. By moving Fermi Surface, we can supress low Q2 events.

New 2p2h Parameter

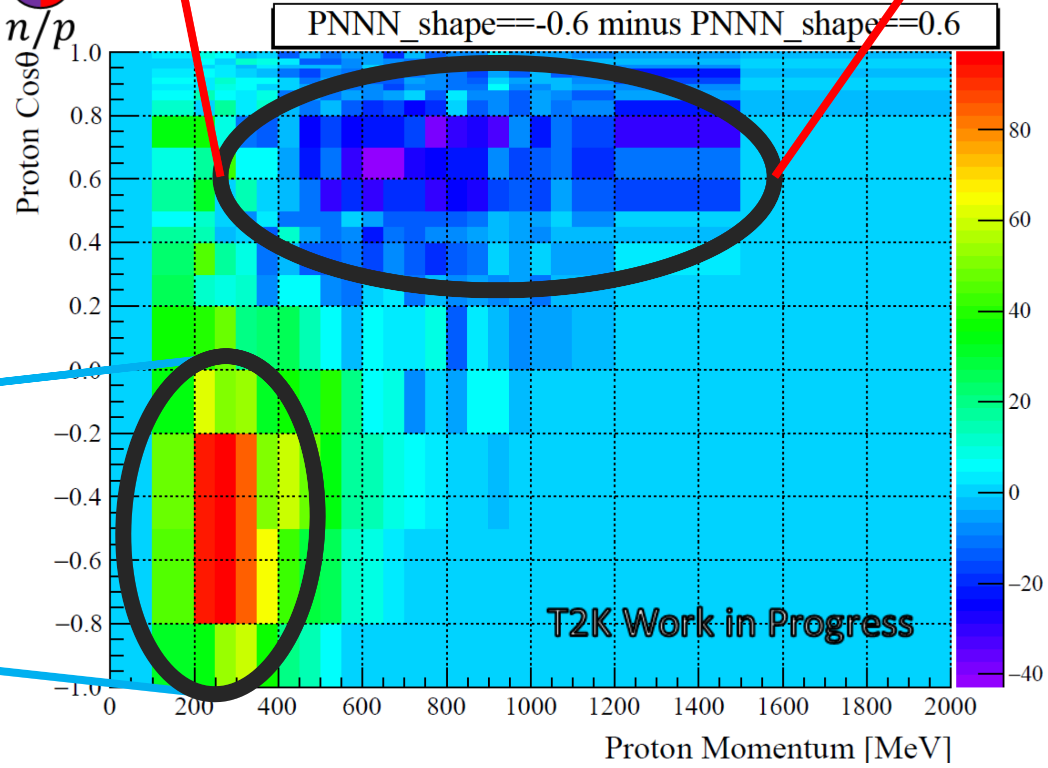
2p2h give similar signature as SRC but physics wise this is different effect as in 2p2h we have meson exchange.



2p2h can happen on either neutron–proton pair or neutron–neutron pair.

I have developed new parameter changing ratio of this pair, which influences proton momentum distribution.

Increase of **pn** shifts events to higher momentum, forward going protons.



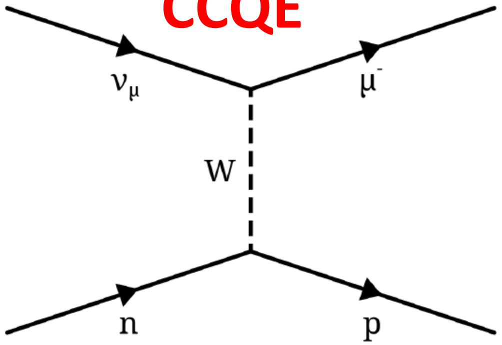
Obviously, we have much more parameters than presented. Those examples should give you idea what kind of effect we are describing in neutrino experiments and that we are approaching precision era in neutrino physics.

Increase of **nn** shifts events to lower momentum, higher angles.

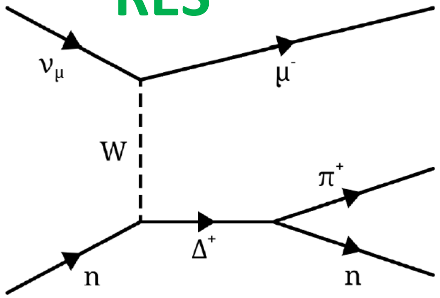
What is Topology

Interaction Mode

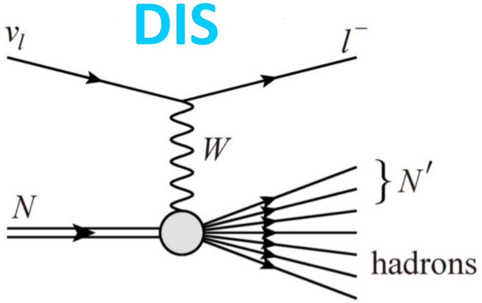
CCQE



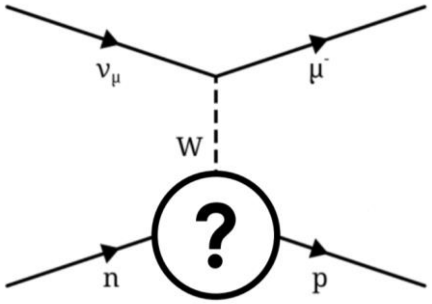
RES



DIS



Interaction Topology



CC0π (CCQE-like)

What we observe in the detector due to physical effects as well reconstruction inefficiency isn't necessarily what really happened.

We differentiate between:

- **Interaction mode** (that truly happened).
- **Interaction Topology** (what we observed).

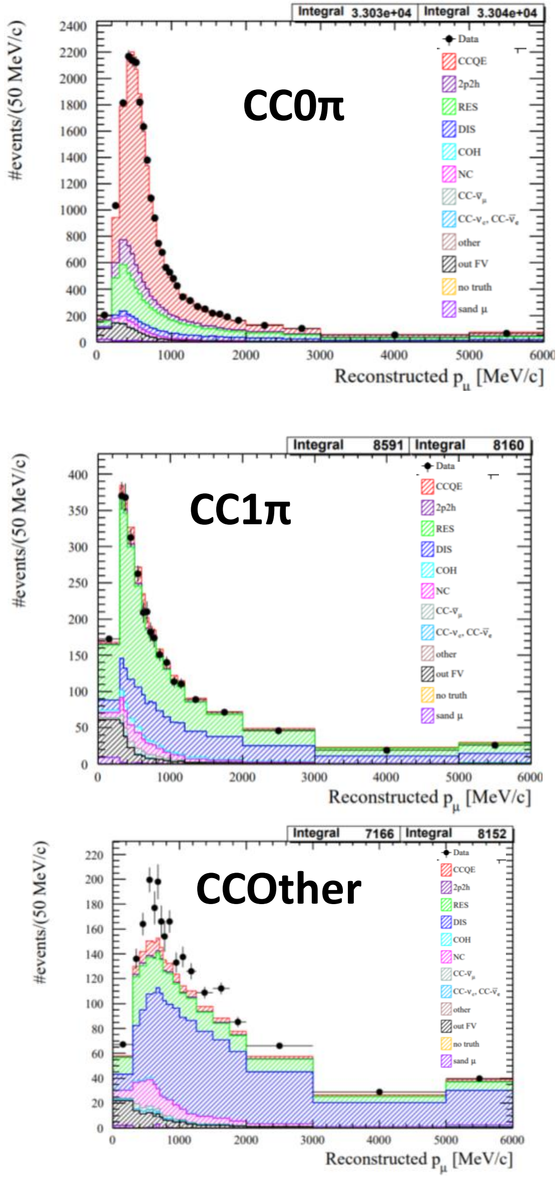
ND Samples

In ND280 we were using several samples:

CC0π mostly constrains CCQE
μ^- and no pions
CC1π mostly constrains RES
μ^- and π^+
CCOther mostly constrains DIS
μ^- and other combinations of pions

Furthermore, each sample has different kinematic properties.

2020 Samples

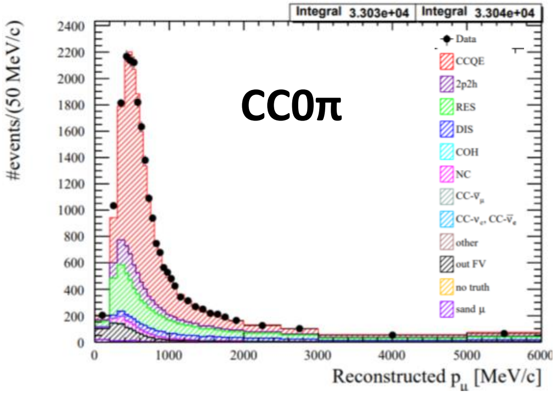


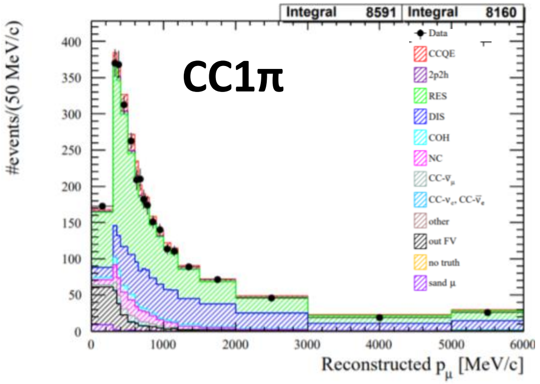
New Samples

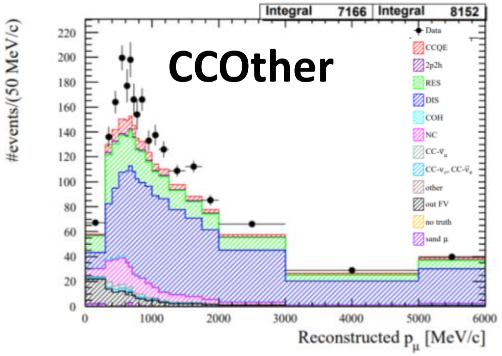
This year we add new information to the fit thanks to photon and proton tagged samples.

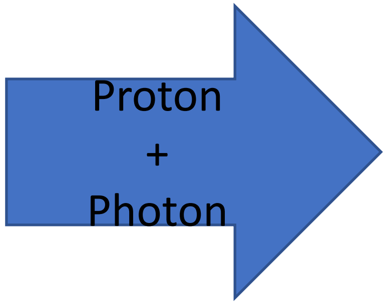
New samples have different muon kinematics and purities for reaction modes.

