Advancing Single Photon Searches in MicroBooNE with PROfit

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July 30, 2026

Nevis Laboratories
Columbia University

NSF

μBooNE

Background

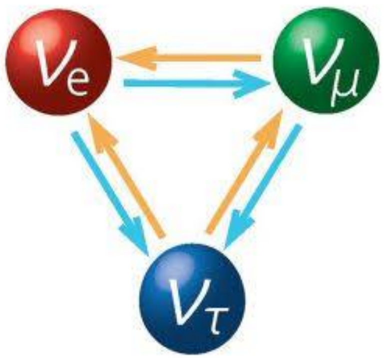
Tools

Background Studies

Signal Sensitivity Study

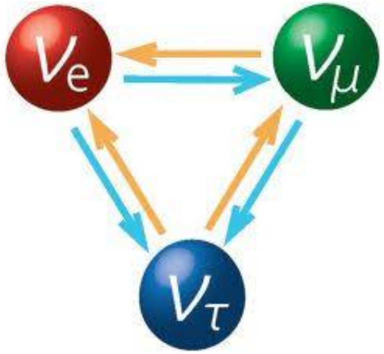
Takeaways

Neutrinos



- Neutral charge + very small mass
- Difficult to detect although incredibly abundant
- Three known flavors: electron, muon, tau
- Oscillations → changing flavors as they travel

Neutrinos



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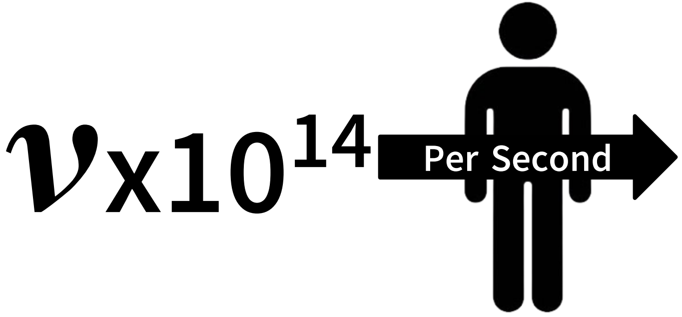

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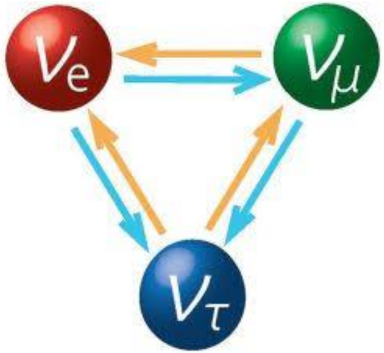

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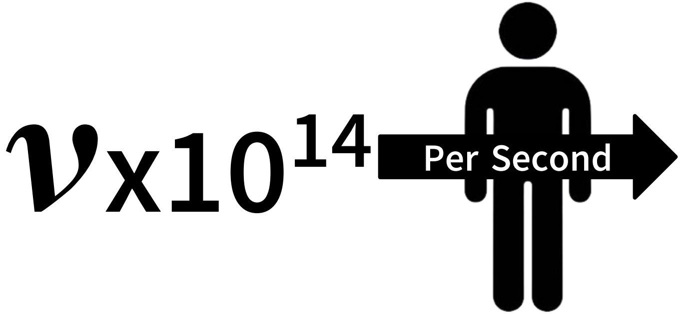
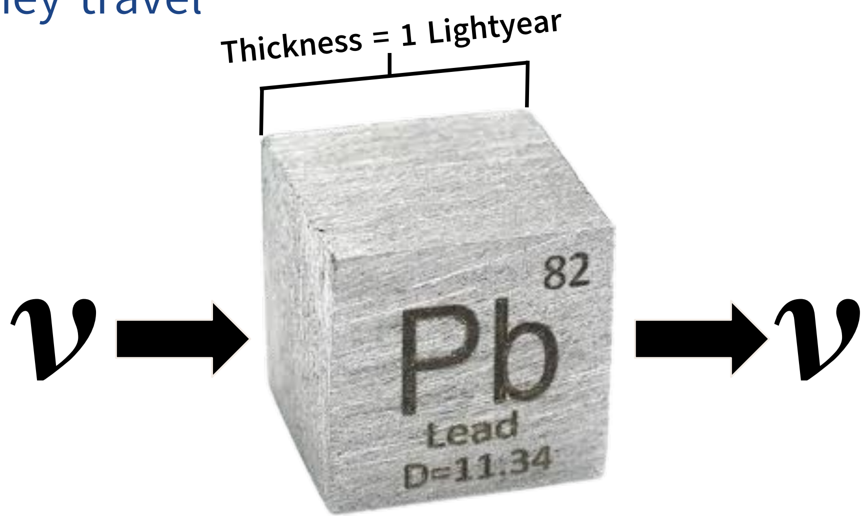
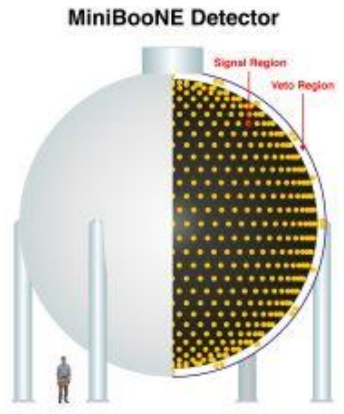




Probability of Interaction = 50%

Oscillation Anomaly - MiniBooNE



MiniBooNE built to study the newly discovered phenomenon of neutrino oscillations

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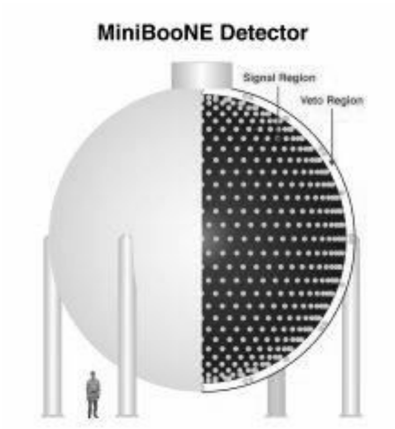

Fermilab

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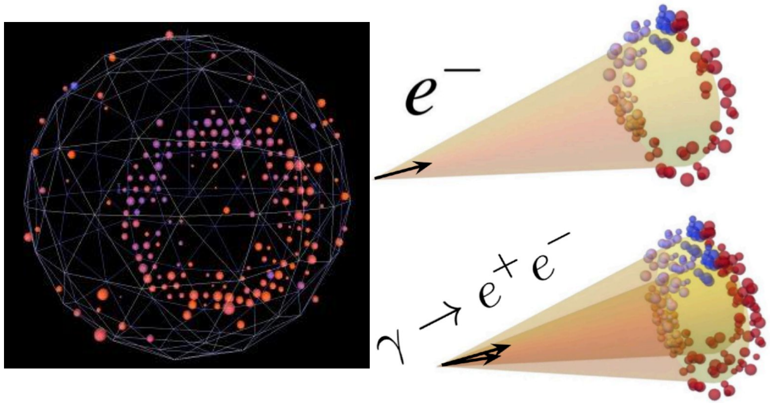


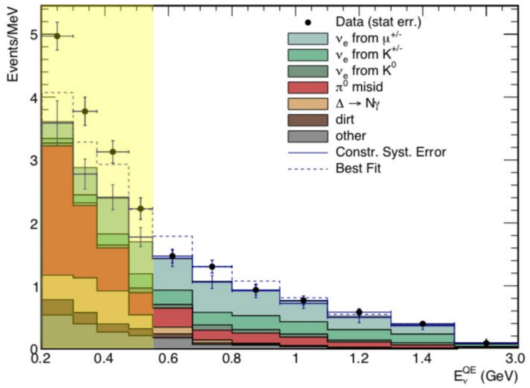
Ambiguous Event Display

Electromagnetic (EM) showers

Cherenkov detector is unable to distinguish between electron and photon events

The Birth of MicroBooNE

MiniBooNE



https://arxiv.org/pdf/2006.16883

4.8σ excess of low-energy EM shower events called the "Low-Energy Excess" (LEE)

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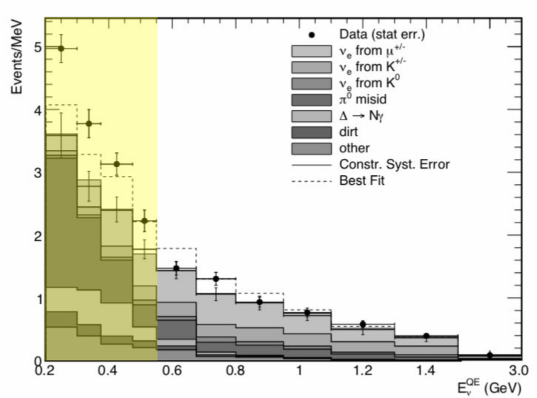

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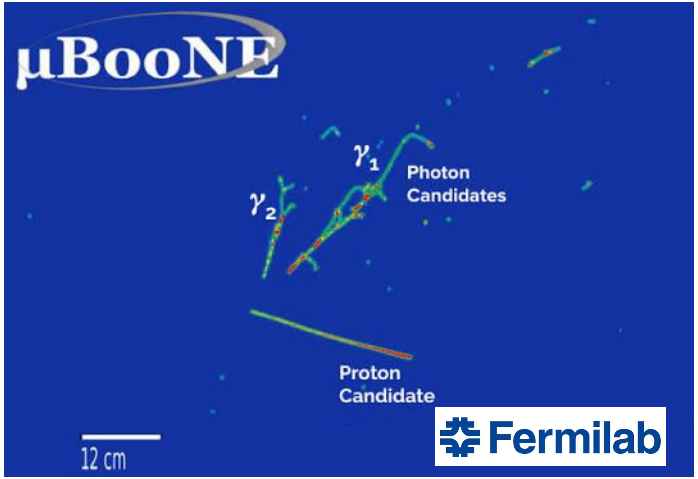
4.8σ excess of low-energy EM shower events called the "Low-Energy Excess" (LEE)

Motivates

MicroBooNE

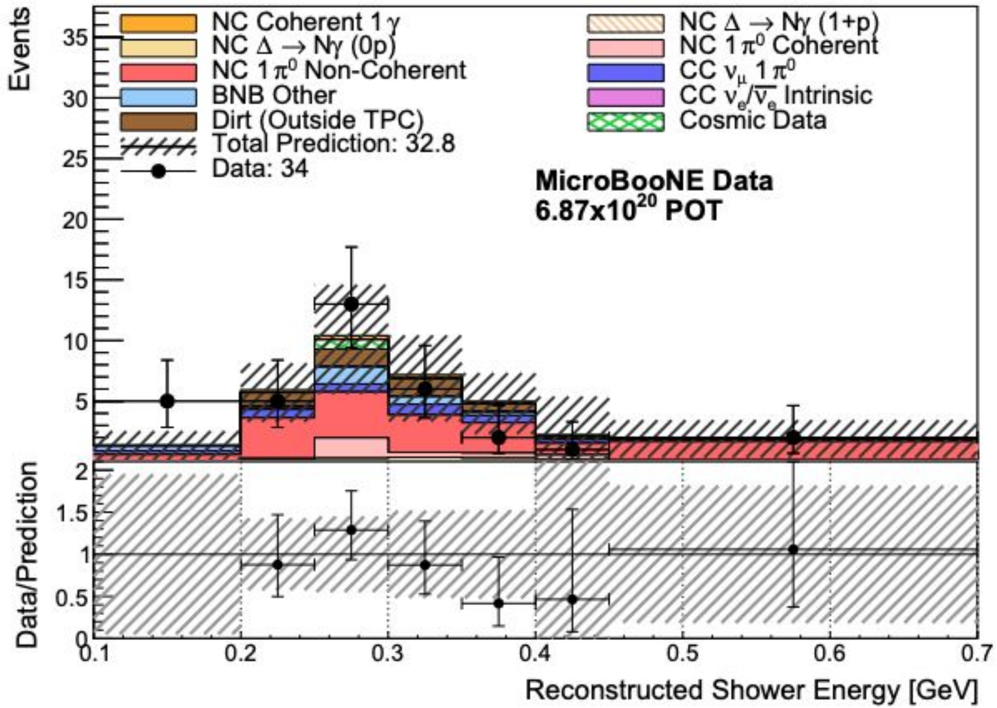
Liquid Argon Time Projection Chamber (LArTPC)…

Charge and light readout allows us to distinguish EM shower sources



Single Photon Search Thus Far

- Hear June's talk about electrons!
- Major constraints on Neutral Current (NC) Δ radiative events



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Single Photon Search Thus Far

- Electron events are probably not the cause
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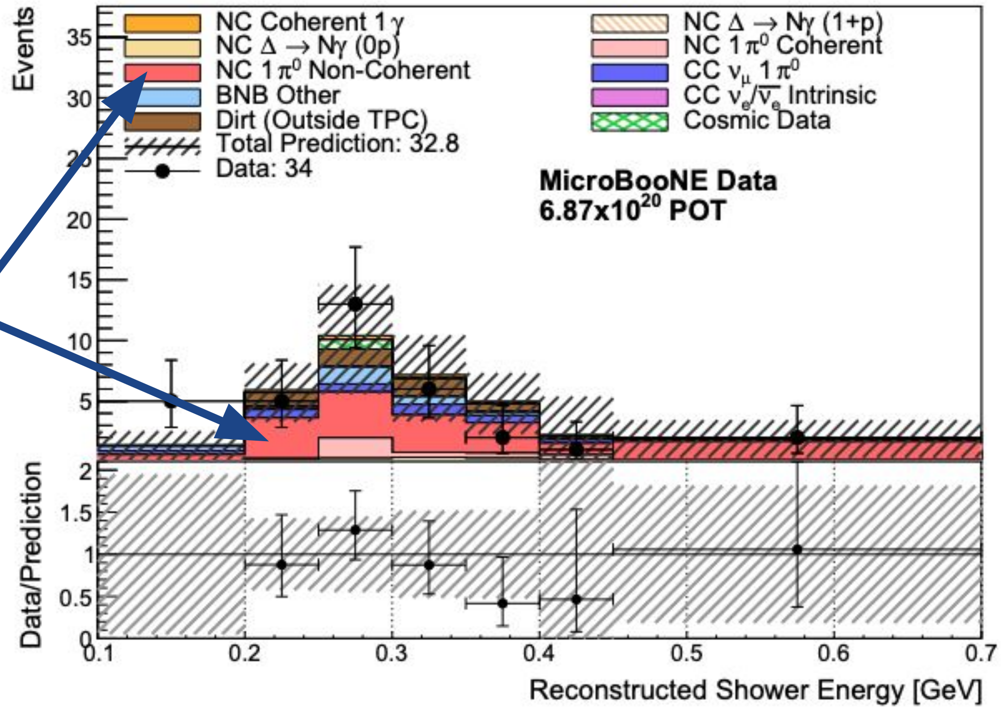
Need to understand backgrounds like NCπ^0



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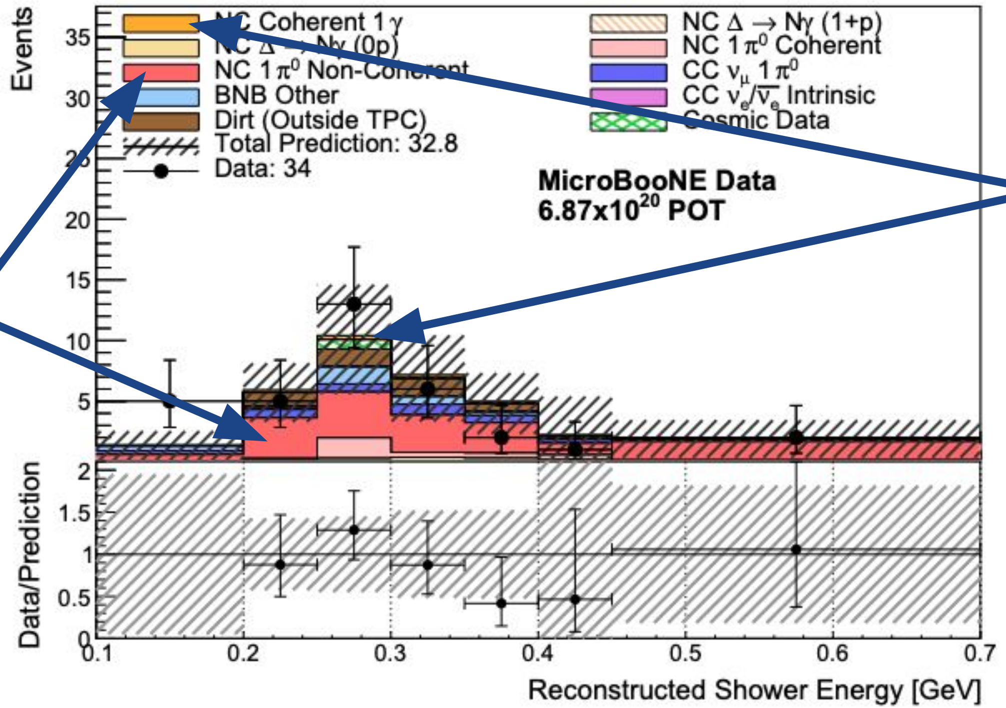

Need to optimize sensitivity to other event types like NC Coherent 1γ

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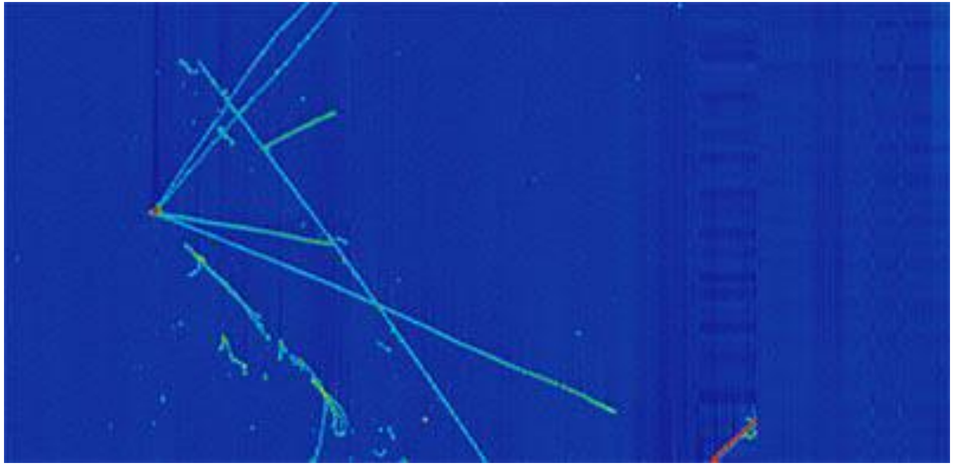
What happens when a neutrino hits Argon?



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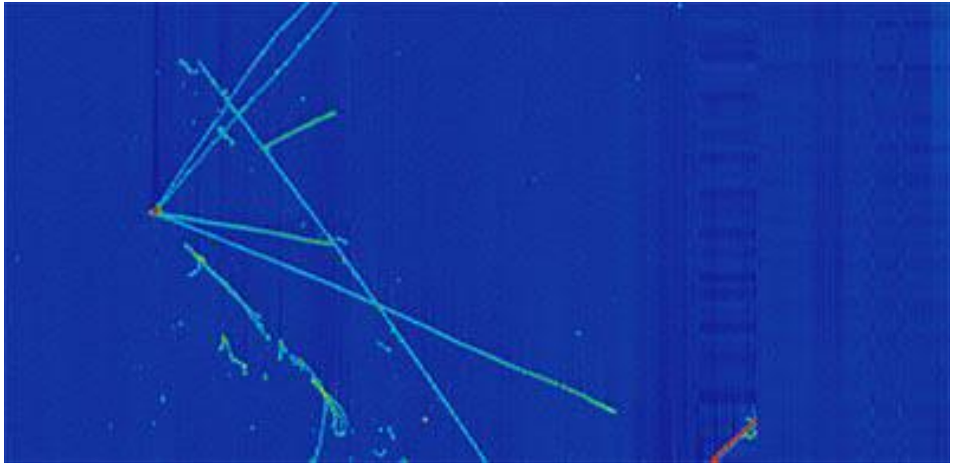

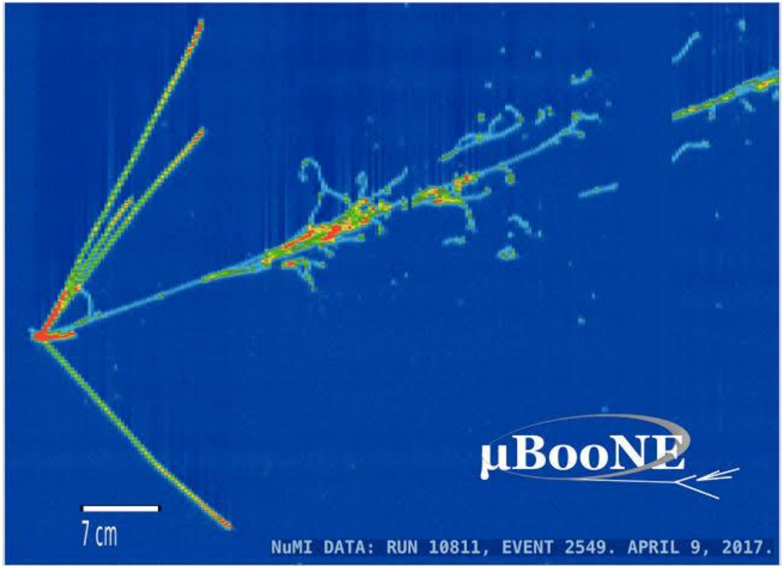

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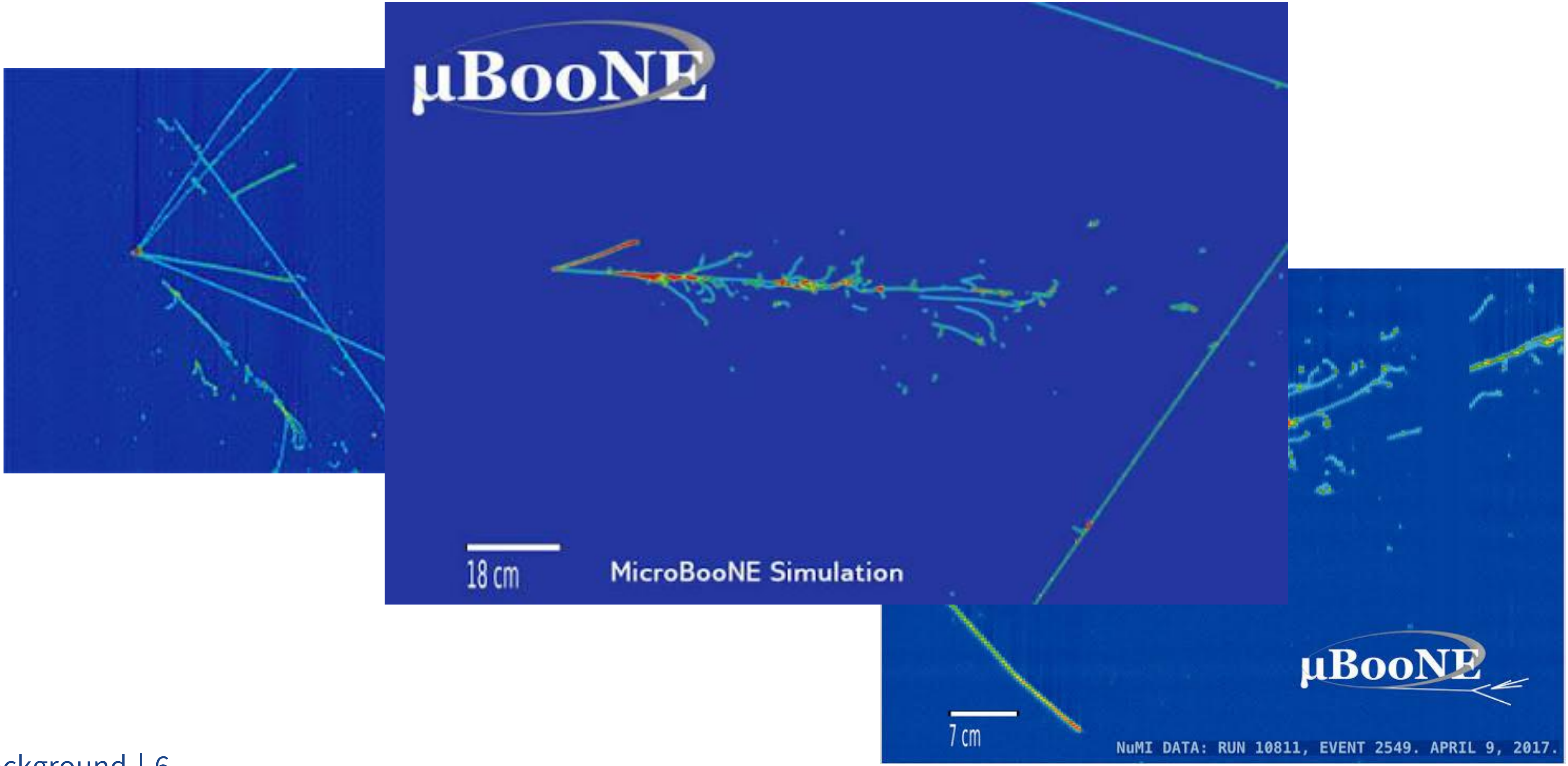