2020 Samples

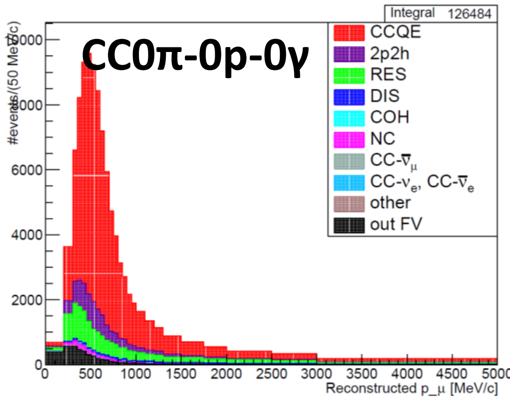


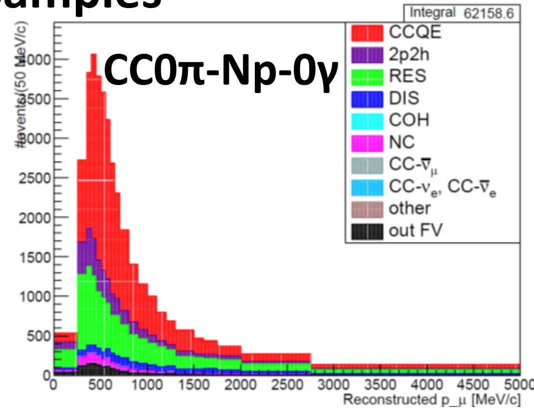


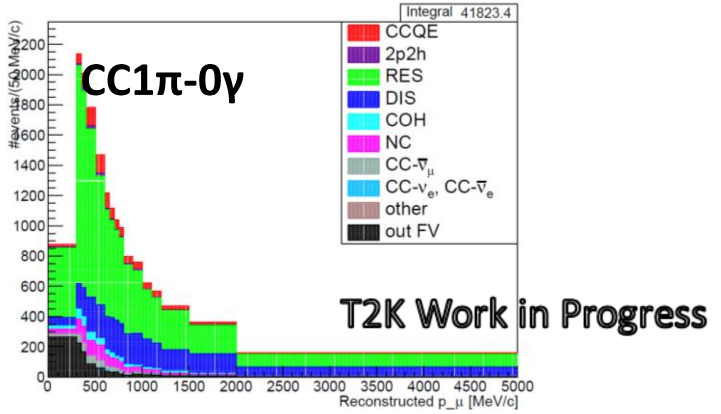


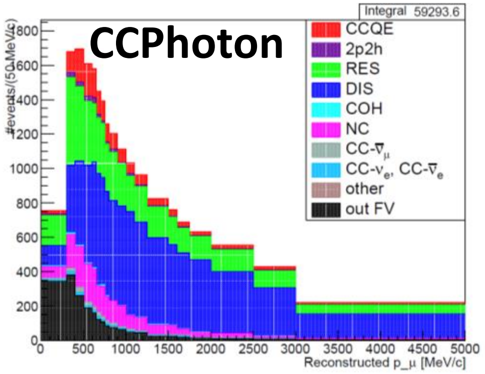


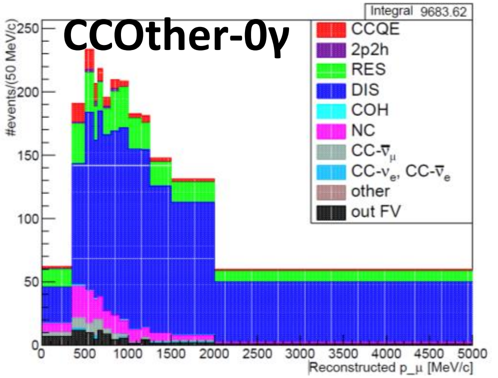
2021 Samples











FGD1 and FGD2

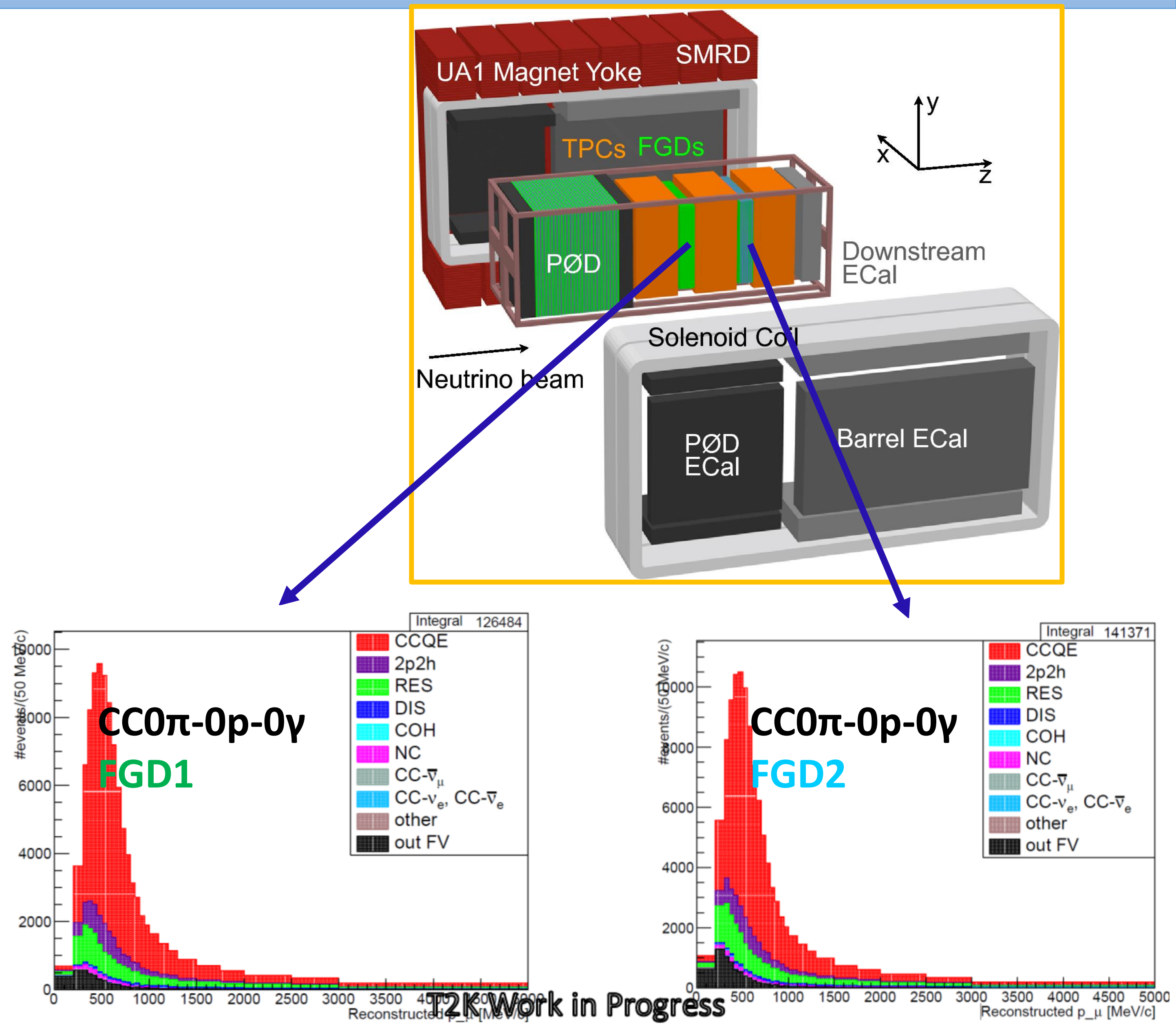
ND280 has two interaction targets which are organic scintillation detectors:

FGD1 is Hydro-carbon detector
FGD2 is hydro-carbon with water layers.

Therefore, we have two types of selection with interaction vertex in FGD1 or FGD2.

Other than that, selection types and cuts are identical in both subdetectors.

T2K far detector is filled with ultra-pure water. Since some parameters are different for carbon and oxygen, we need FGD2 samples to better constrain them. For example, Pauli Blocking can be slightly different for both elements.



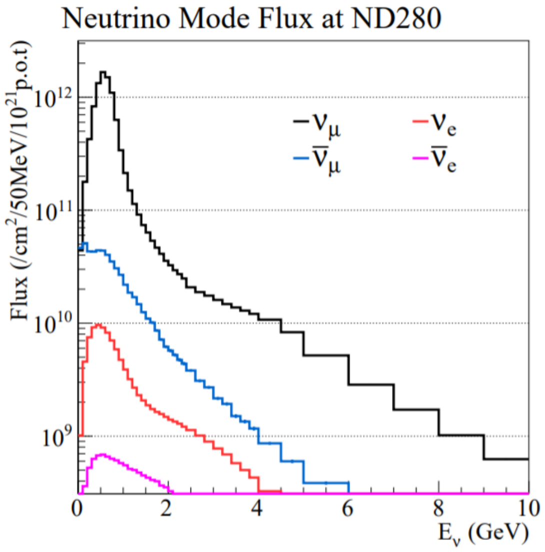
ND280 Samples

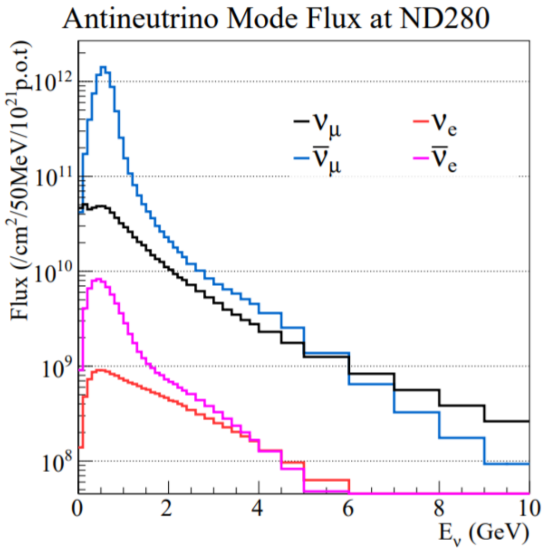
T2K has also antineutrino beam mode samples. They are exactly the same as in previous analysis. Only pion information is used.

Furthermore, there is neutrino background in antineutrino mode.

Far detector cannot differentiate between positive and negatively charged particles, so ND information is critical.

There are plans to expand RHC selection in the future.





All Reconstructed Events

FHC ν_μ CC Inclusive (FGD1 and FGD2)	RHC $\bar{\nu}_\mu$ CC Inclusive (FGD1 and FGD2)	RHC ν_μ CC Inclusive (FGD1 and FGD2)
↓	↓	↓
CC0π-0p-0γ	CC0π	CC0π
CC0π-Np-0γ	CC1π	CC1π
CC1π-0γ	CCOther	CCOther
CCOther-0γ		
CCPhoton		

Neutrino beam mode samples Antineutrino beam mode samples

Two Fitters

ND analysis is based on fitting MC samples to data by changing model parameters.

At **ND fit** two groups are working using different frameworks and methods which give very similar results.

BANFF

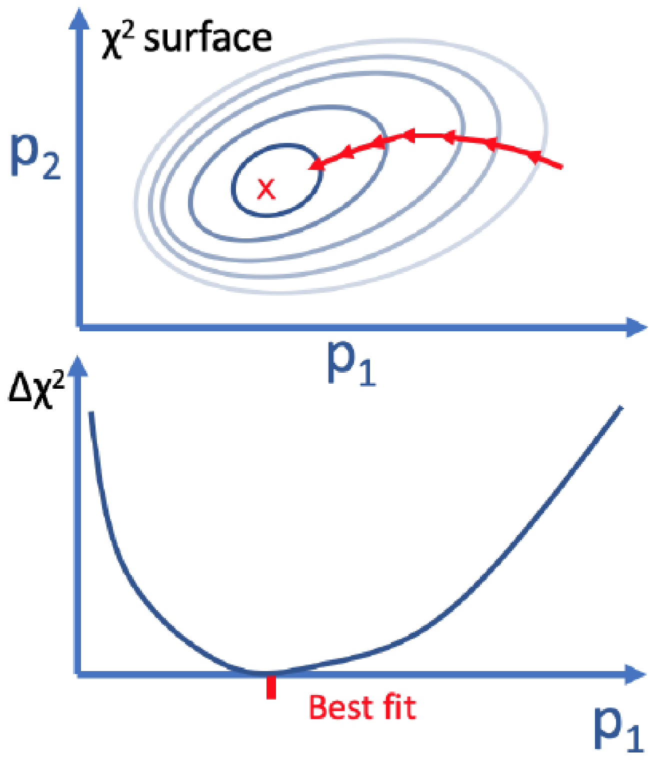
- MINUIT minimizer
- Frequentist approach
- Gives postfit covariance matrix to FD fitters

MaCh3

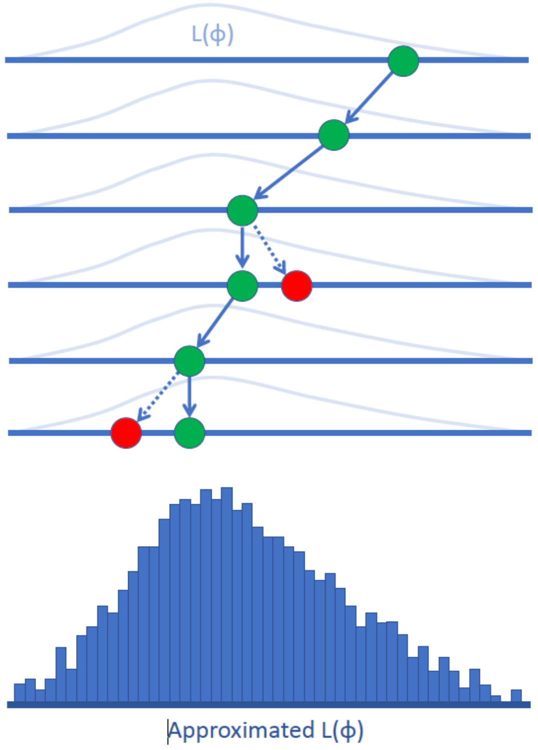
- Markov Chain Monte Carlo Fitter
- Bayesian approach
- Used in MaCh3 ND+FD joint fit

I am working in the latter so I will focus on it only.

Minuit Fitter
BANFF



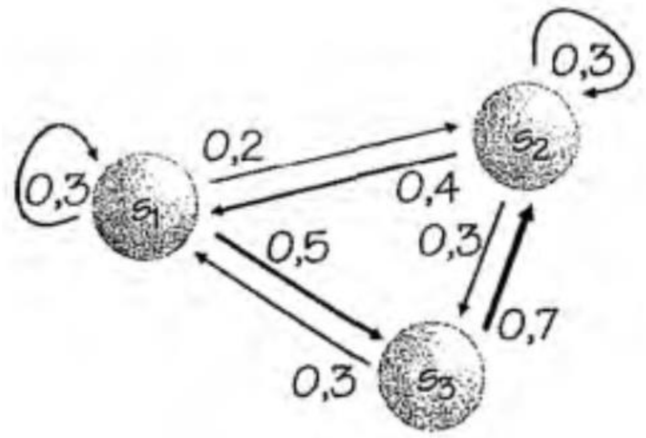
Markov Chain
Monte Carlo
MaCh3



Markov Chain Monte Carlo

Transition Matrix

Consider a simple board game with 3 fields. Pawn can be only on one field at the time. Transition between different fields is given by some probability. This can be represented by **Markov Diagrams**.



We can translate the diagram into **Transition Matrix**.

End state

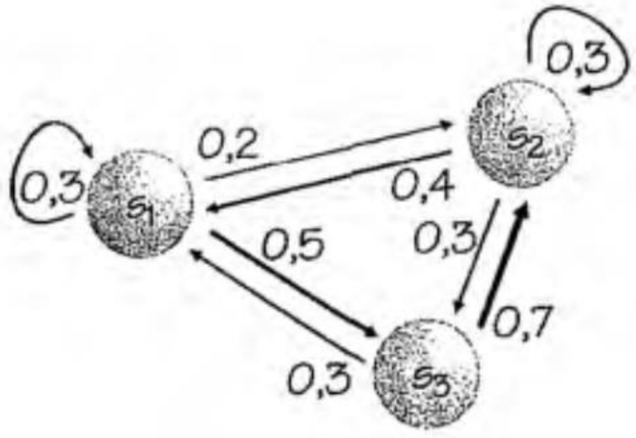
Initial state

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} = \begin{pmatrix} 0{,}3 & 0{,}2 & 0{,}5 \\ 0{,}4 & 0{,}3 & 0{,}3 \\ 0{,}3 & 0{,}7 & 0{,}0 \end{pmatrix}$$

Remark: probability in given row always sums up to **1,** isn’t true for columns.