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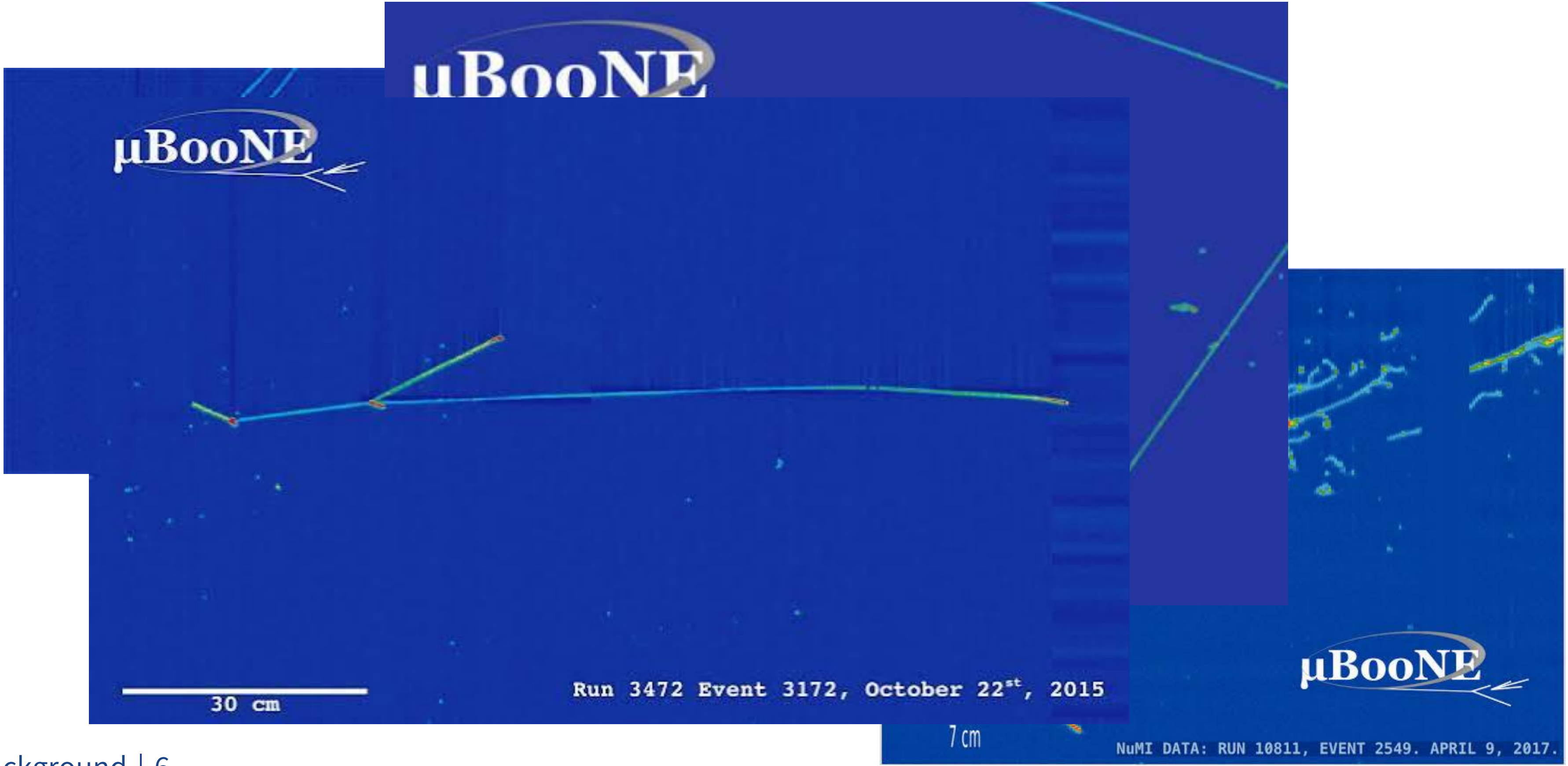

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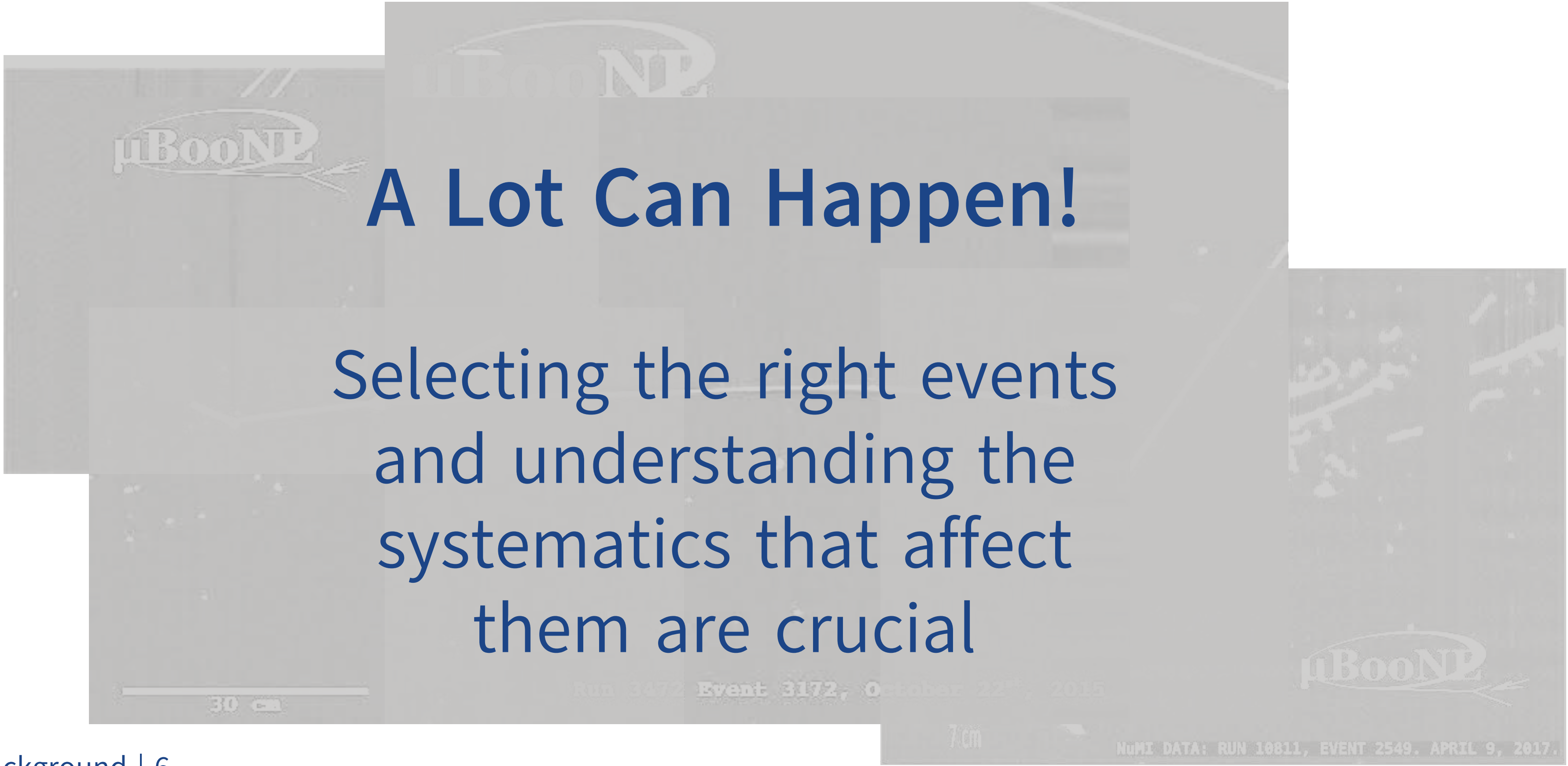

A Lot Can Happen!

Selecting the right events and understanding the systematics that affect them are crucial

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BAGELS

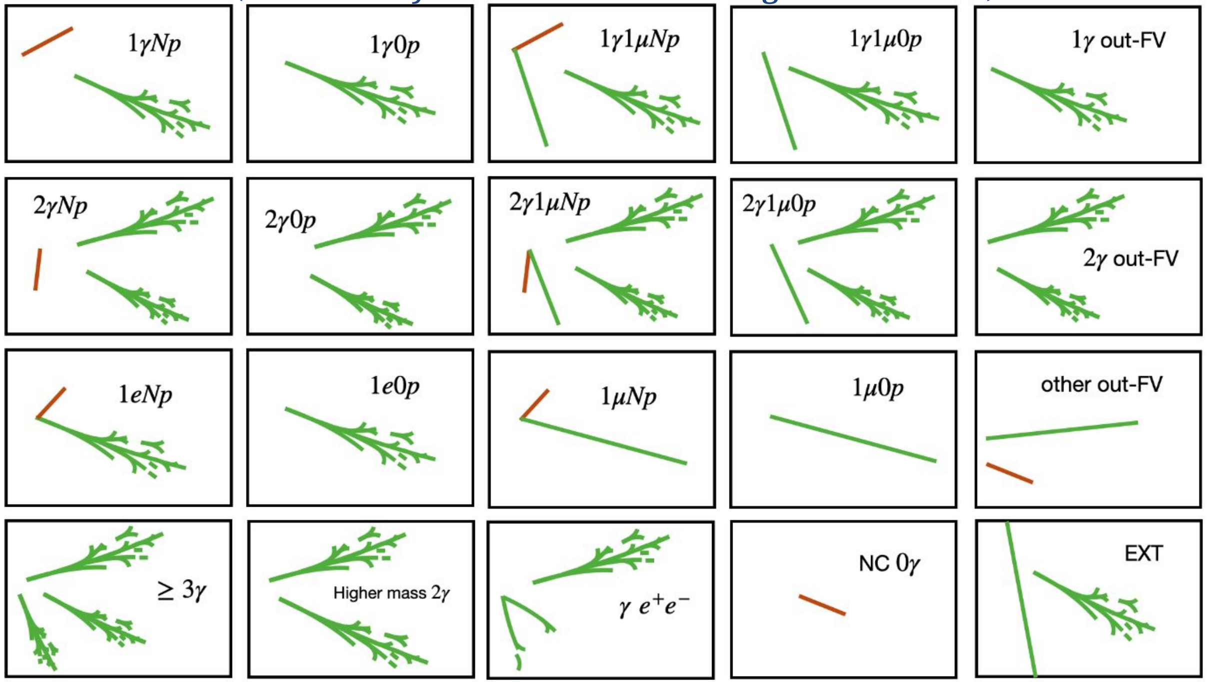







BAGELS

(Broad Array of General ELectromagnetic Showers)



- Machine learning framework for classifying electromagnetic-shower events
- Combines information from multiple reconstruction frameworks
- Uses information to train BDT

Boosted Decision Trees (BDTs)

- Machine learning algorithm that classifies events into signal and background

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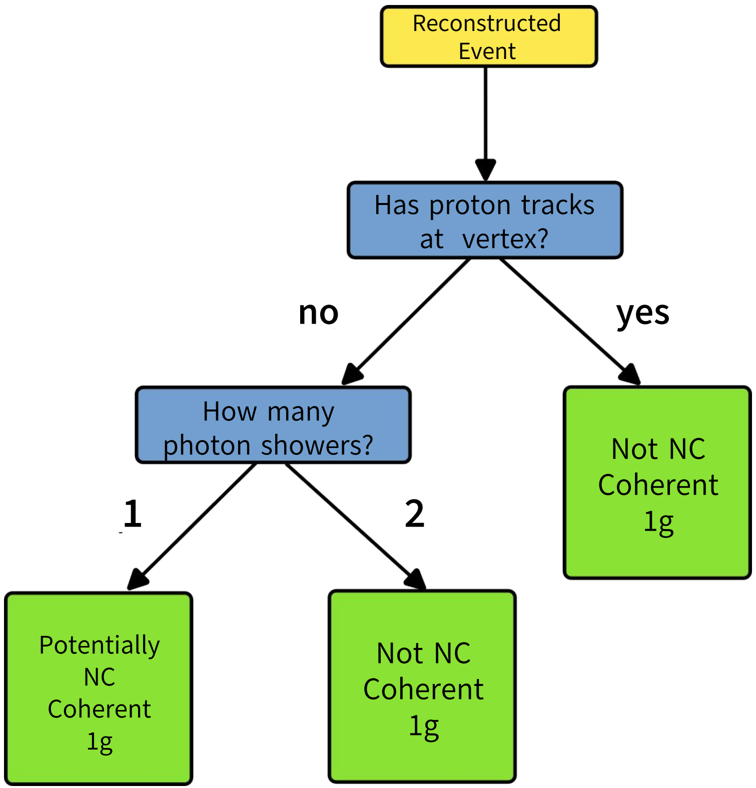
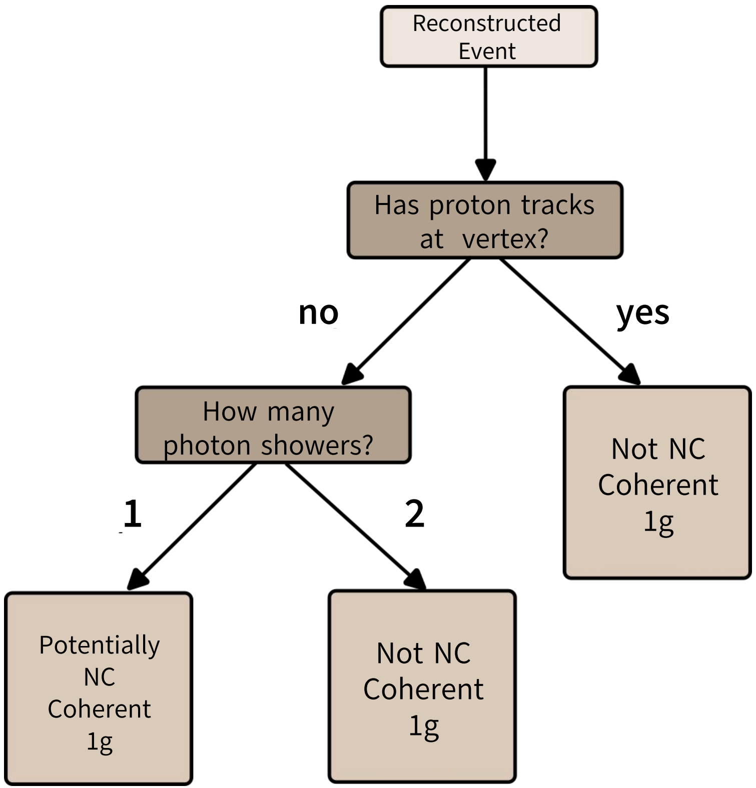
- A series of cuts differentiates events by the patterns they contain



Boosted Decision Trees (BDTs)

- Machine learning algorithm that classifies events into signal and background
- A series of cuts differentiates events by the patterns they contain
- Next tree is designed to correct errors in previous
- Assigns a probability score to each event based on how confident it is that the event is signal



Robust best fits with physics and nuisance parameters

Draw physics conclusions from complex simulation and detector data

PROfit

Allows for direct study of parameters via manual injection into the model

Control which topologies are signal, background, or omitted from a study

Github:
https://github.com/markrosslonergan/Elephant_Vanishes

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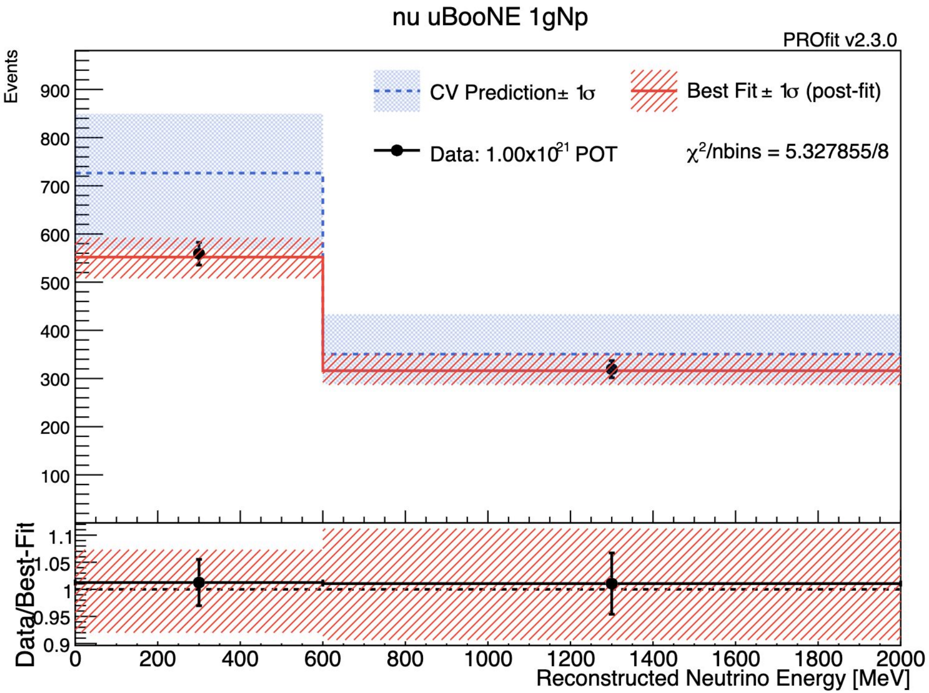
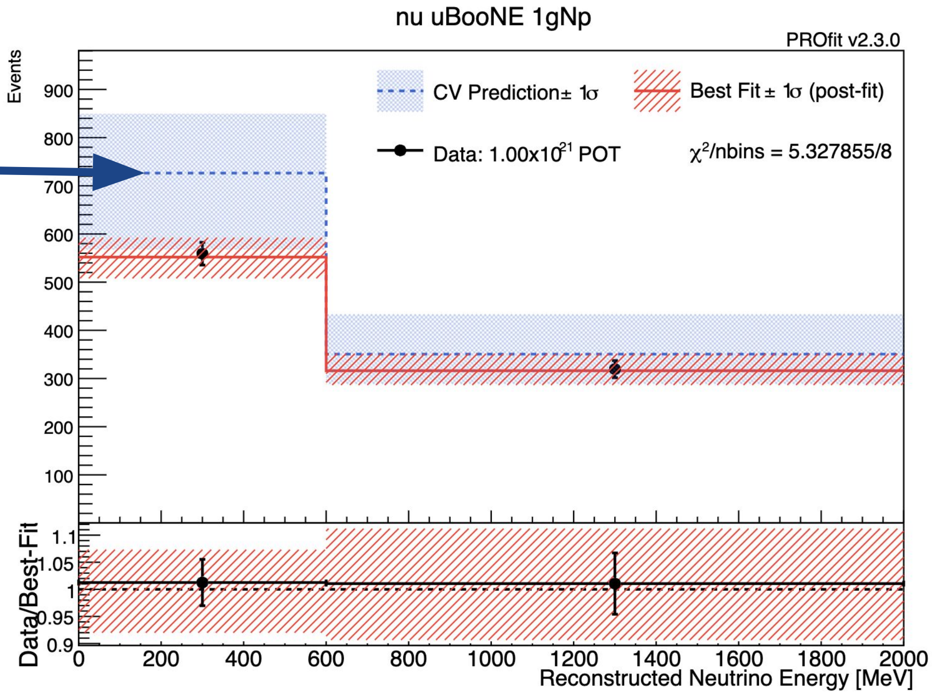
An Aside on Understanding Fits



An Aside on Understanding Fits

Central value (CV) prediction is the models prediction



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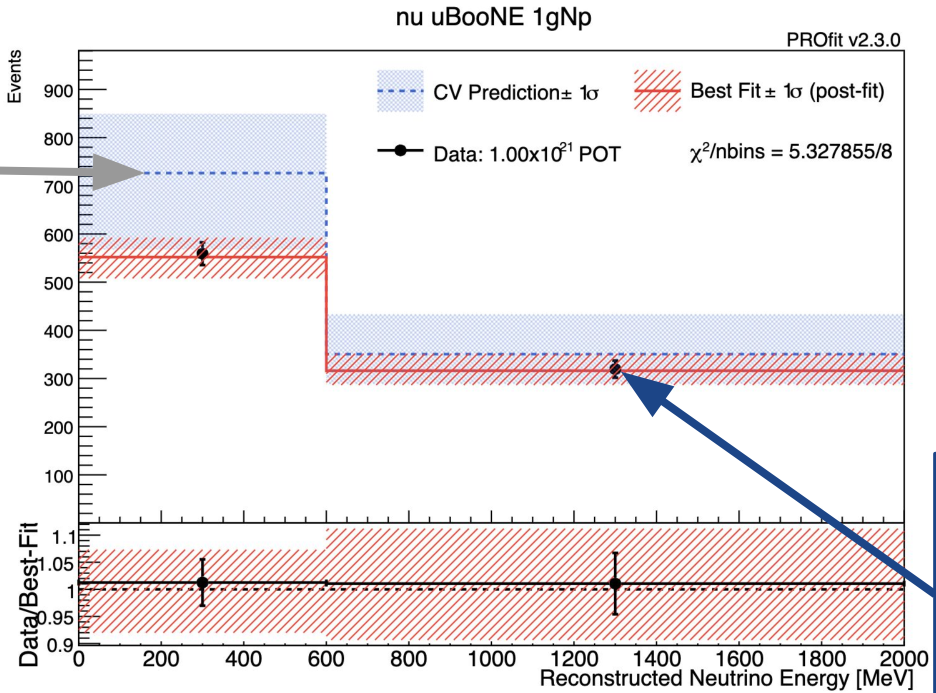

Either fake data or real observation (assume fake for these studies unless explicitly stated otherwise)