Markov property

X_n - **random variable** describing the state at step n. We can think of this as measurement of the state at n-th time interval.



Example: P($X_1 = s_1 | X_0 = s_3$) = 0.3
Example: P($X_{13} = s_1 | X_{12} = s_3$) = 0.3

$$P(X_n = x_n \mid X_{n-1} = x_{n-1}, \ldots, X_0 = x_0) = P(X_n = x_n \mid X_{n-1} = x_{n-1})$$

Markov property - conditional probability distribution of future states of the process depends **only** upon the present state.

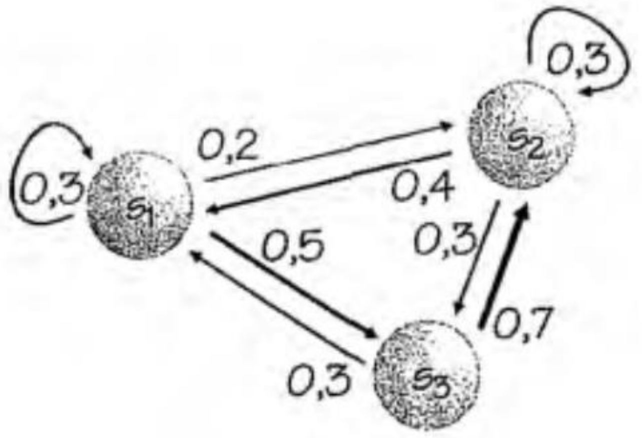
A process with this property is known as Markovian or a Markov process. Brownian motion is well-known Markov process.

This property is also referred to as **memorylessness.**

State transition

$$(p_1(0), p_2(0), p_3(0)) \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} = (p_1(1), p_2(1), p_3(1))$$

(1 ; 0 ; 0) **P** = (0.3 ; 0.2 ; 0.5)



This tells us about probability of being in given state (s_1, s_2 , s_3) for given step (n). Now let's look at transition from n=1 to n=2.

$$(p_1(1), p_2(1), p_3(1)) \begin{pmatrix} 0.3 & 0.2 & 0.5 \\ 0.4 & 0.3 & 0.3 \\ 0.3 & 0.7 & 0.0. \end{pmatrix} = (p_1(2), p_2(2), p_3(2))$$

$(p_1(2), p_2(2), p_3(2))$=(0.32; 0.47; 0.21)

Table shows probabilities of being in given state for 10 consecutive steps.

Compare first and last values in columns 2,3,4 and 5,6,7, respectively.

n	$p_1(n)$	$p_2(n)$	$p_3(n)$	$p_1(n)$	$p_2(n)$	$p_3(n)$
0	1,0000	0,0000	0,0000	0,0000	0,0000	1,0000
1	0,3000	0,2000	0,5000	0,3000	0,7000	0,0000
2	0,3200	0,4700	0,2100	0,3700	0,2700	0,3600
3	0,3470	0,3520	0,3010	0,3270	0,4070	0,2660
4	0,3352	0,3857	0,2791	0,3407	0,3737	0,2856
5	0,3386	0,3781	0,2833	0,3374	0,3802	0,2825
6	0,3378	0,3795	0,2827	0,3380	0,3792	0,2827
7	0,3379	0,3793	0,2827	0,3379	0,3793	0,2828
8	0,3379	0,3793	0,2828	0,3379	0,3793	0,2828
9	0,3379	0,3793	0,2828	0,3379	0,3793	0,2828

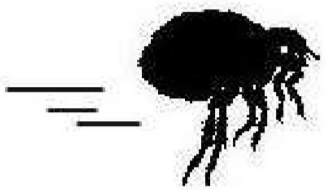
Stationary distribution

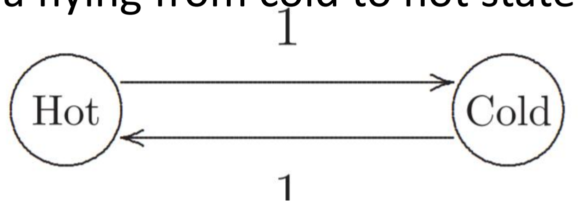
Clearly, periodicity of the chain will interfere with convergence to an equilibrium distribution as $t \to \infty$.

Stationary Markov Chain must be **aperiodic**

- Markov Chain has to be **irreducible** **-** any state can be reached with positive probability from any other state in a finite number of steps.
- Markov Chain has only one stationary distribution independent of initial state if it is **ergodic** **(irreducible** and **aperiodic).**
- Sufficient but not necessary condition for existence of stationary state is **Detailed Balance** (known from statistical physics). It states that at equilibrium, each elementary process is in equilibrium with its reverse process.

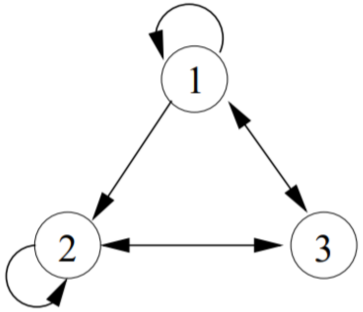
Consider flea flying from cold to hot state.



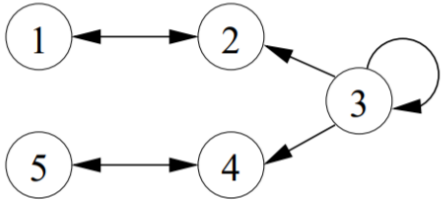


It clearly doesn't have stationary state.

$$p(0) = (1,0)$$
$$p(1) = (0,1)$$
$$p(2) = (1,0)$$



Irreducible



Not irreducible

$$\boxed{\pi(x)P(x' \mid x) = \pi(x')P(x \mid x')}$$

This equation will come back in MCMC.

Real life example

In 1913 there was 300th anniversary of **Romanov** rule in Russia.

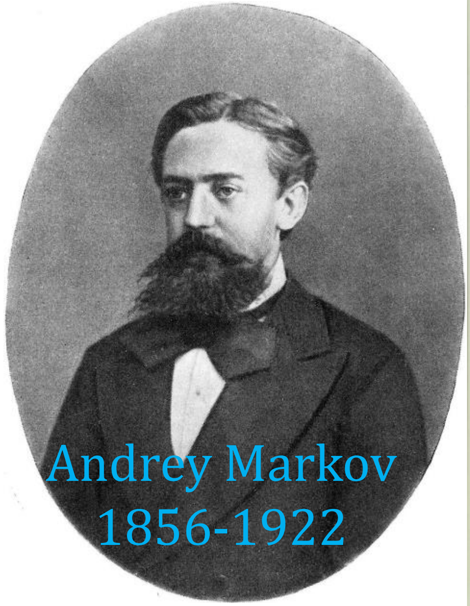
Markov was part of liberal movement in Russia.
In 1913 there was also 200 anniversary of discovery **Bernoulli law of large numbers.**

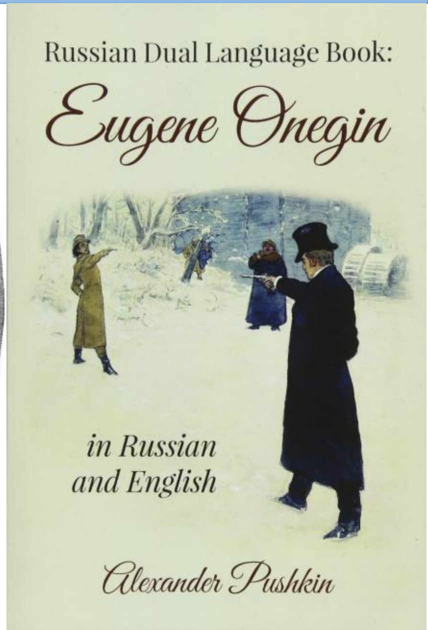
Markov organized counter-celebration and analyzed 20000 letters of **Alexander Pushkin** book „*Eugene Onegin*”.

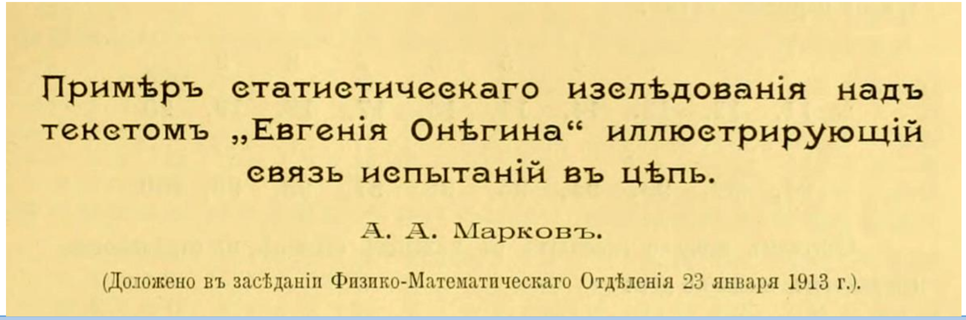
By dividing letters consonants and vowel he created transition matrix

Then he found stationary state **π**=[0.432, 0.568], which suggested that „*Eugene Onegin*” consisted in 43.2% of vowels and in 56.8% of consonants.

And this is in fact true!






Примѣръ статистическаго изслѣдованія надъ текстомъ „Евгенія Онѣгина“ иллюстрирующій связь испытаній въ цѣпь.

А. А. Марковъ.

(Доложено въ засѣданіи Физико-Математическаго Отдѣленія 23 января 1913 г.).

	vowel	consonants
vowel	0.128	0.872
consonants	0.663	0.337

Markov Chain Monte Carlo Introduction

Detailed balance equation

$$\pi(x)P(x' \mid x) = \pi(x')P(x \mid x')$$

This can be represented as

$$\frac{P(x'|x)}{P(x|x')} = \frac{\pi(x')}{\pi(x)}$$

Transition probability is split into proposal (or auxiliary) distribution $\boldsymbol{g(x'|x)}$ and „acceptance" probability $A(x', x)$ – probability of accepting new state.

$$P(x' \mid x) = g(x' \mid x)A(x', x).$$

Finally, we achieve:

$$\boxed{\frac{A(x',x)}{A(x,x')} = \frac{\pi(x')g(x|x')}{\pi(x)g(x'|x)}}$$

Metropolis–Hastings algorithm part 1

Up to this point, derivations of all MCMC are the same.

$$\frac{A(x',x)}{A(x',x)} = \frac{\pi(x')g(x|x')}{\pi(x)g(x'|x)}$$

Differences come in g distributions and most importantly in $A(x',x)$.

Metropolis–Hastings algorithm:

$$A(x',x) = min\left(1, \frac{\pi(x')g(x|x')}{\pi(x)g(x'|x)}\right)$$

We can rephrase $A(x',x)$ using Likelihood ratio.

$$\boxed{A(x^{'},x) = min\left(1, \frac{\mathcal{L}(x^{'})}{\mathcal{L}(x)}\right)}$$

In ND fit we use Poissonian likelihood with MC statistic correction (Barlow-Beeston) and systematic penalty term.

$$\Delta\chi^2 = 2\sum_i \left[N_i^{\mathrm{MC}}(\vec{\theta}) - N_i^{\mathrm{data}} + N_i^{\mathrm{data}} \ln\left(\frac{N_i^{\mathrm{data}}}{N_i^{\mathrm{MC}}(\vec{\theta})}\right) + \frac{(\beta_i - 1)^2}{2\sigma^2_{\beta_i}} \right]$$

If in proposed step data-MC agreement is better, we always accept such step, if agreement is worse, we might accept step. How does it work?

Metropolis–Hastings algorithm part 2

- Let's build initial state $x_0 = (x_0^0, x_0^1, x_0^2, x_0^3 \dots)$. x_0 is vector of parameter values, for example , $x_0^0\ is\ PauliBlocking = 0$

$$A(x', x) = min\left(1, \frac{\pi(x')g(x|x')}{\pi(x)g(x'|x)}\right)$$

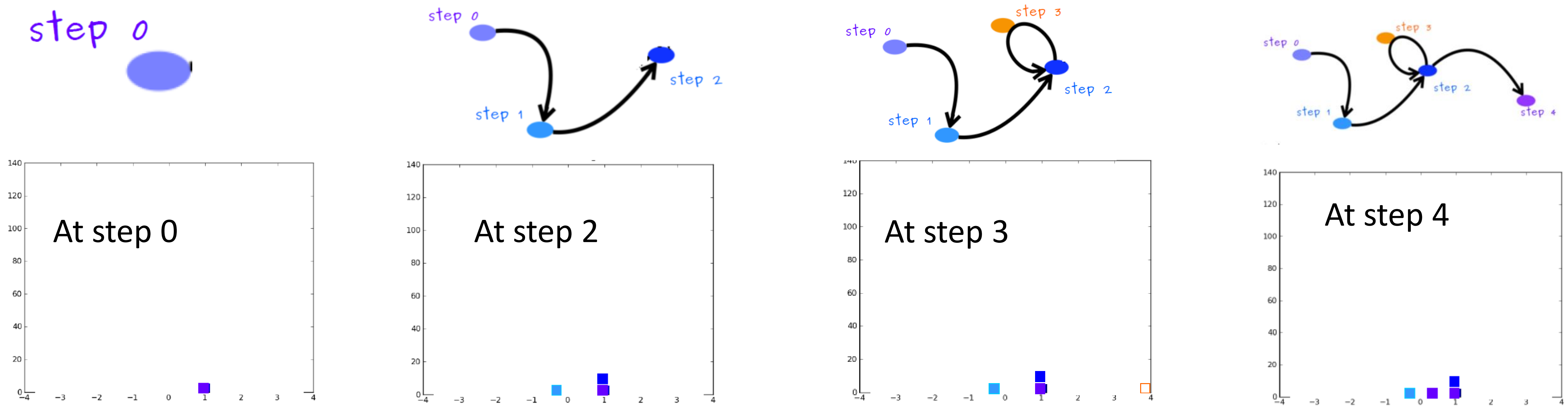
- Propose new state x' from $g(x'|x)$ - There is a large freedom in selecting $g(x'|x)$. We use Gaussian proposal with width of distribution dictated by prior parameter error.