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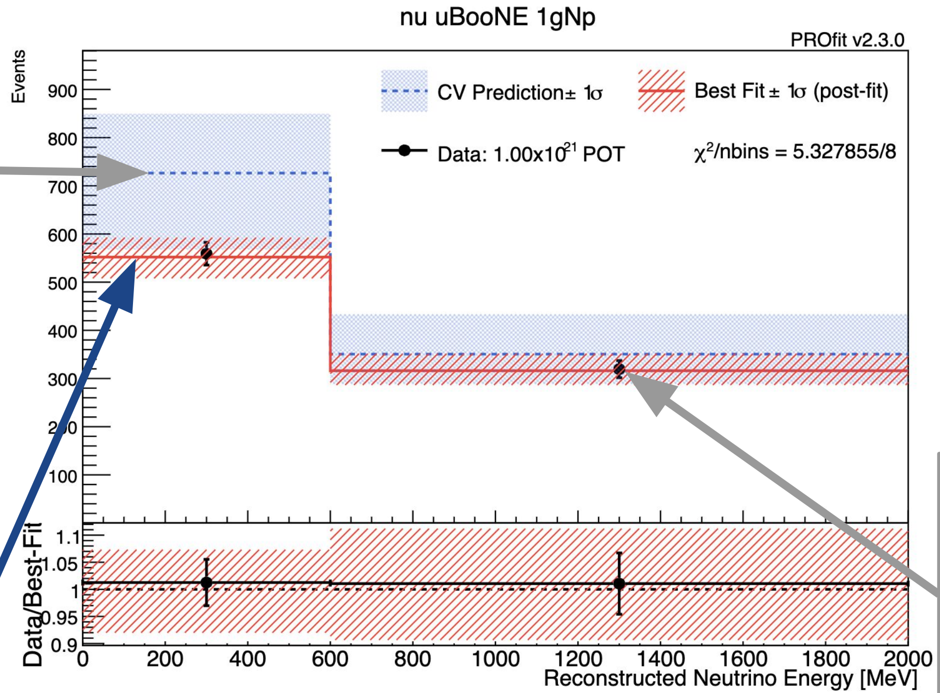

Best fit is the closest the model can come to reproducing the data by varying its parameters

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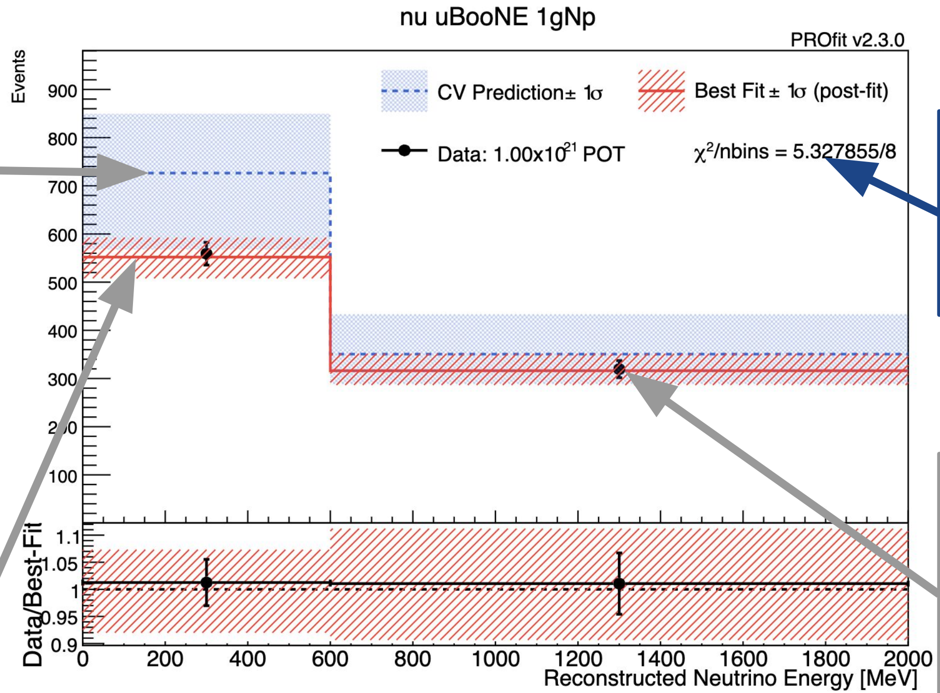

χ^2 measures disagreement between fit and data

Either fake data or real observation (assume fake for these studies unless explicitly stated otherwise)

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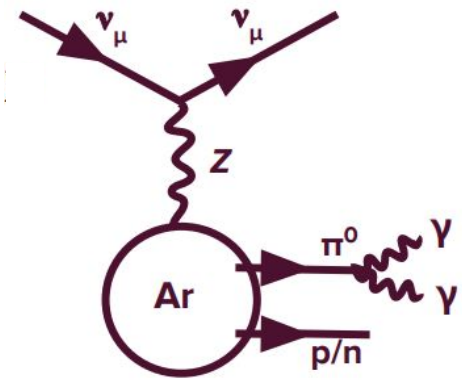
Understanding the Biggest Background: Neutral Current π^0

What is NCπ^0?

$\nu_\mu + \mathrm{Ar} \rightarrow \nu_\mu + \mathrm{Ar'} + \pi^0 + \mathrm{X}$

$\pi^0 \rightarrow \gamma + \gamma$

X = protons and neutrons



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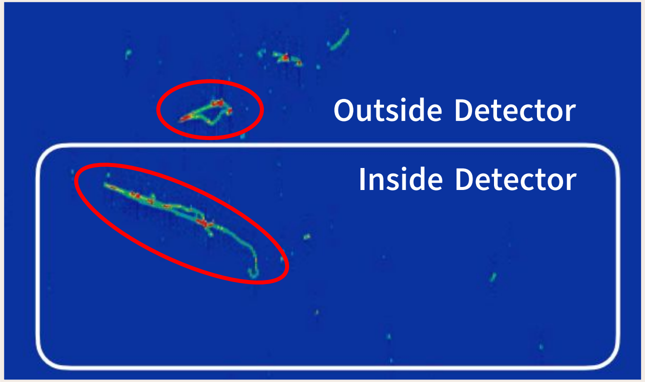
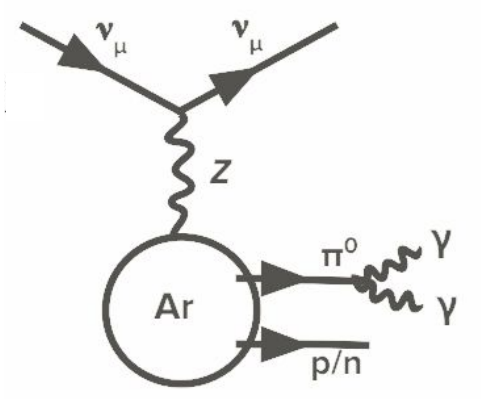


NCπ^0 event with no protons



If one shower escapes the detector, the event mimics a single photon event

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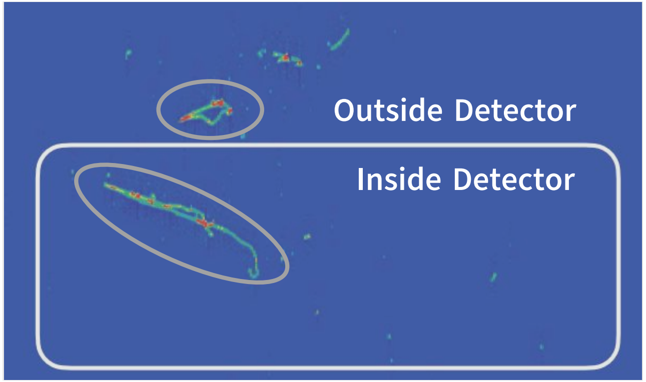

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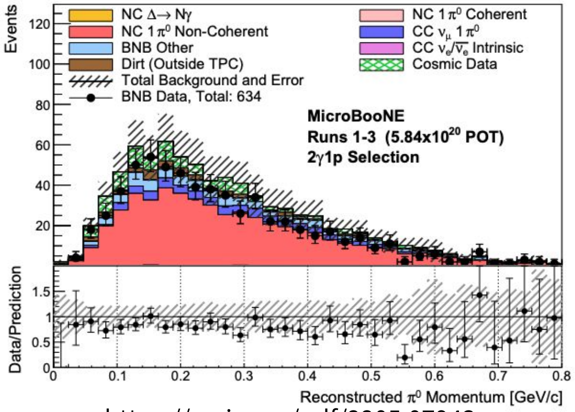
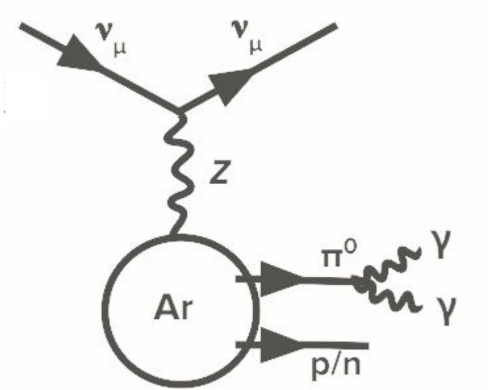


https://arxiv.org/pdf/2205.07943

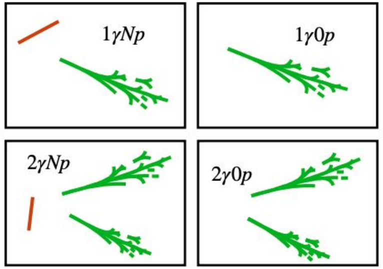


If one shower escapes the detector, the event mimics a single photon event

Motivated by previously observed deficit, we asked, “Can an isolated 20% NC1π^0Np deficit be explained by systematics?”

(Np = ≥ 1 proton)

Can a 20% NC1π^0Np Deficit Be Explained by Systematics?



- Analysis contained to these four channels/topologies
- Manually inject a 20% deficit into NC1π^0Np (also called 2γNp) to identify systematic pulls reproducing this configuration

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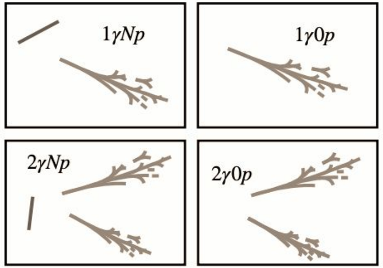

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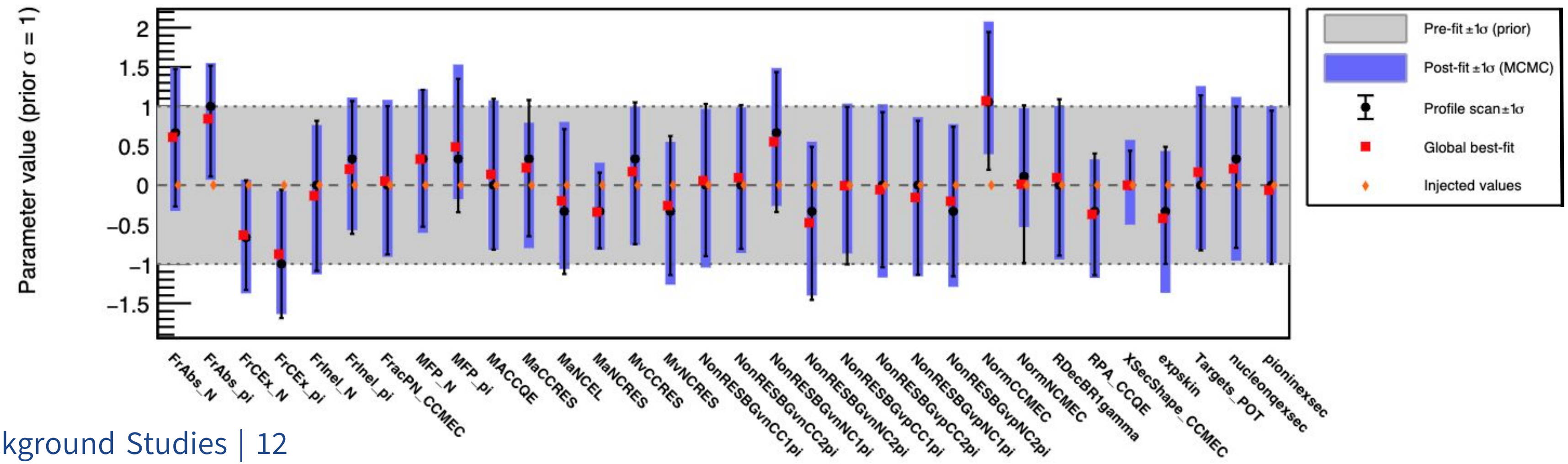