- Now we have to decide if we accept new state
  - If $A(x', x) = 1$ - we always accept new candidate
  - If $A(x', x) < 1$ – we draw random number 0< *u* <1
    - $A(x', x)$>= *u*: we accept x'
    - $A(x', x)$< *u*: we stay in state x

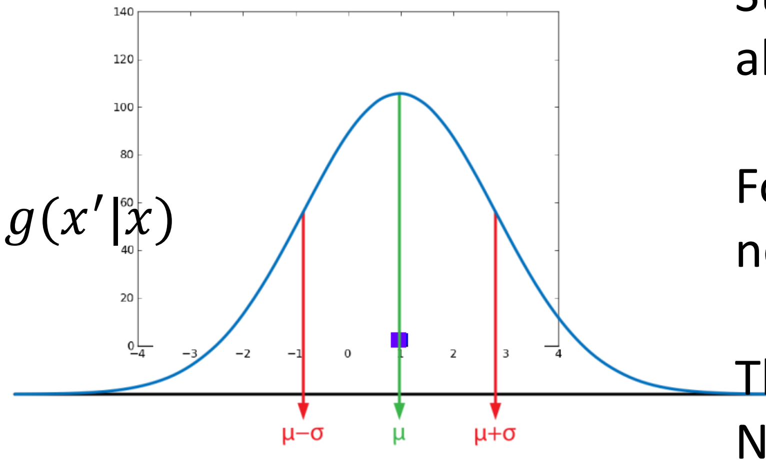
$$\boxed{A(x', x) = min\left(1, \frac{\mathcal{L}(x')}{\mathcal{L}(x)}\right)}$$

- Propose new state x' from $g(x'|x)$ and so on…

1D MCMC Visualization



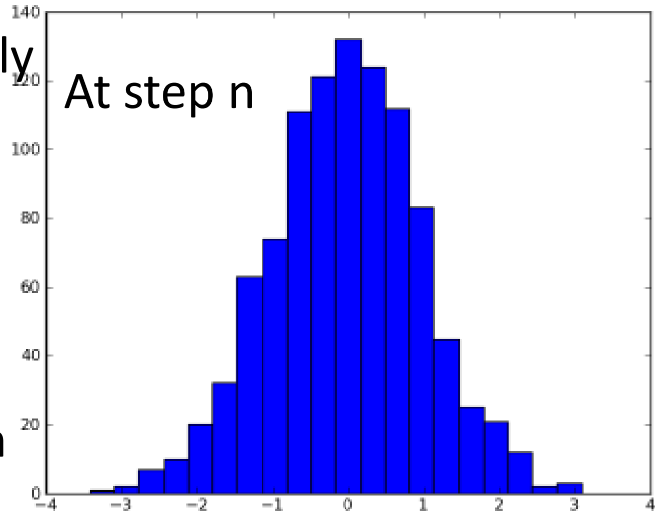
Let's assume proposal probability to be Gaussian.
Then we draw value x' from Gaussian.



Step is a value of parameter within some physically allowed range.

For example, normalization parameter cannot be negative, so we reject such steps.

This is just an example in 1D, in ND fit we perform N dimensional walk.

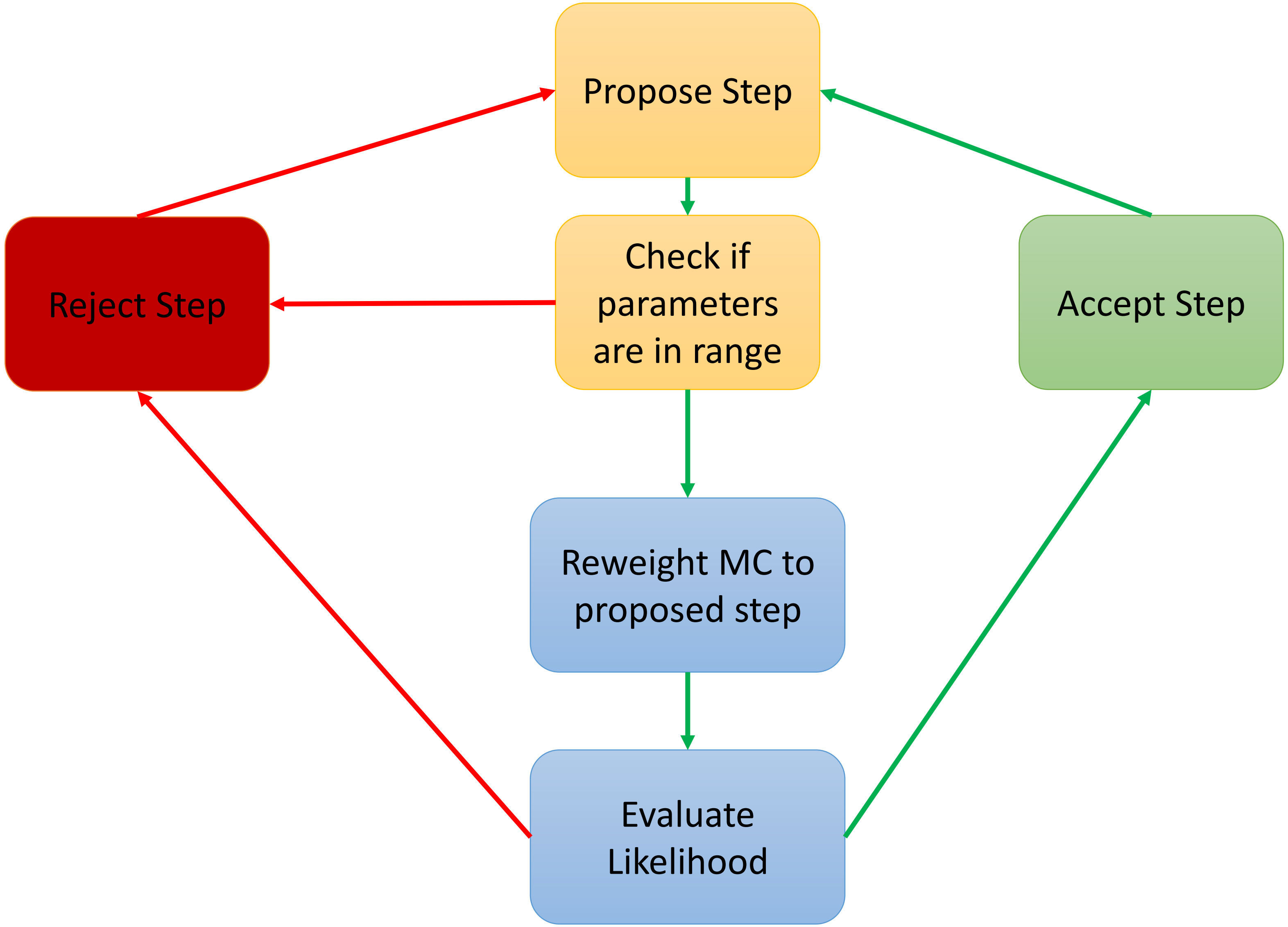


How MCMC Works

MCMC is an iterative process with basic unit being step.

To properly sample the whole space, we need lots of steps.

To obtain big number of steps in a reasonable time we are using GPU and extensively using multithreading.



Reweighting

Reweighting basics

Imagine you have neutrino MC, you made mistake and you produced it with twice larger xsec then it should be.
What to do: ½ = New Xsec / Old Xsec.

You can assign weight ½ to each event.

N_Events = weight * N_{MC}

Imagine you made different mistake: you produced MC with twice larger $CCQE$ xsec and two times lower for RES

N_Event = $weigth_{CCQE} * N_{MC}^{CCQE} + weight_{RES} * N_{MC}^{RES}$ + …

Those were easy examples, but you can see that using reweighting we can modify MC by indirectly modifying xsec.

Splines and Reweighting

Imagine you can calculate xsec precisely. Although in general xsec depends on many parameters, let's focus on Axial Mass (MAQE) which can modify form factor for CCQE.

$$F_A(Q^2) = \frac{g_A}{\left(1 + \frac{Q^2}{M_A^{QE}}\right)^2}$$

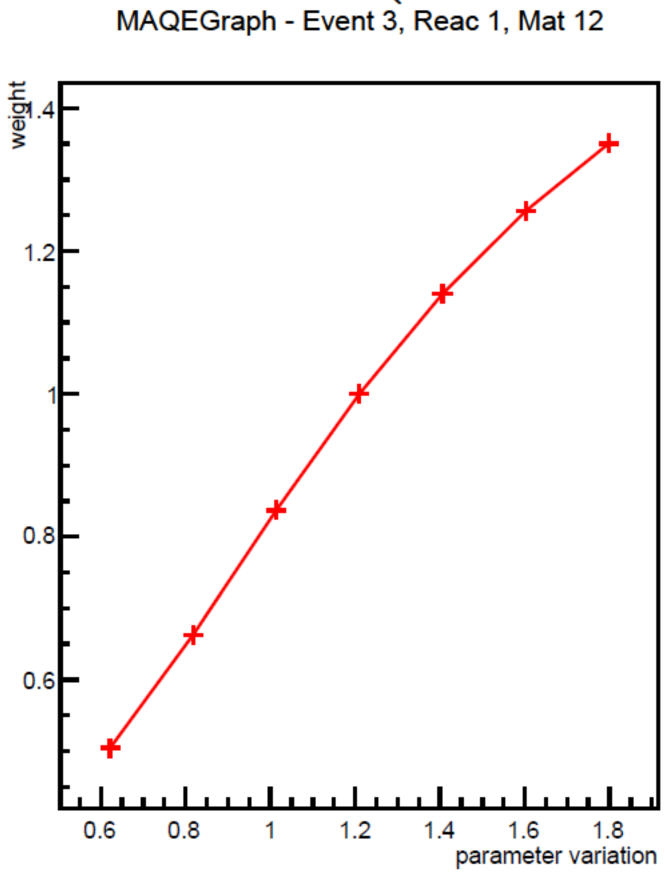
When you change **MAQE** you change xsec, so you can calculate weight as a ratio of new xsec and xsec of produced MC.

$$weight = \frac{New\ Xsec}{Old\ Xsec}$$

Then you can create spline which holds weights as values of **MAQE** variation. Making a spline allows to use those precalculated weights during the fit. We produce spline for each event.

We produced MC with **MAQE** = 1.21, so for **MAQE**=1.21 we get weight 1.

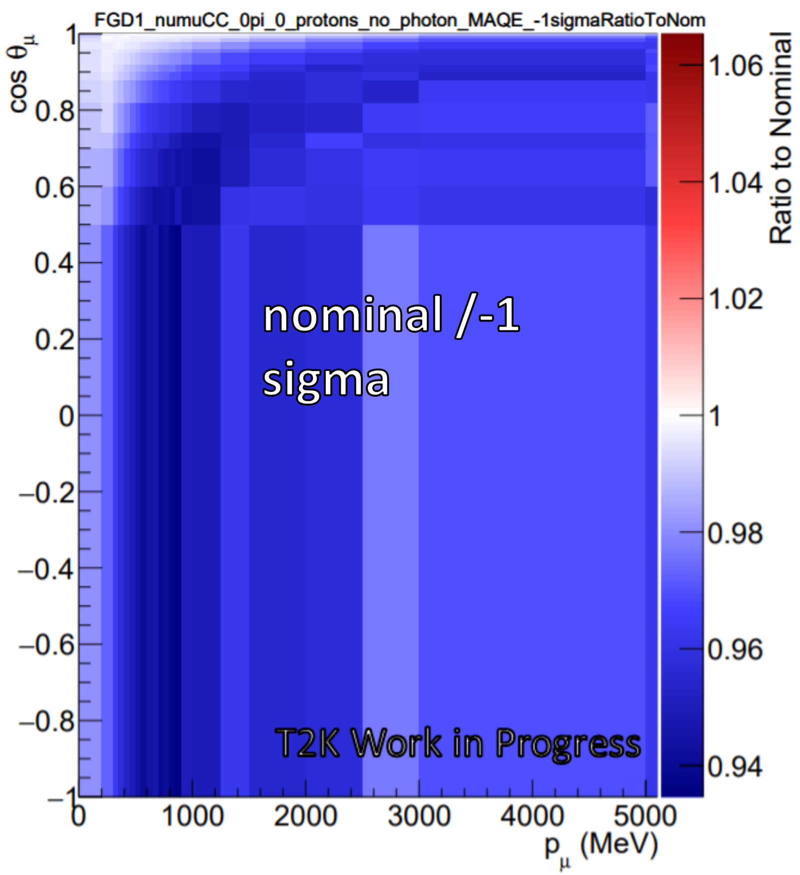
Producing new MC can take days, weeks month. We can reweight full MC in less than 0.1 s !!!