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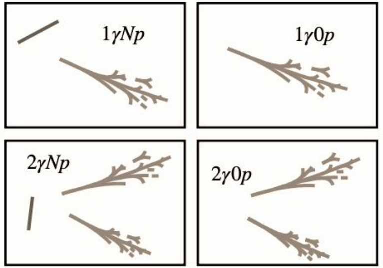

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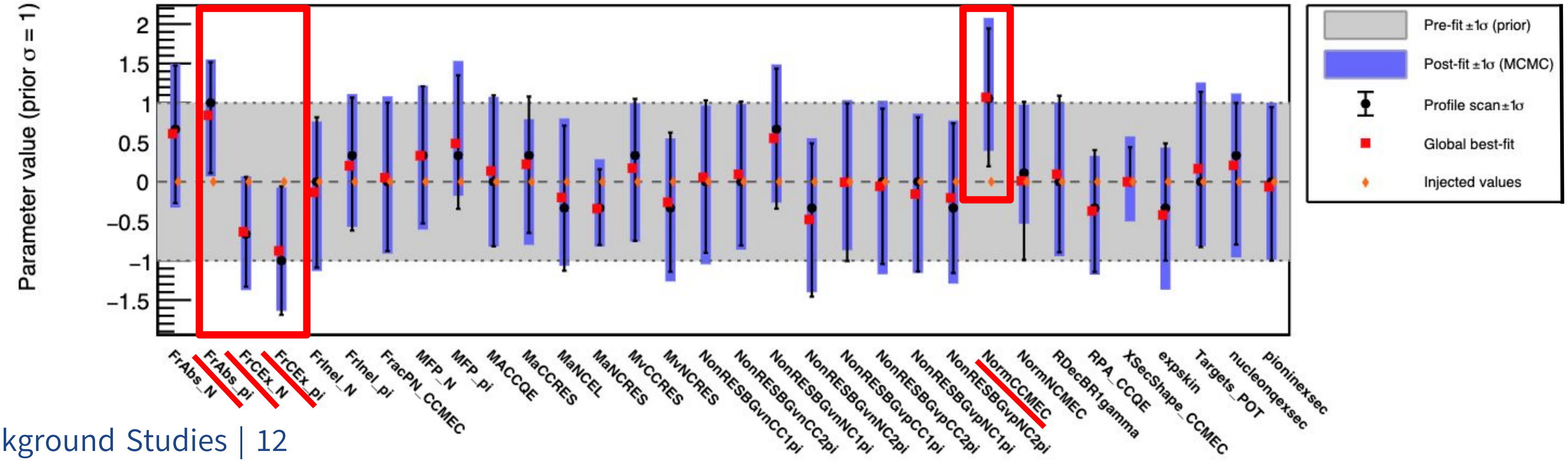
- Selected most pulled systematics, denoted by red outline



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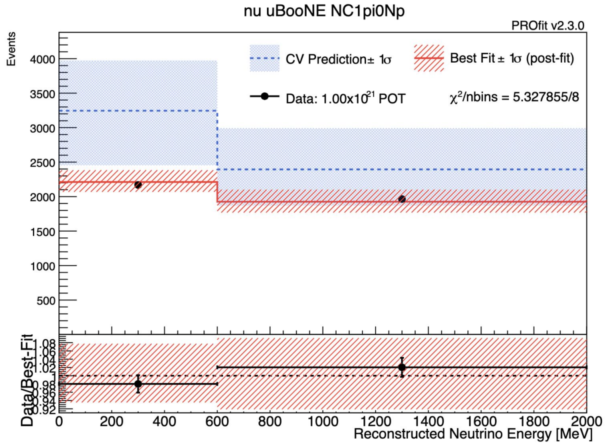
- 20% deficit removed
- Best fits rerun with important systematics injected at -3σ and 3σ to test extremes
- For each bin, the best fit shift from the CV was calculated
- Here is a histogram for one of the tests
- Certainly a deficit, but…



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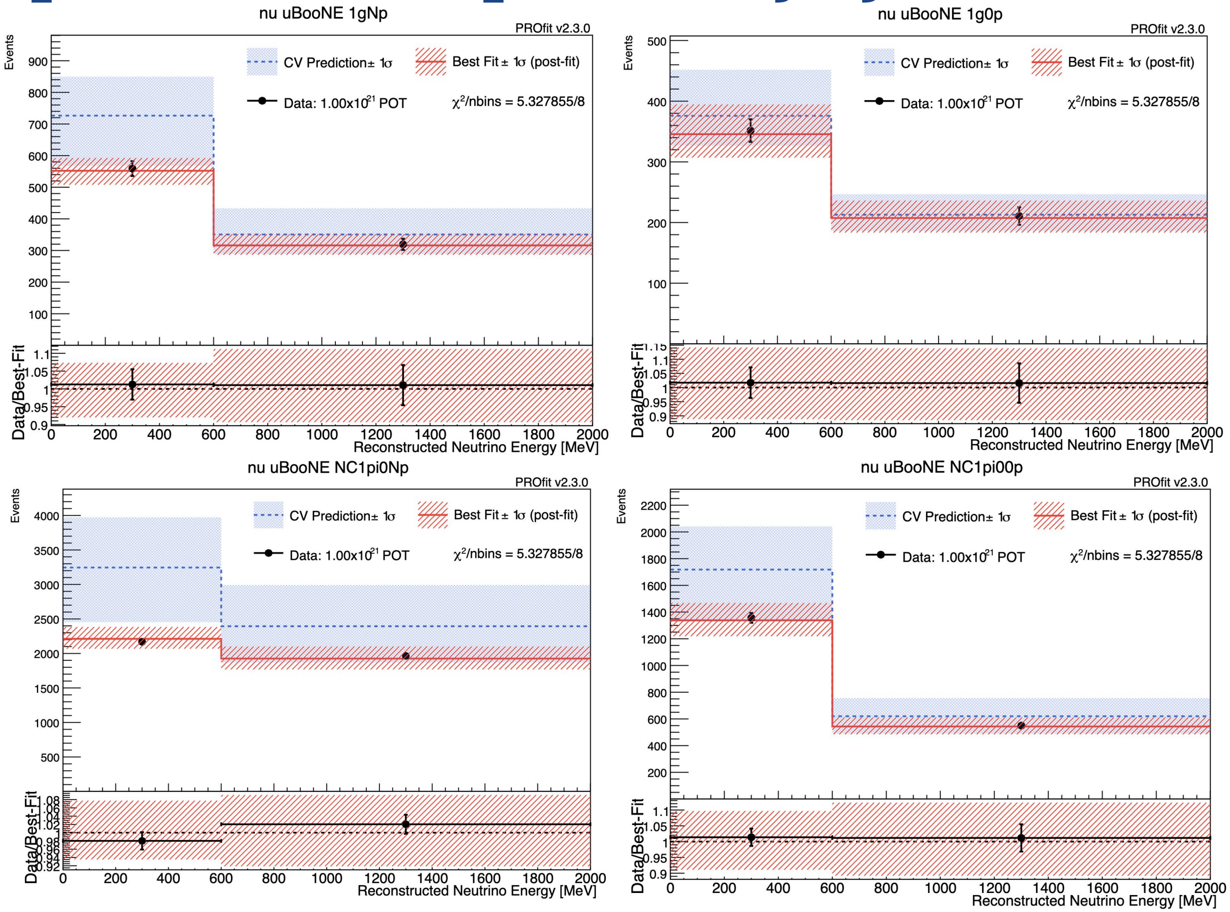
Not isolated!



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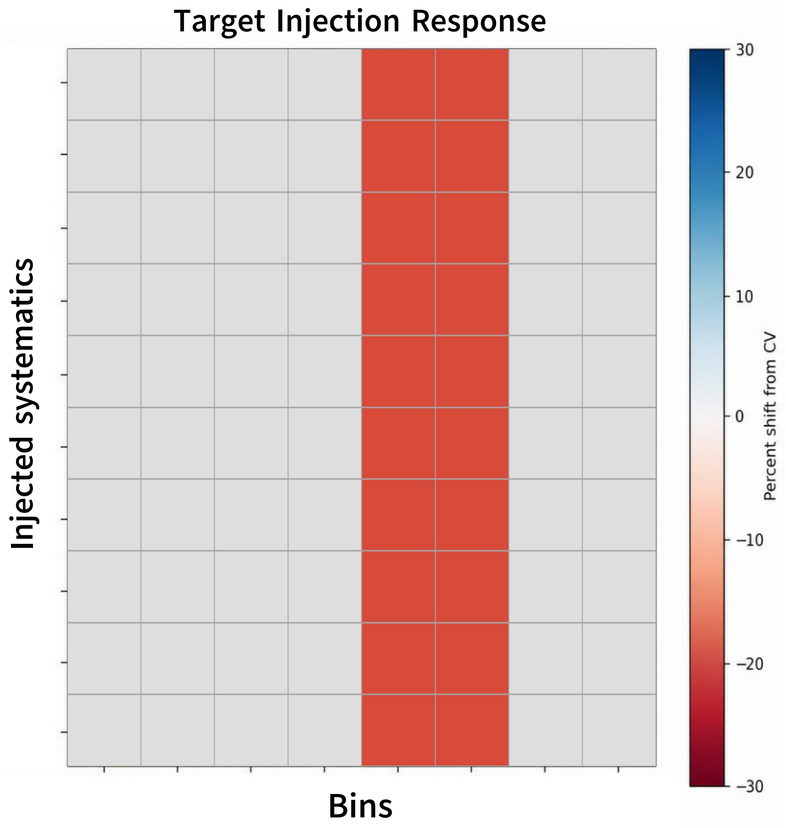

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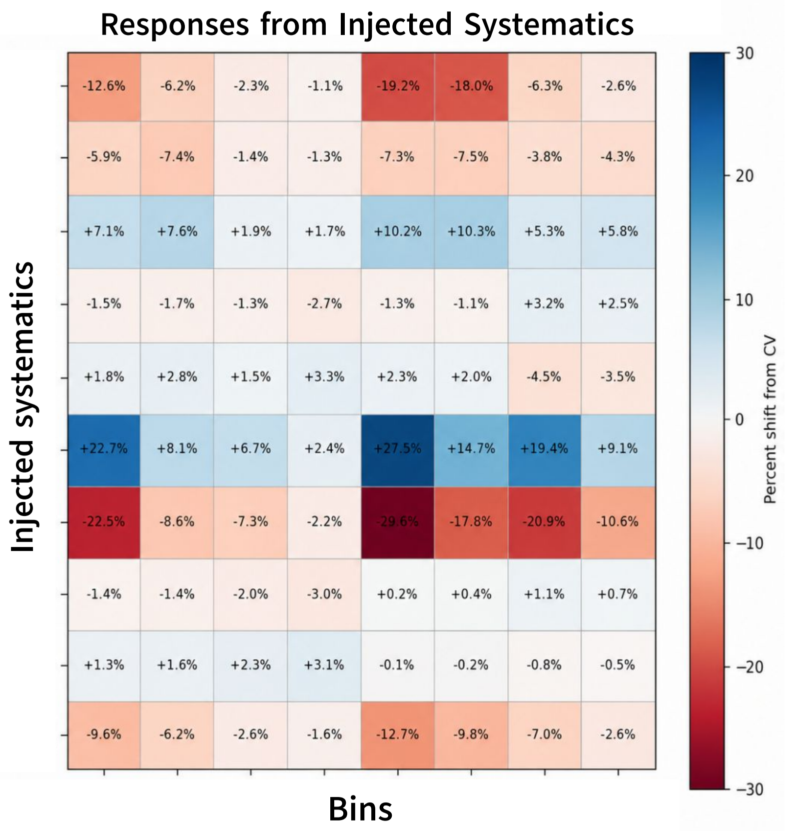