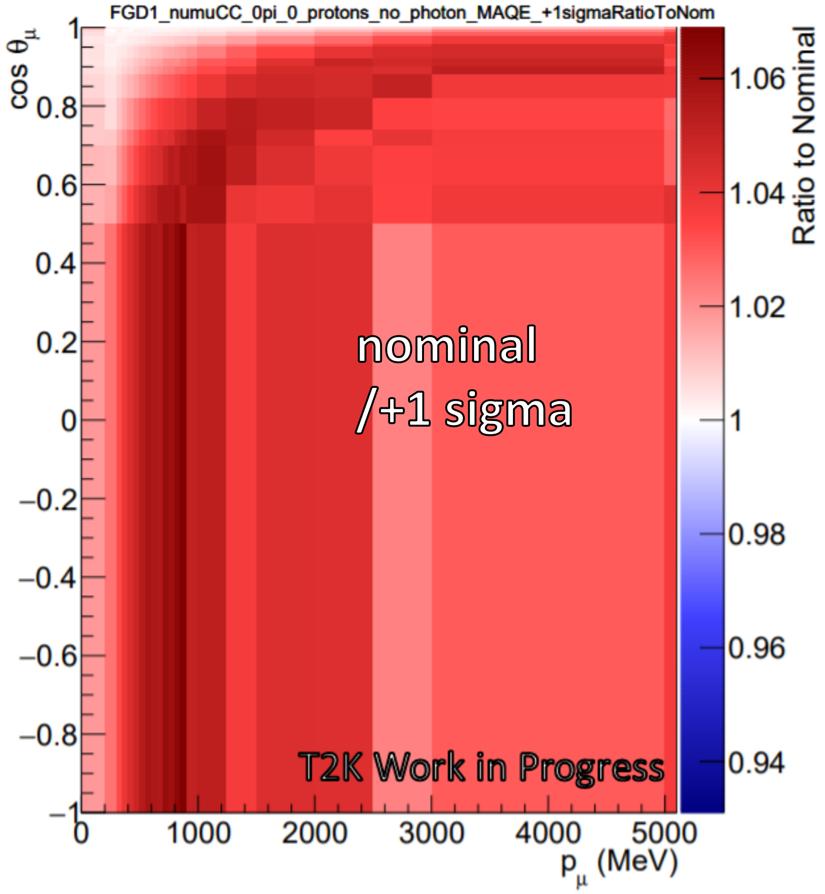
Reweighting Example

Changing value of **MAQE** and reweighting MC clearly changes our MC distribution.

Obviously in the fit we have much more parameters and fitter is trying to find values which fit data best.



We produce MC which has at least 10 times more events than data, otherwise such method would not work.



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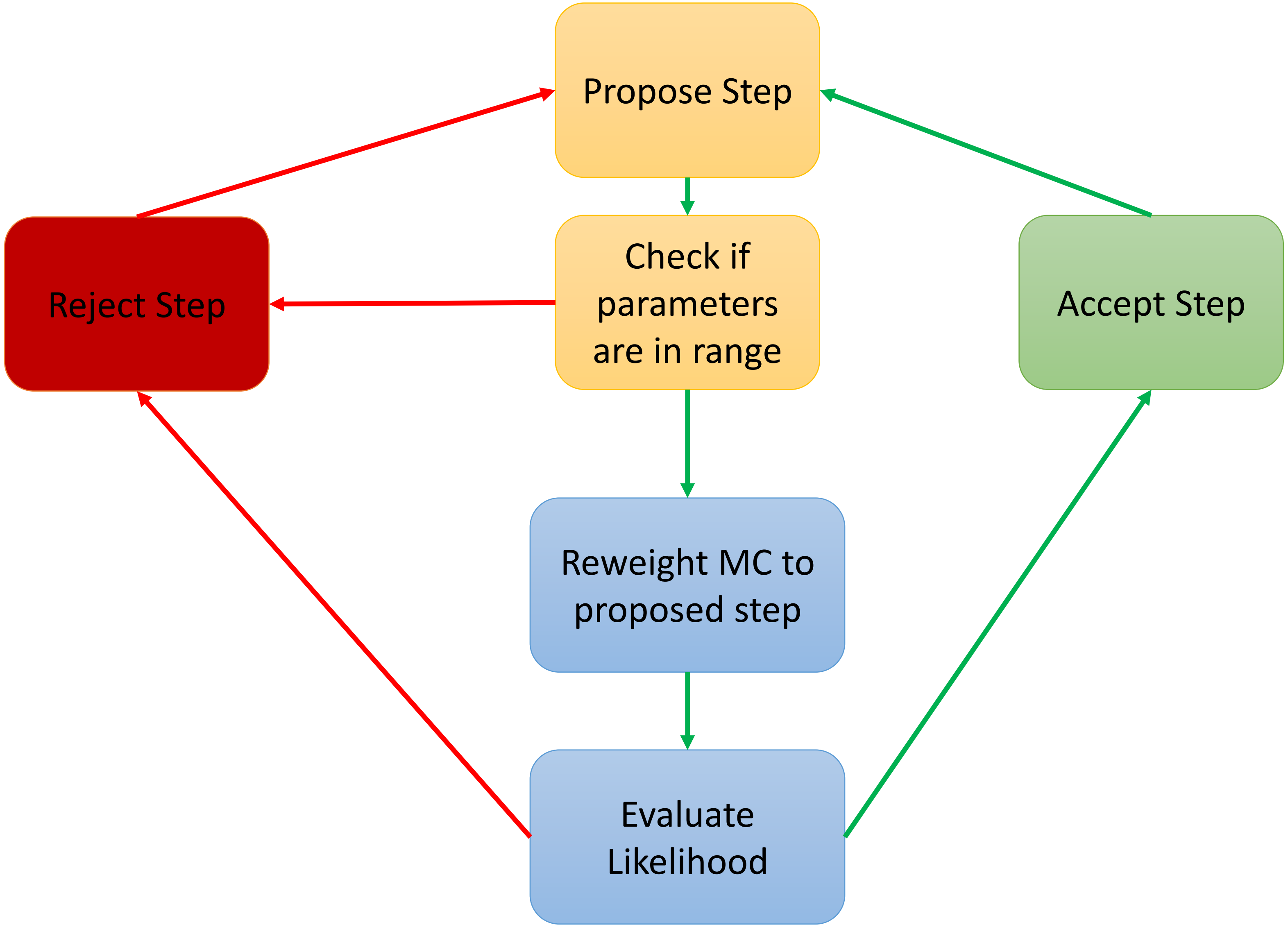


Posterior Distribution

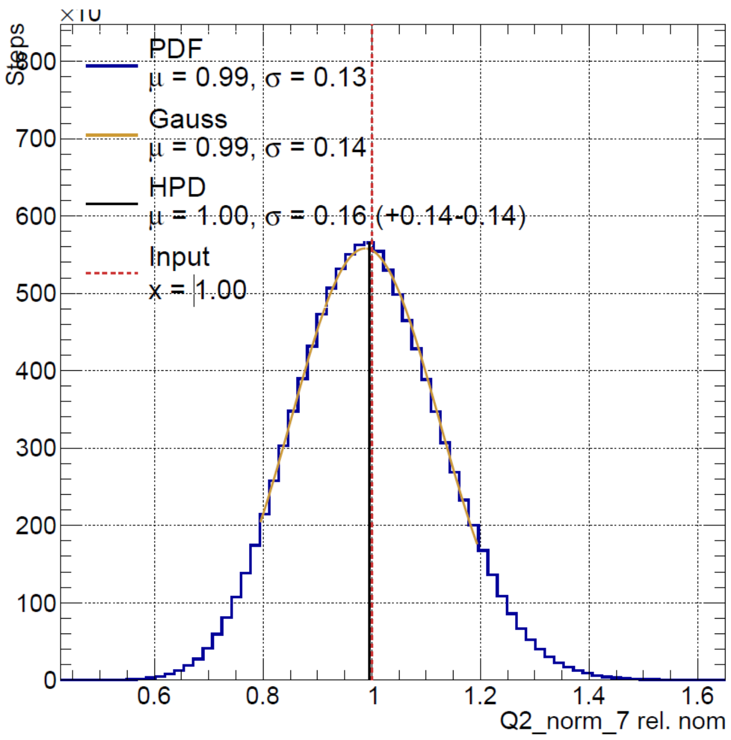
The main output from the MCMC is posterior distribution.

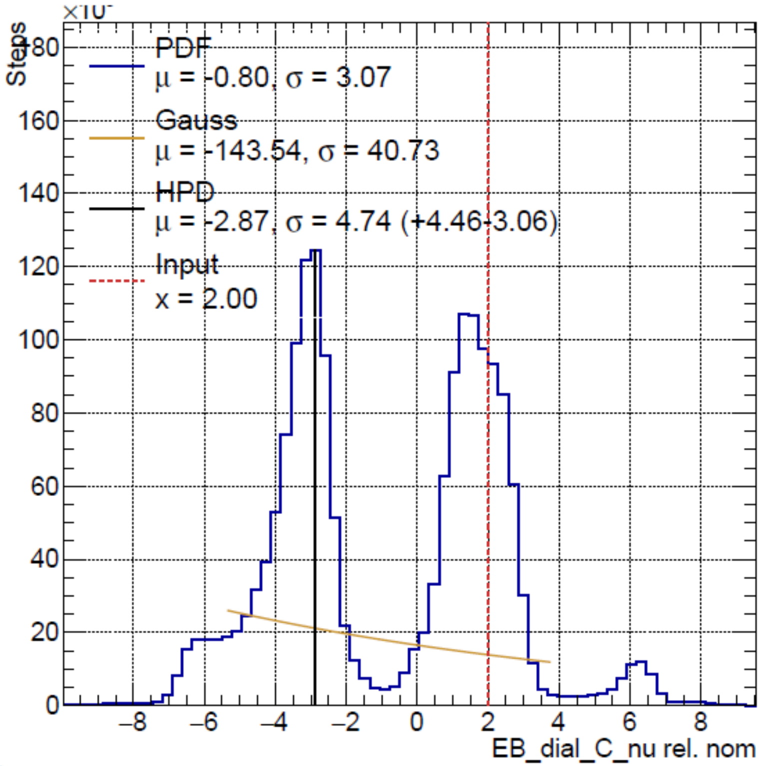
Peak of distribution can be associated with best fit value and spread of distribution with the error.

Since we don't use best fit value, we don't have event rate spectra, rather Posterior Predictive Distribution of such quantity.

Bayes Theorem

$$\boxed{P(\vec{\theta}|Z)} = \frac{P(Z|\vec{\theta})P(\vec{\theta})}{P(Z)}$$



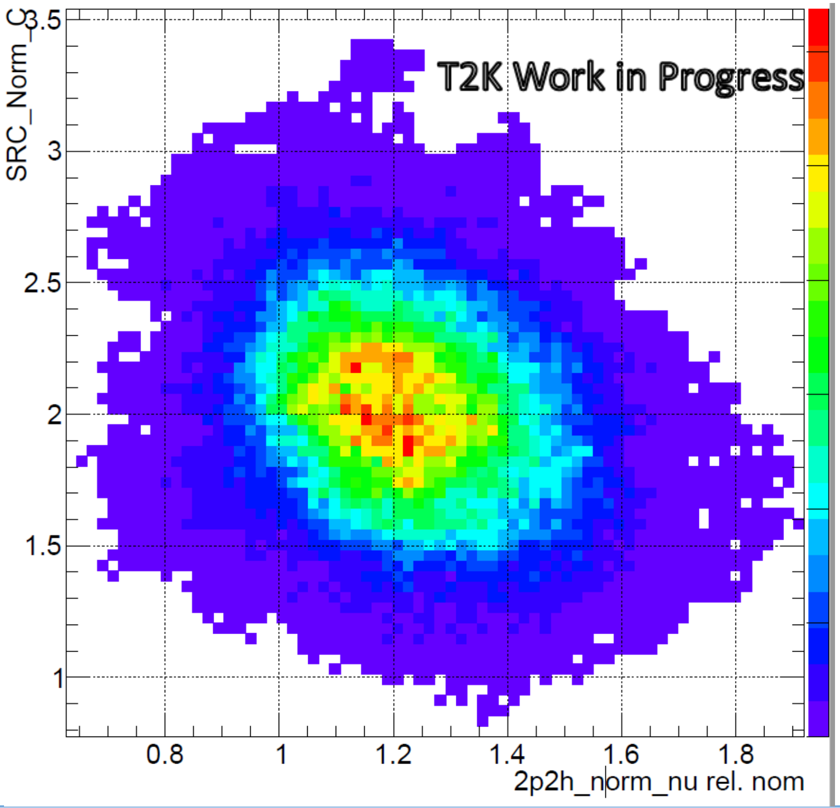


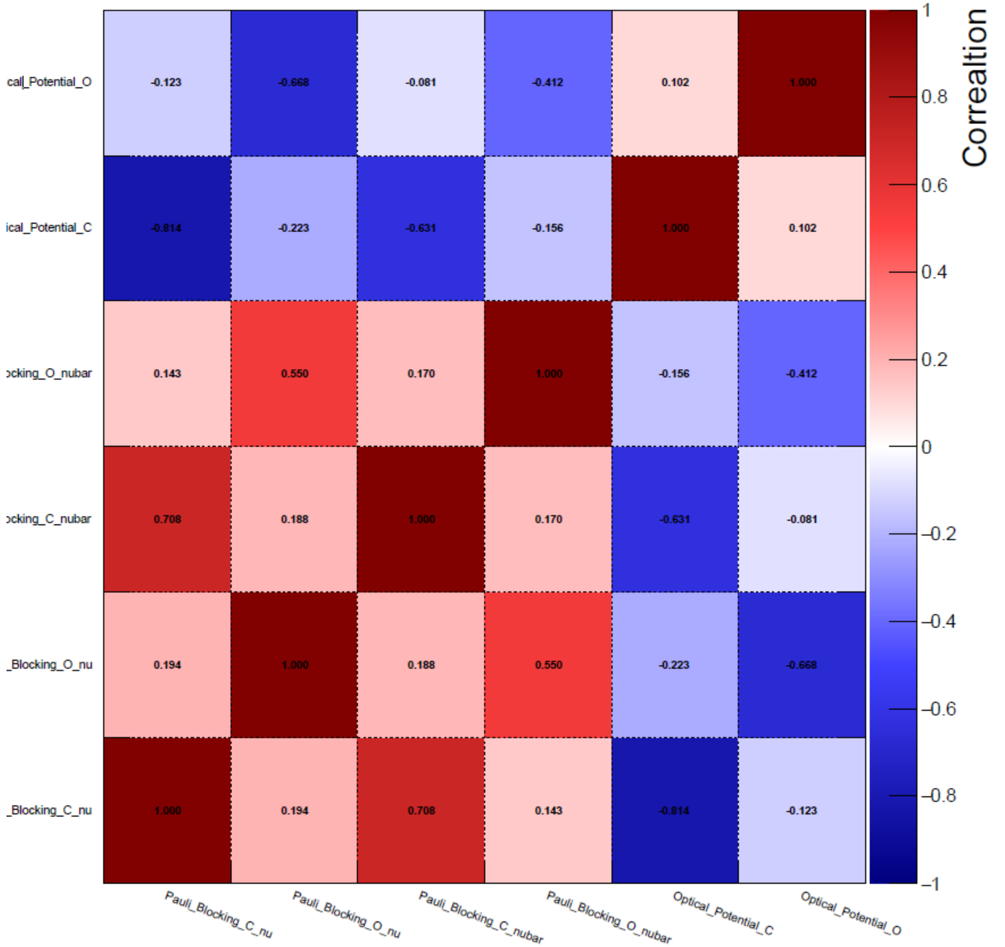
Correlations

MCMC has also very intuitive way of showing correlation. MCMC fit is very high dimensional distribution. If we marginalize this distribution to 2D we can see how two parameters were behaving.

Correlation Matrix of chosen parameters

Single entry is one MCMC step. Based on this we can easily calculate correlation/covariance.

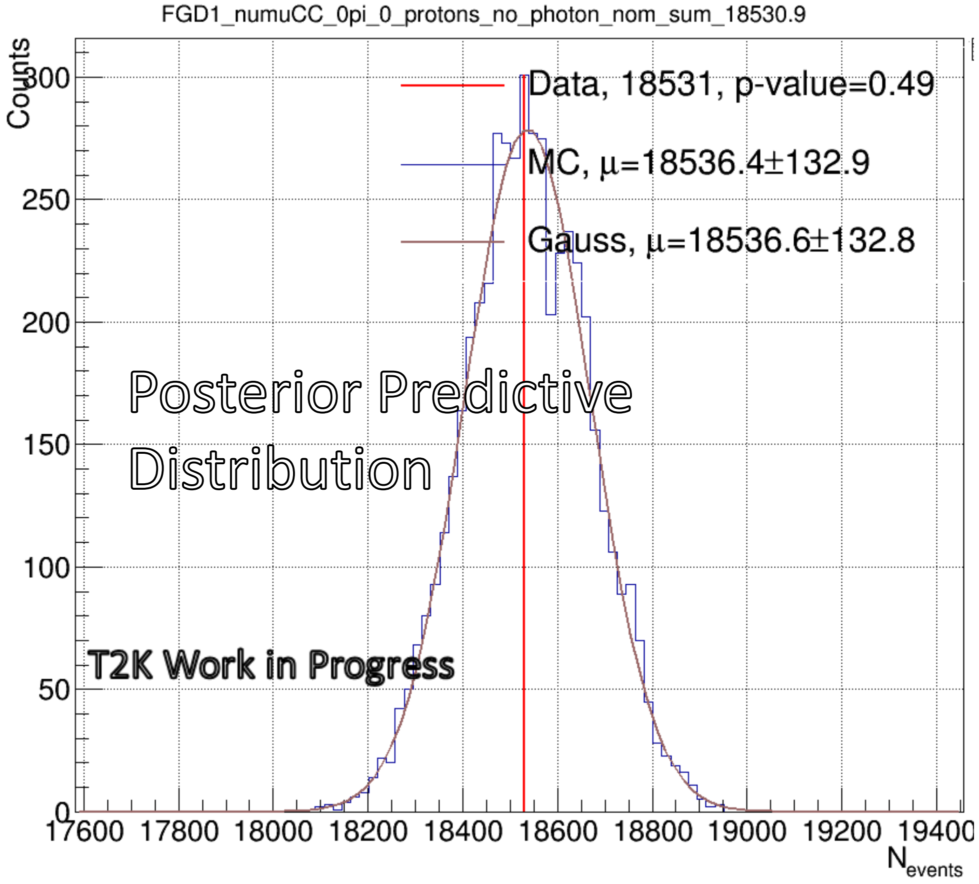




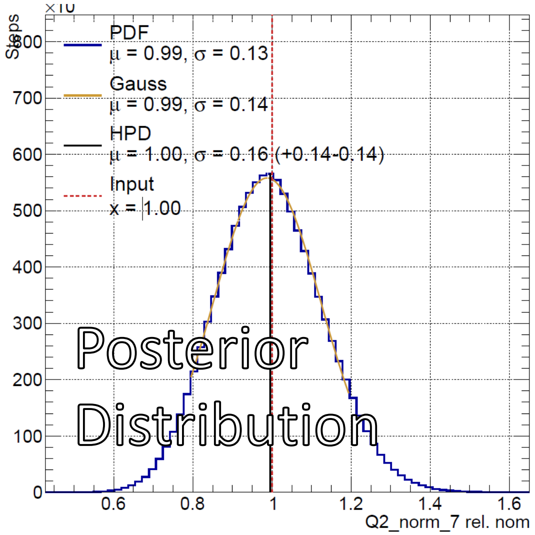
Posterior Predictive Distribution

$$p(Z_{pred}|Z) = \int_{\vec{\theta}} p(Z_{pred}, \vec{\theta}|Z) d\vec{\theta} = \int_{\vec{\theta}} p(Z_{pred}|\vec{\theta}, Z) \boxed{p(\vec{\theta}|Z)} d\vec{\theta}$$

After the data Z have been observed, we can predict an unknown observable Z_{pred}, from repeated measurement



$$\boxed{P(\vec{\theta}|Z)} = \frac{P(Z|\vec{\theta})P(\vec{\theta})}{P(Z)}$$



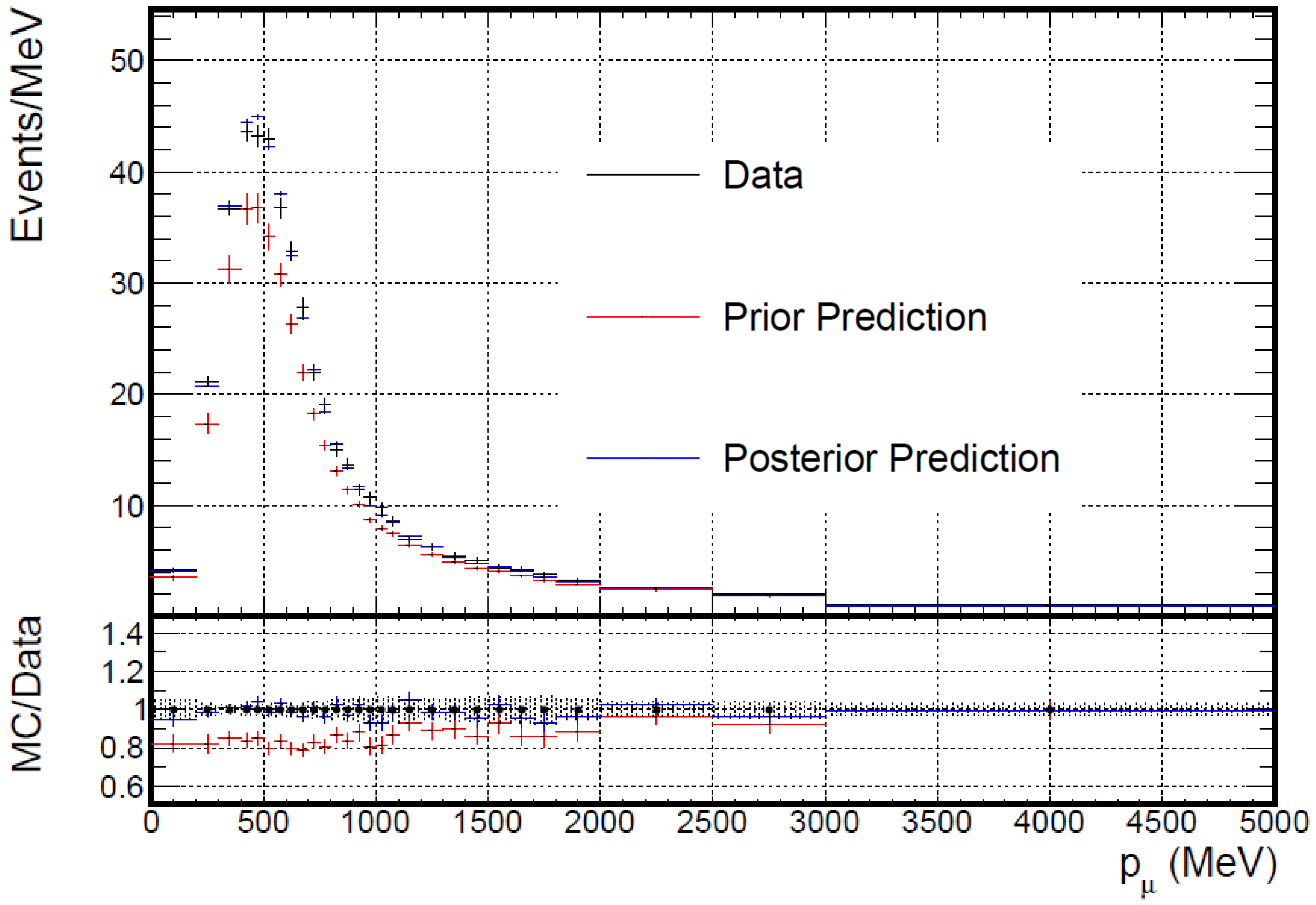
We draw value for each parameter from posterior distribution.

Then we reweight MC creating so called toy experiment.

We create more toys each time choosing new parameters. Then we plot number of event and voila this is Posterior Predictive Distribution

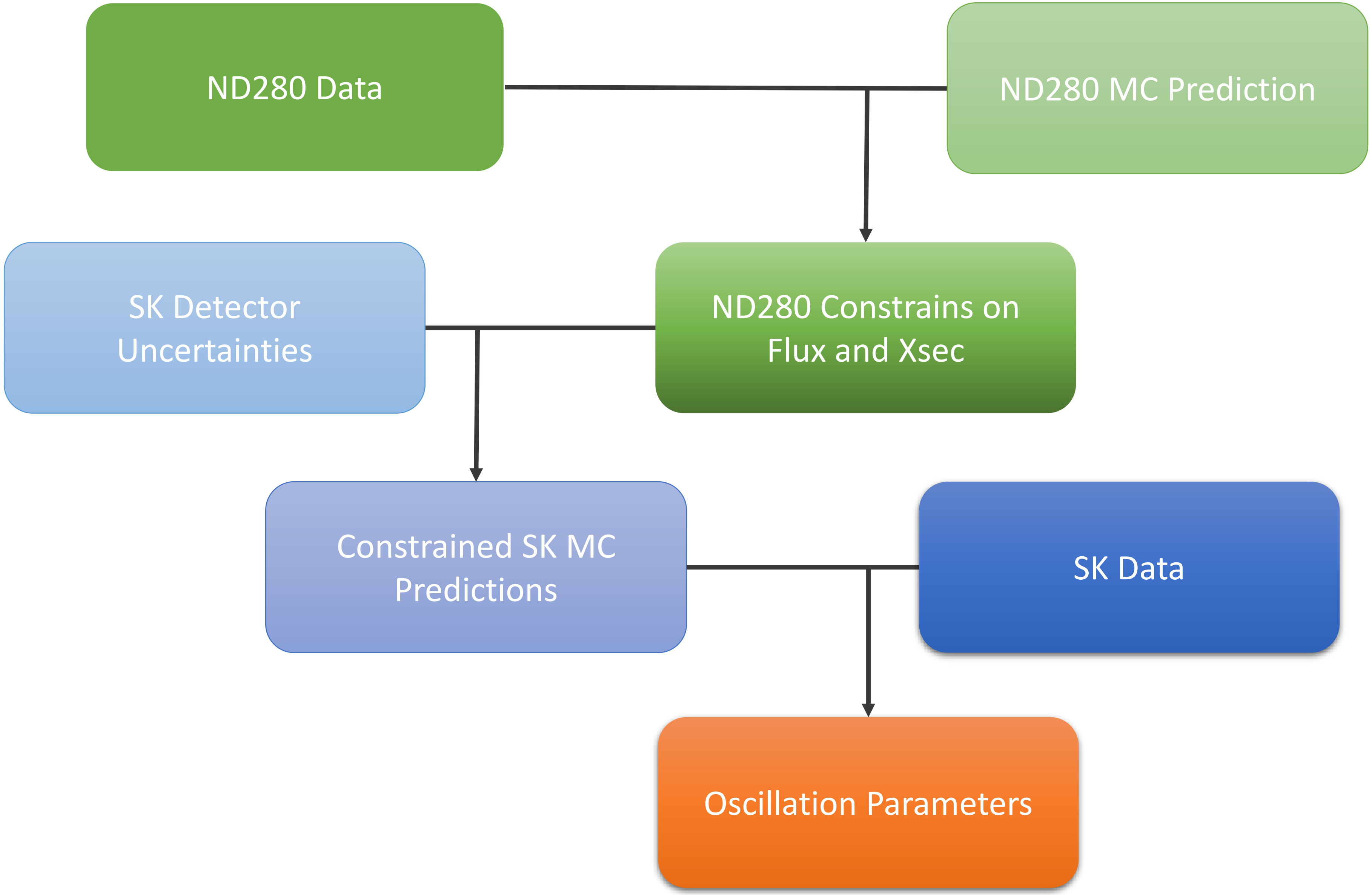
Prior/Posterior Predictive Distributions

We can compare Prior and Posterior distributions to see whether after ND fit MC is in better agreement with the data and if the errors are much smaller.