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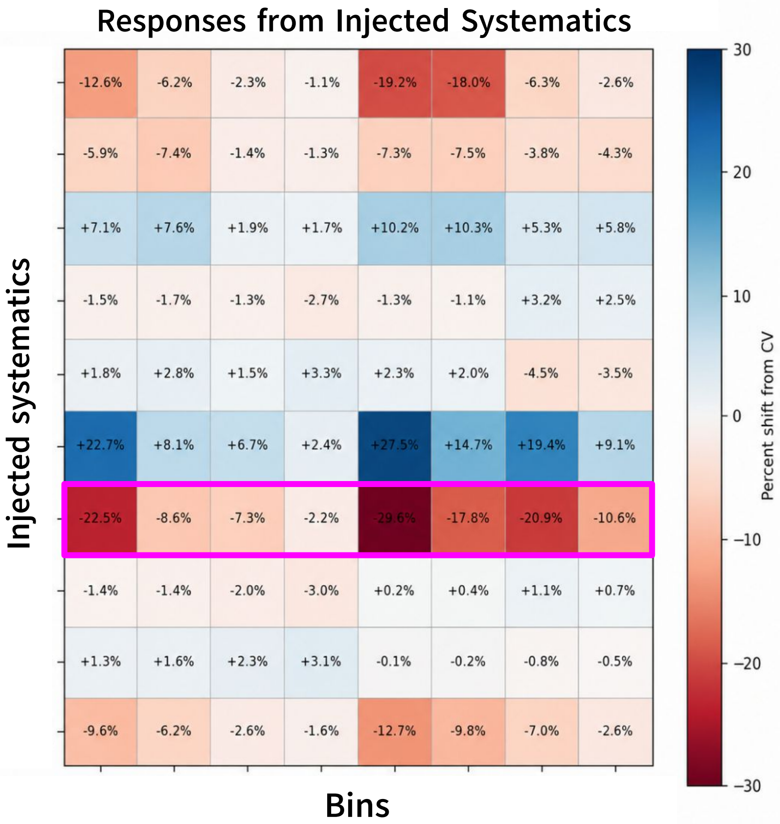

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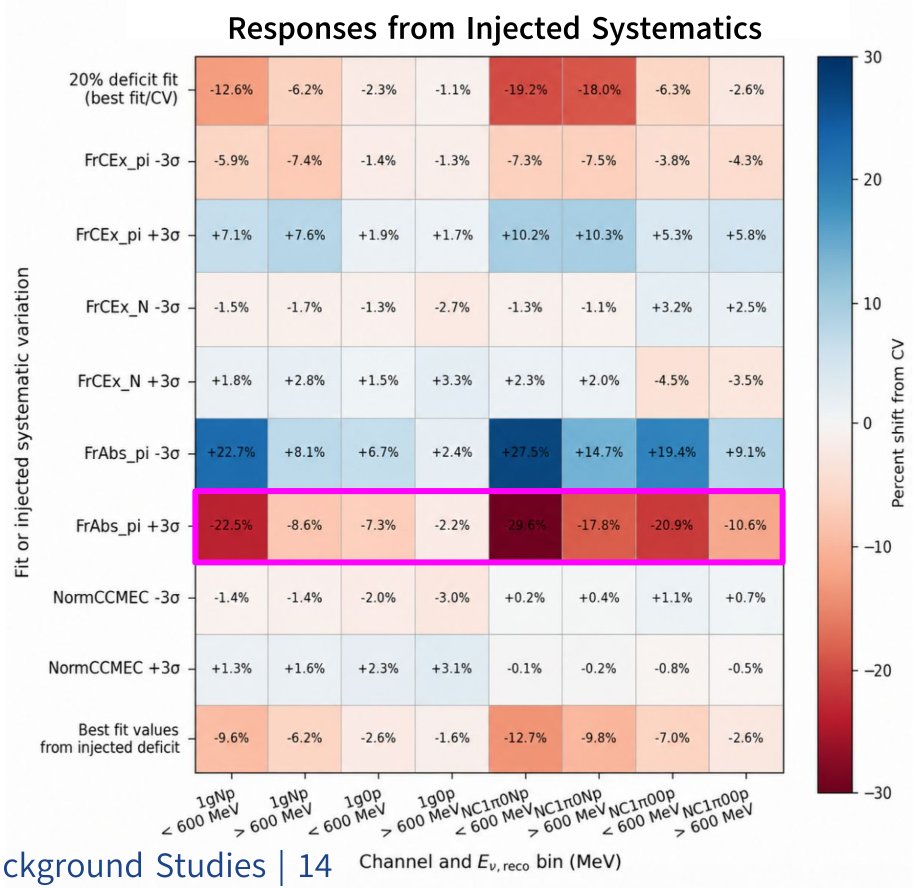

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- These results with further restriction studies indicates:

The 20% NC1π^0Np deficit can be mimicked by a systematic, but it is not a unique or isolated explanation.

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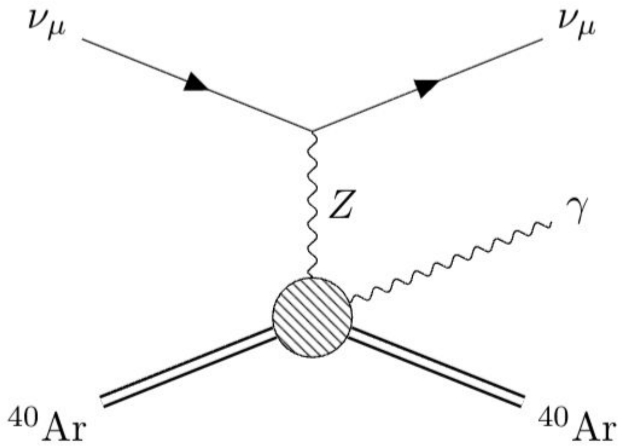
Signal Sensitivity Study

Takeaways

NC Coherent 1γ

What is it?

- Very rare Standard Model process
- Sub-dominant source of single photons



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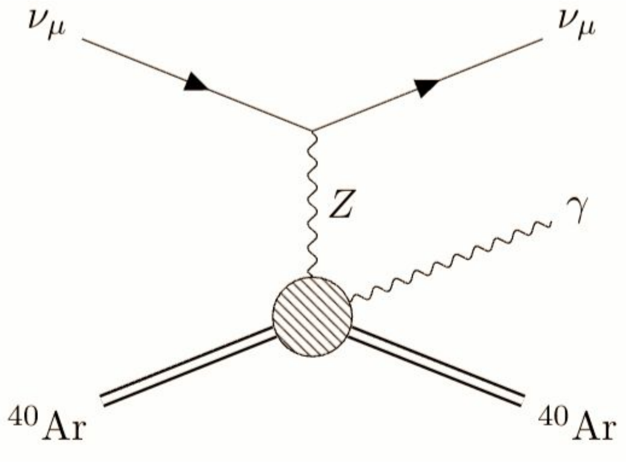

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Goal

Find analysis configuration to become as sensitive to NC Coherent 1γ events as possible

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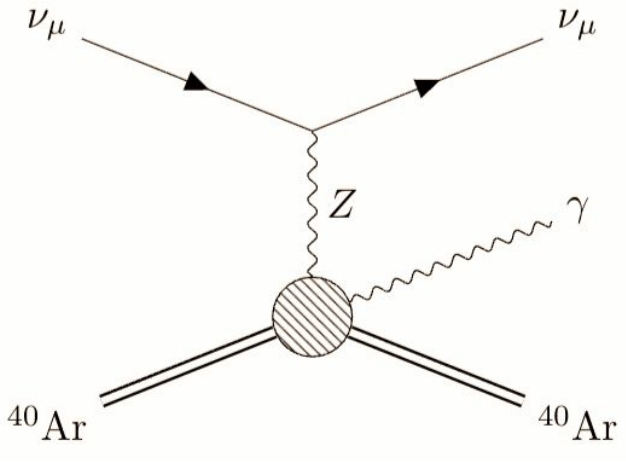

$$\nu_\mu + {}^{40}\mathrm{Ar} \rightarrow \nu_\mu + {}^{40}\mathrm{Ar} + \gamma$$

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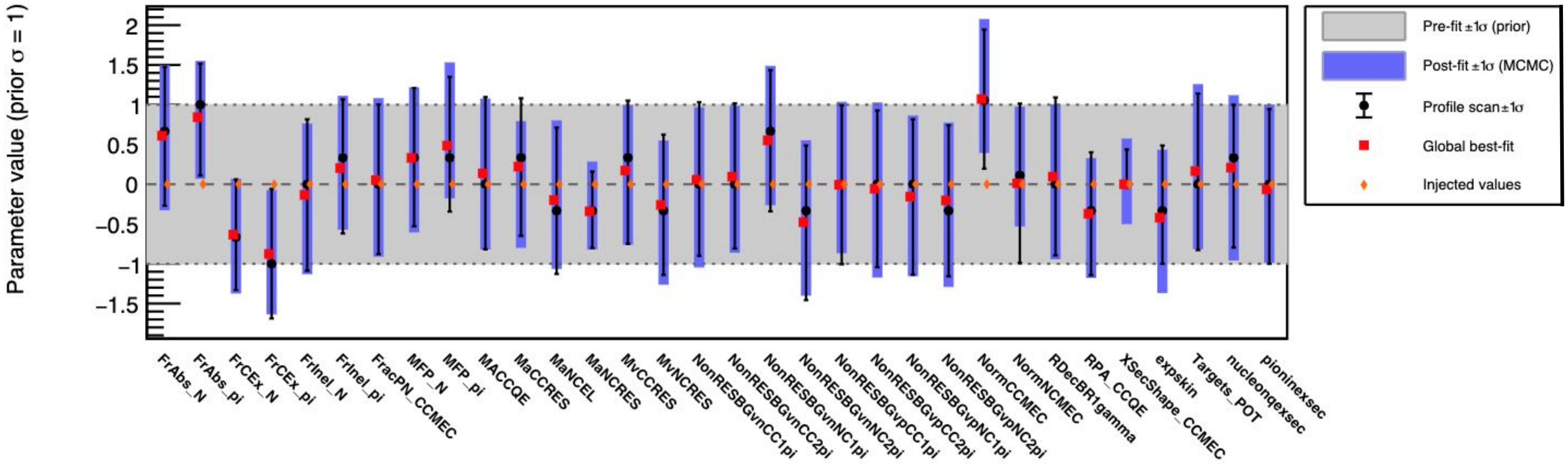
Find analysis configuration to become as sensitive to NC Coherent 1γ events as possible

Obstacle

- Lots of binning variables to test
- Many ways to bin
- Lots of sideband combinations

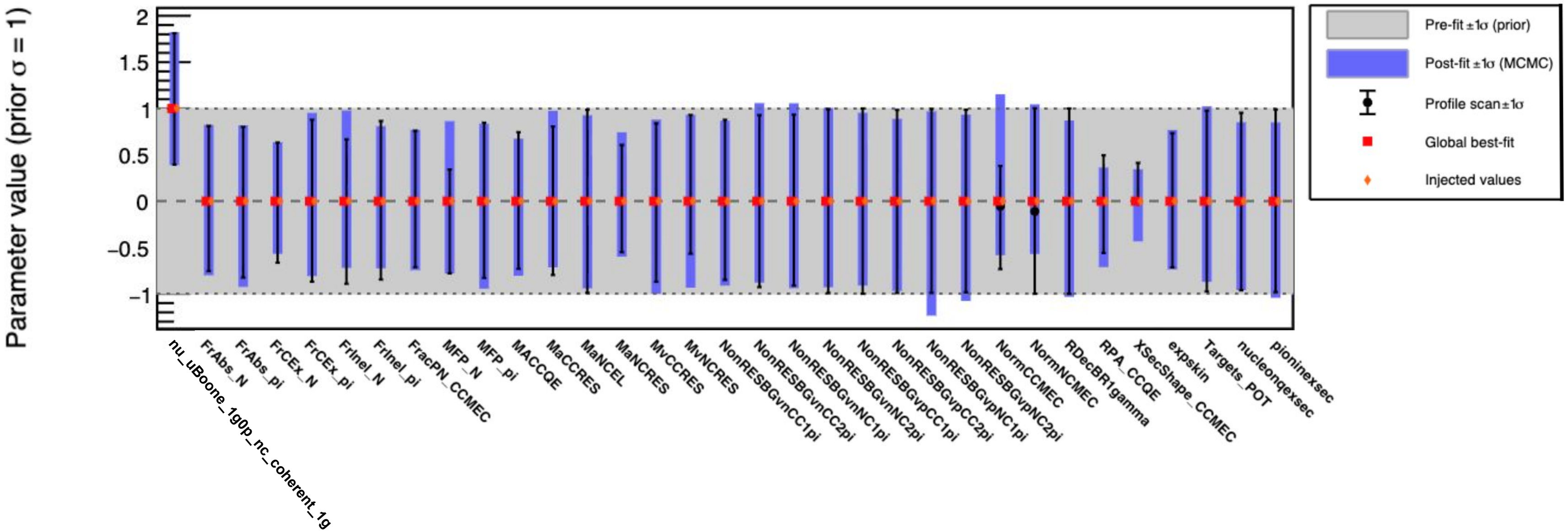
How to determine sensitivity?