Towards Oscillation Fit

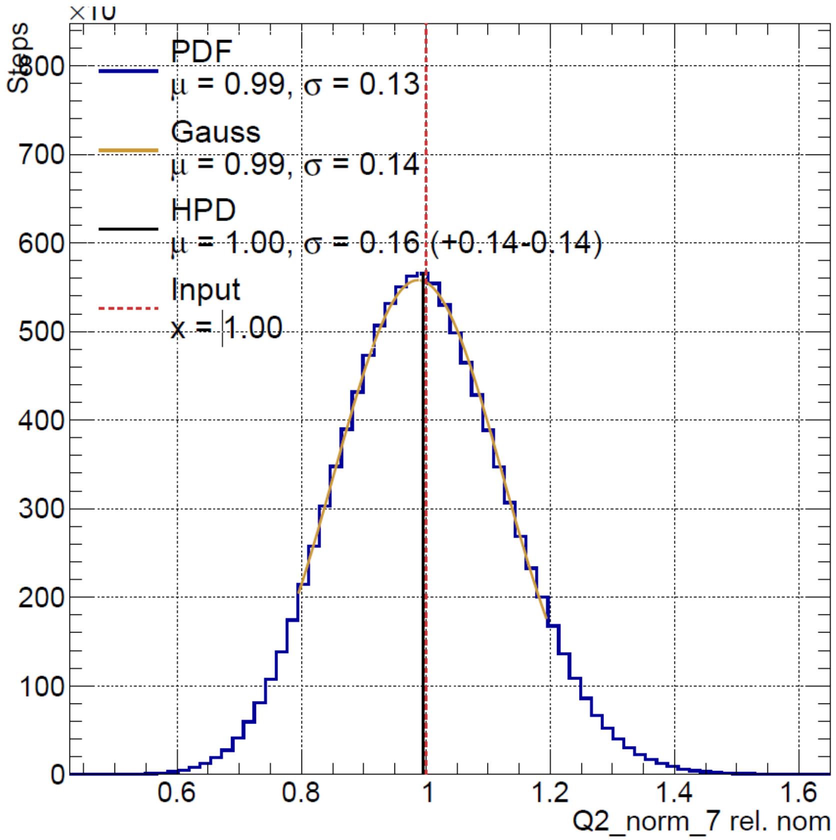
Oscillation Analysis - OA



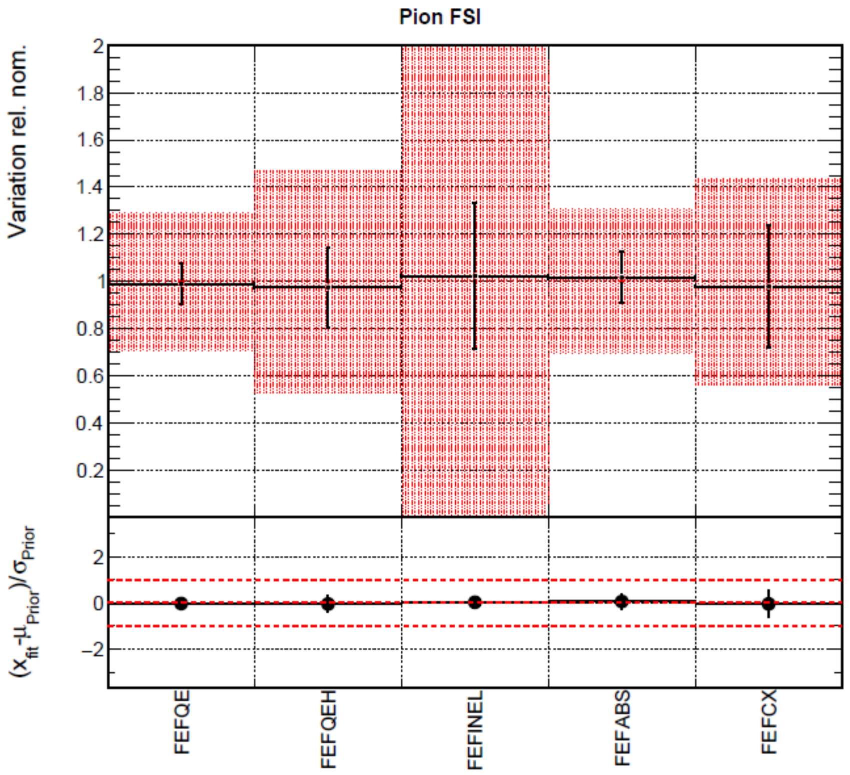
Asimov Fit

Asimov fit – fit where data is replaced with fake data created with known parameter values. In such case we know expected results, but we can validate framework.

Asimov fit can show constrain power of ND280 fit, as **postfit** error are much smaller than **prefit.**



Red - prefit
Black -postfit



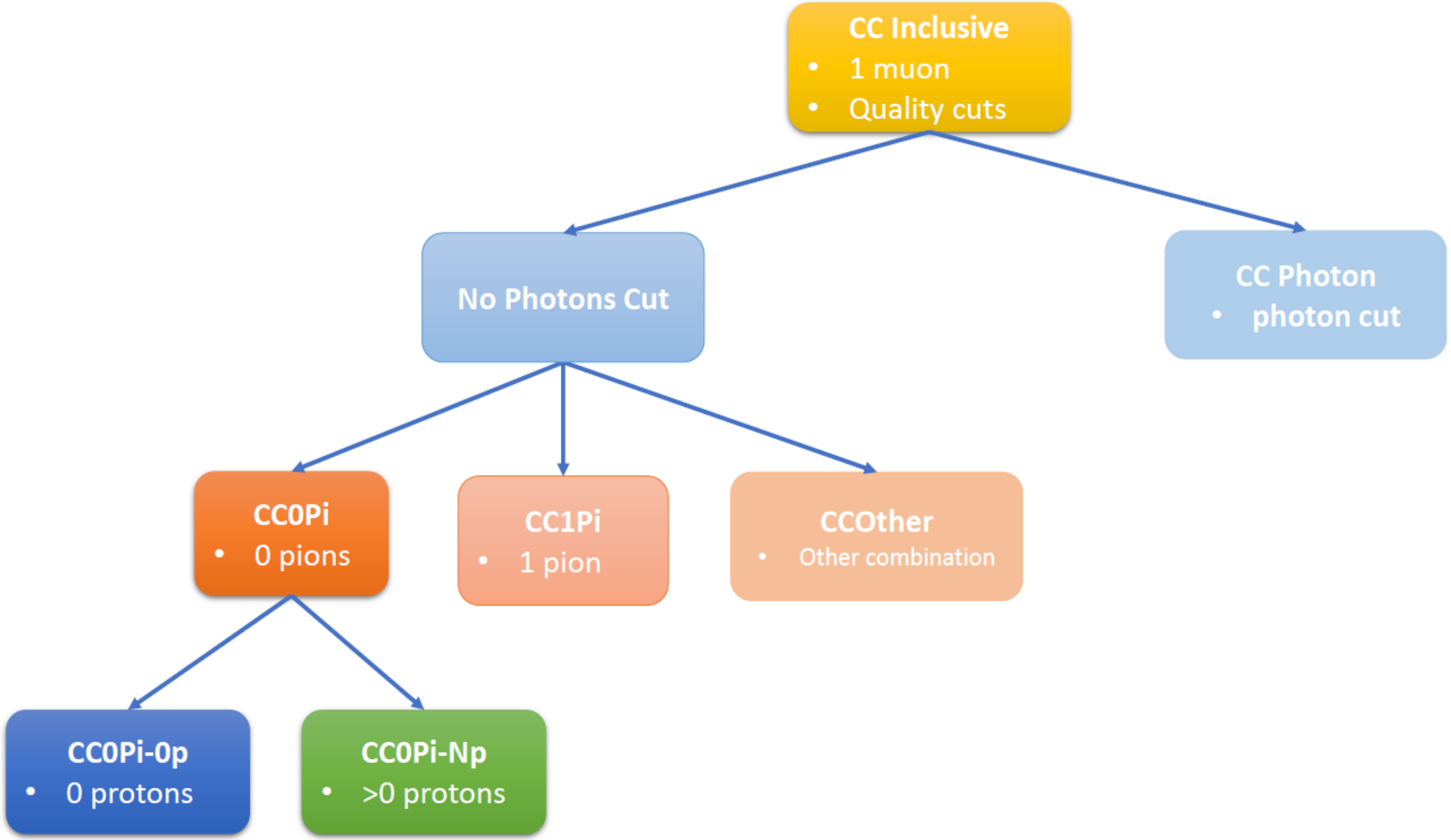
Summary

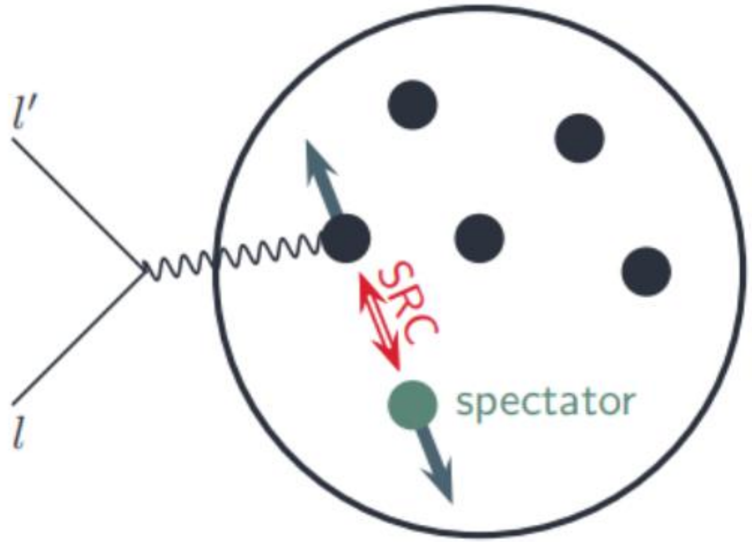
This year T2K oscillation analysis brings many improvements

- New ND selections with proton and photon information.
- Improved cross section model with more sophisticated description of nucleus shell structure.
- ND part of the analysis is mostly finalized.
- Final results expected around summer vacation so stay tuned!!!

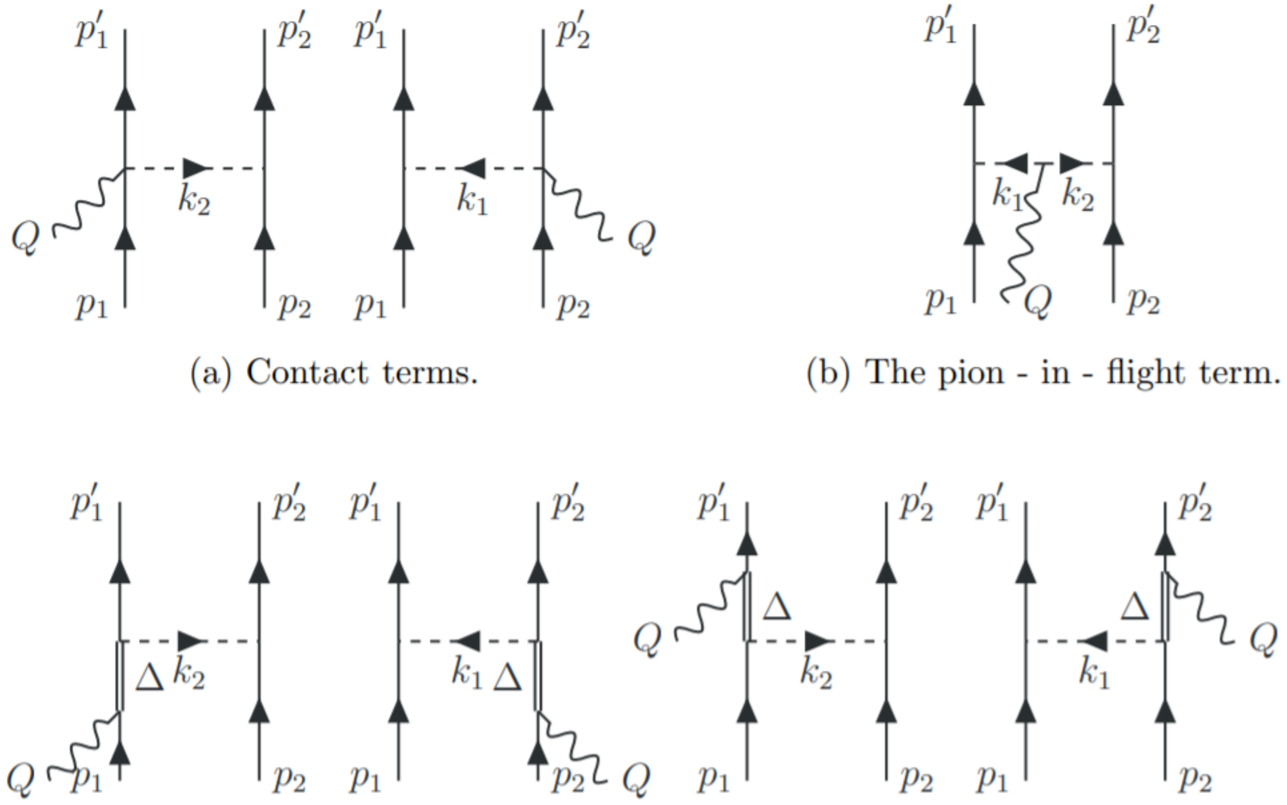
BACKUP

ND selection flow





2p2h



(a) Contact terms.

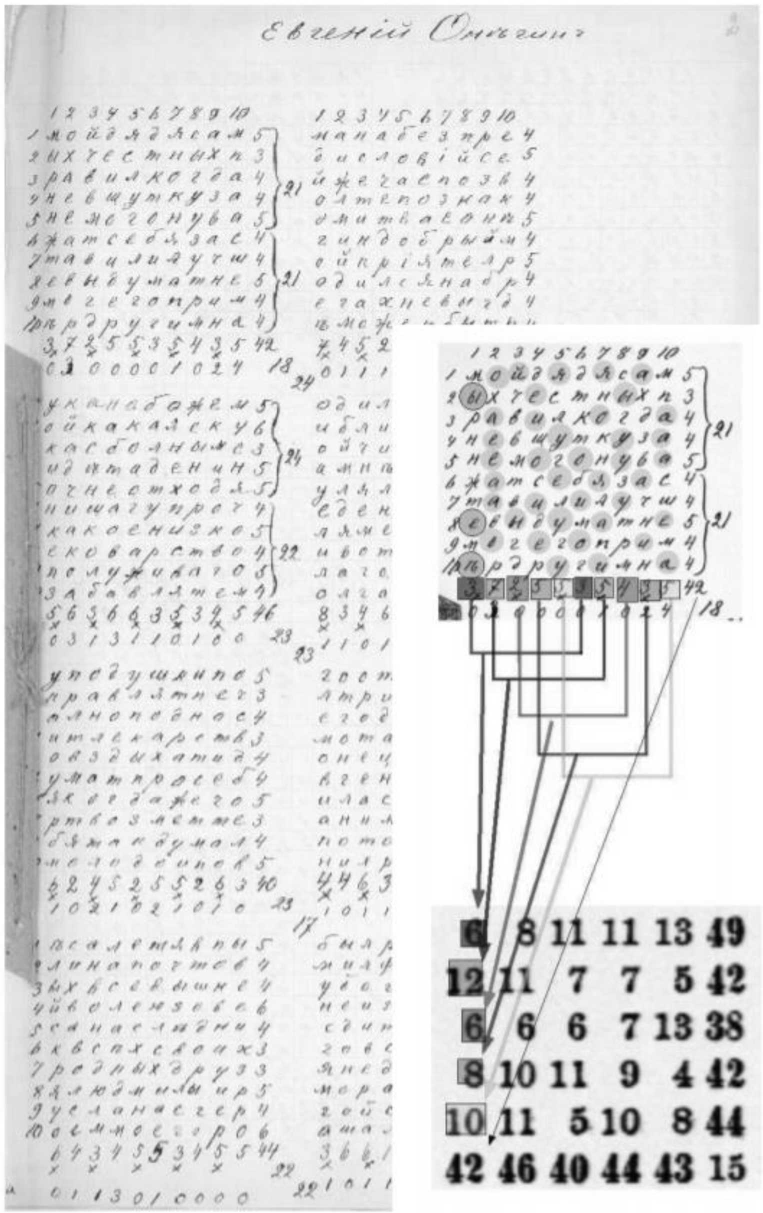
(b) The pion - in - flight term.

(c) Δ pole and Δ pole crossed terms.

Eugene Onegin

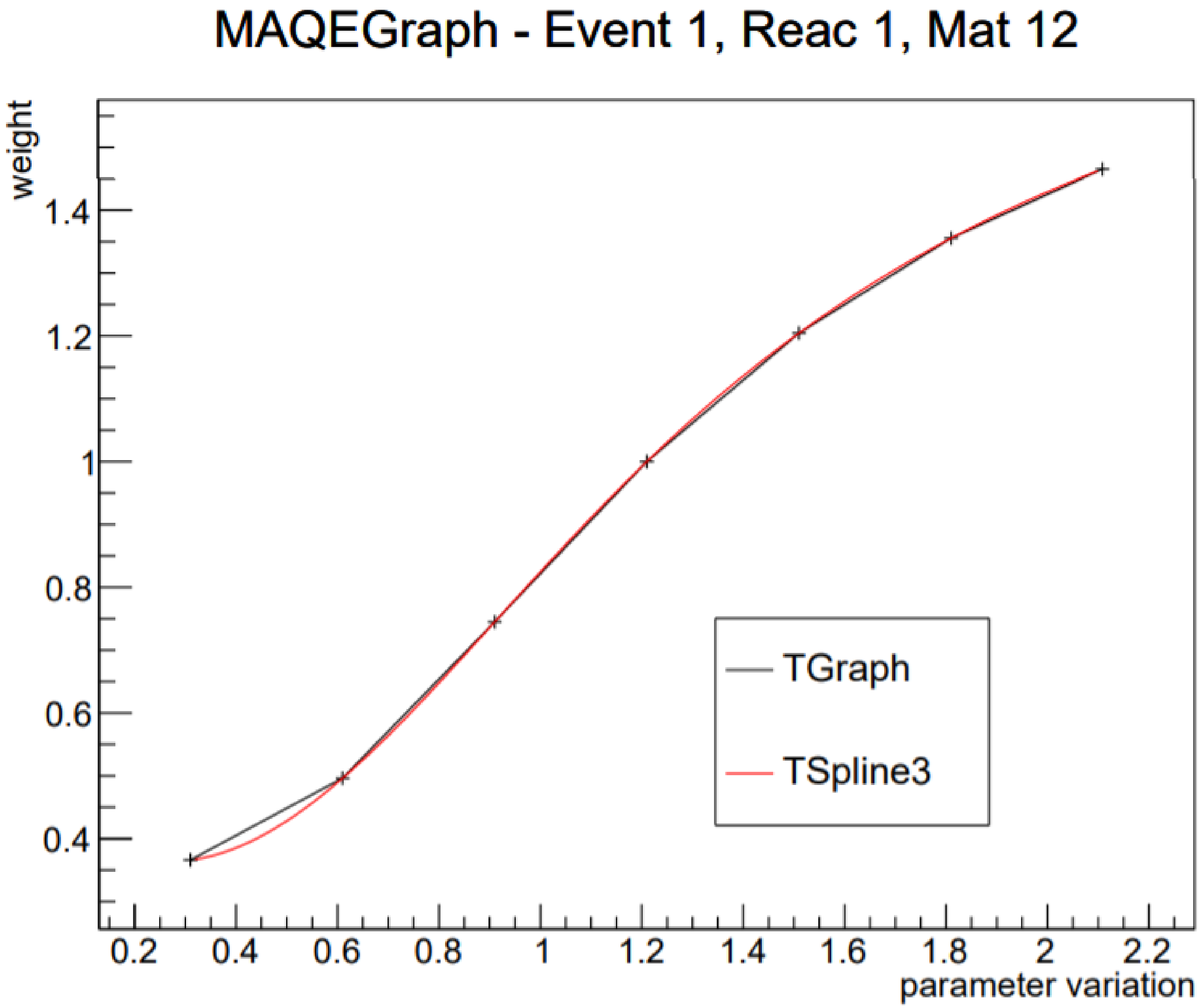
Left background: The first 800 letters of 20,000 total letters compiled by Markov and taken from the first one and a half chapters of Pushkin's poem "*Eugene Onegin*" Markov omitted spaces and punctuation characters as he compiled the Cyrillic letters from the poem.

Right foreground: Markov's count of vowels in the first matrix of 40 total matrices of 10 × 10 letters. The last row of the 6 × 6 matrix of numbers can be used to show the fraction of vowels appearing in a sequence of 500 letters. Each column of the matrix gives more information. Specifically, it shows how the sums of counted vowels are composed by smaller units of counted vowels. Markov argued that if the vowels are counted in this way, then their number proved to be stochastically independent.



Kolmogorov speculated that if physics in Russia had reached the same high level as it had in some Western European countries, where advanced theories of probability tackled distributions of gas and fluids, Markov would not have picked Pushkin's book from the shelf for his own experiments.

Spline

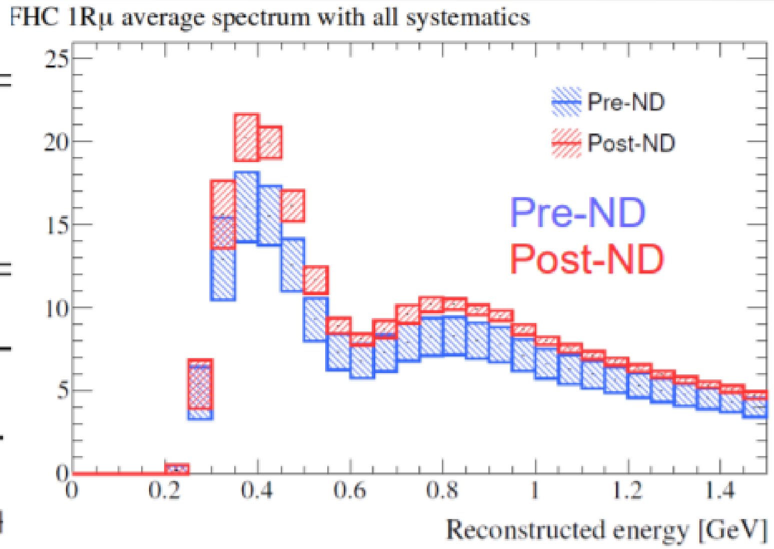


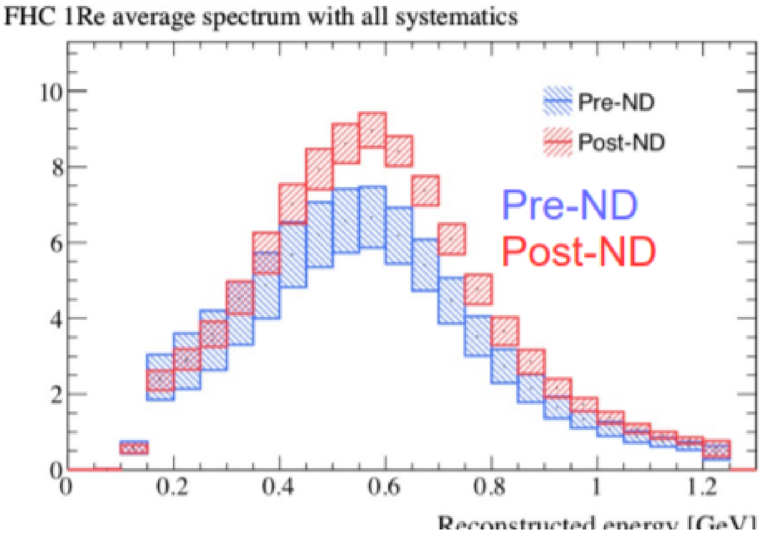
MAQEGraph - Event 1, Reac 1, Mat 12
weight
1.4
1.2
1
0.8
0.6
0.4
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2
parameter variation
TGraph
TSpline3

ND constrains

Pre fit Error source	1Rμ FHC	1Rμ RHC	FHC	RHC	1Re FHC CC1π^+
Flux	5.1%	4.7%	4.8%	4.7%	4.9%
Cross-section (all)	10.1%	10.1%	11.9%	10.3%	12.0%
SK+SI+PN	2.9%	2.5%	3.3%	4.4%	13.4%
Total	11.1%	11.3%	13.0%	12.1%	18.7%

Post fit Error source (units: %)	1Rμ FHC	1Rμ RHC	FHC	RHC	1Re FHC CC1π^+
Flux	2.9	2.8	2.8	2.9	2.8
Xsec (ND constr)	3.1	3.0	3.2	3.1	4.2
Flux+Xsec (ND constr)	2.1	2.3	2.0	2.3	4.1
Xsec (ND unconstrained)	0.6	2.5	3.0	3.6	2.8
SK+SI+PN	2.1	1.9	3.1	3.9	13.4
Total	3.0	4.0	4.7	5.9	14.3





Abstract

T2K (Tokai to Kamioka) is a long-baseline neutrino oscillation experiment located in Japan. One of the most challenging tasks of T2K is to study whether CP is violated in the lepton sector, which is suggested by recent T2K results. By utilizing the near detector (ND280) data, T2K can constrain neutrino interaction and flux uncertainties by fitting a parameterized model to data. This allows for a significant reduction of the systematic uncertainties in neutrino oscillation analyses.

One of two fitters responsible for ND fit uses Markov Chain Monte Carlo (MCMC) Method. Great benefit of MCMC is that it returns distribution for each parameter rather than one just one best fit value.

ND280 fit analysis, planned to be released this year, introduced lots of improvement, including the new photon-proton selection and new systematic parameter giving lots of freedom in nuclear effect description like Short Range Correlations and Pauli Blocking.