Remember me?



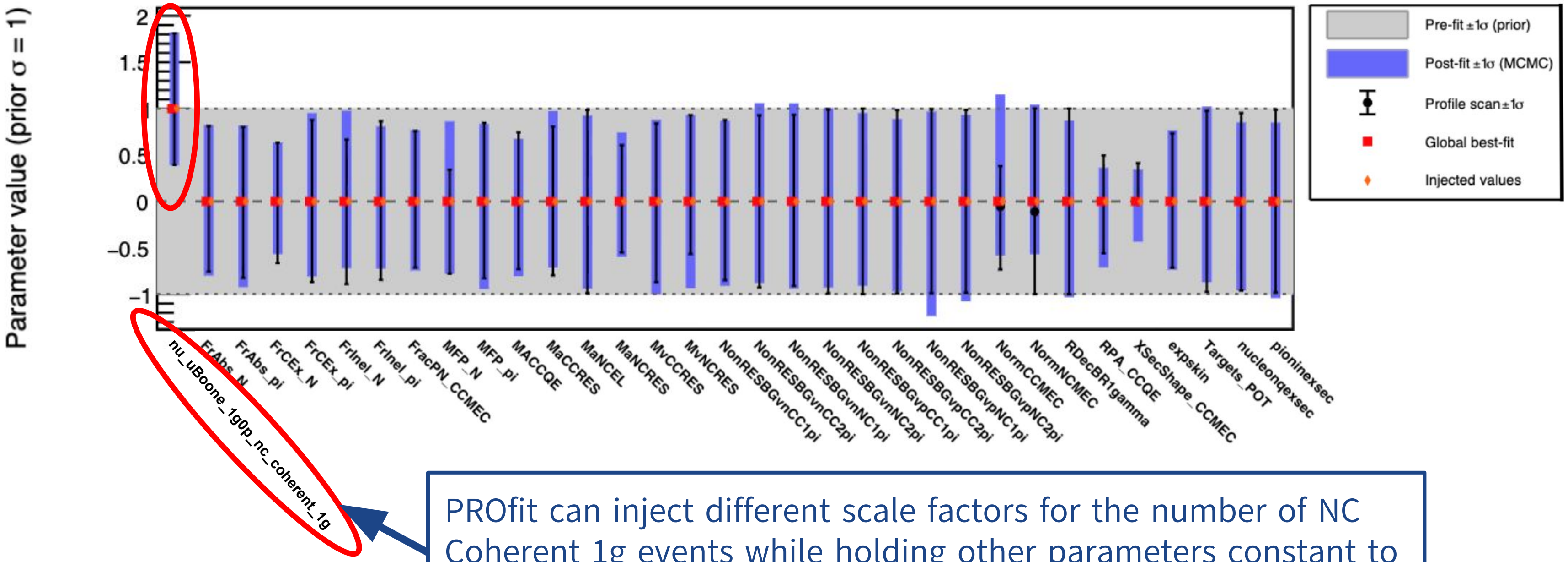
How to determine sensitivity?

How about now?



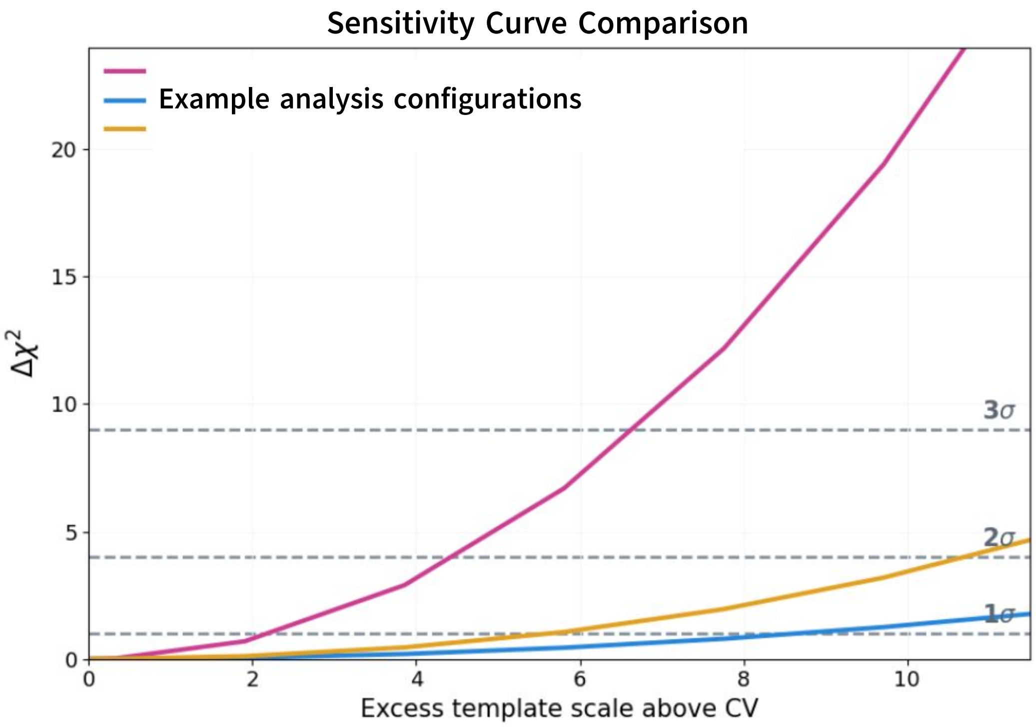
How to determine sensitivity?

Template fit parameter!



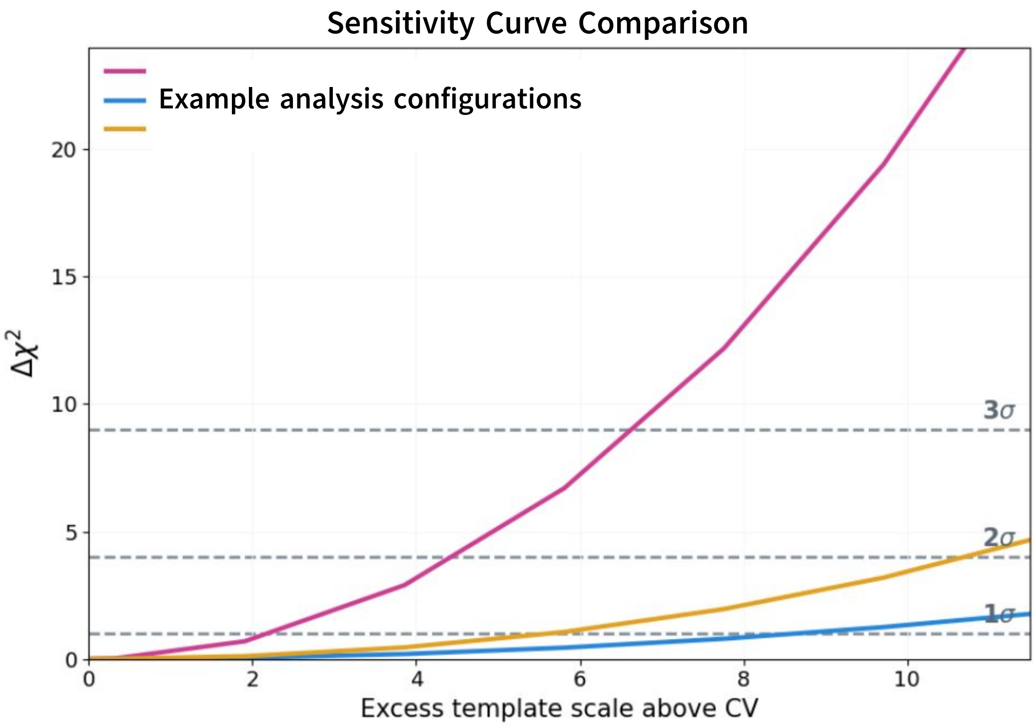
PROfit can inject different scale factors for the number of NC Coherent 1g events while holding other parameters constant to see how χ^2 reacts

How to determine sensitivity?



This is the sensitivity curve plot with three different analysis configurations:

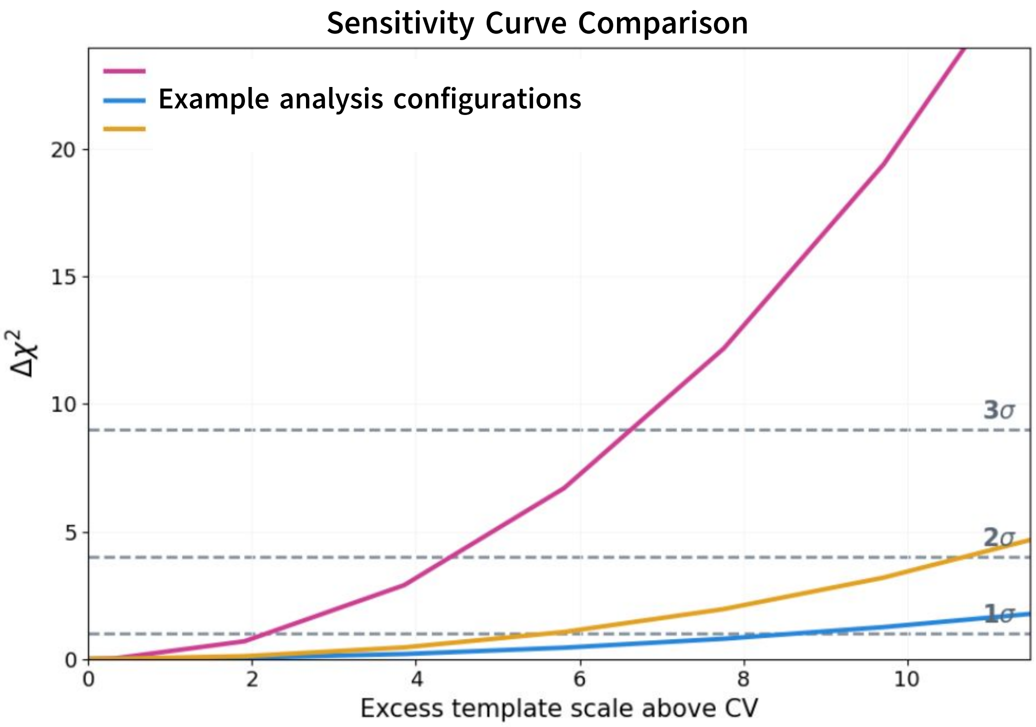
How to determine sensitivity?



This is the sensitivity curve plot with three different analysis configurations:

- The pink configuration beats the yellow and blue (steeper is better)

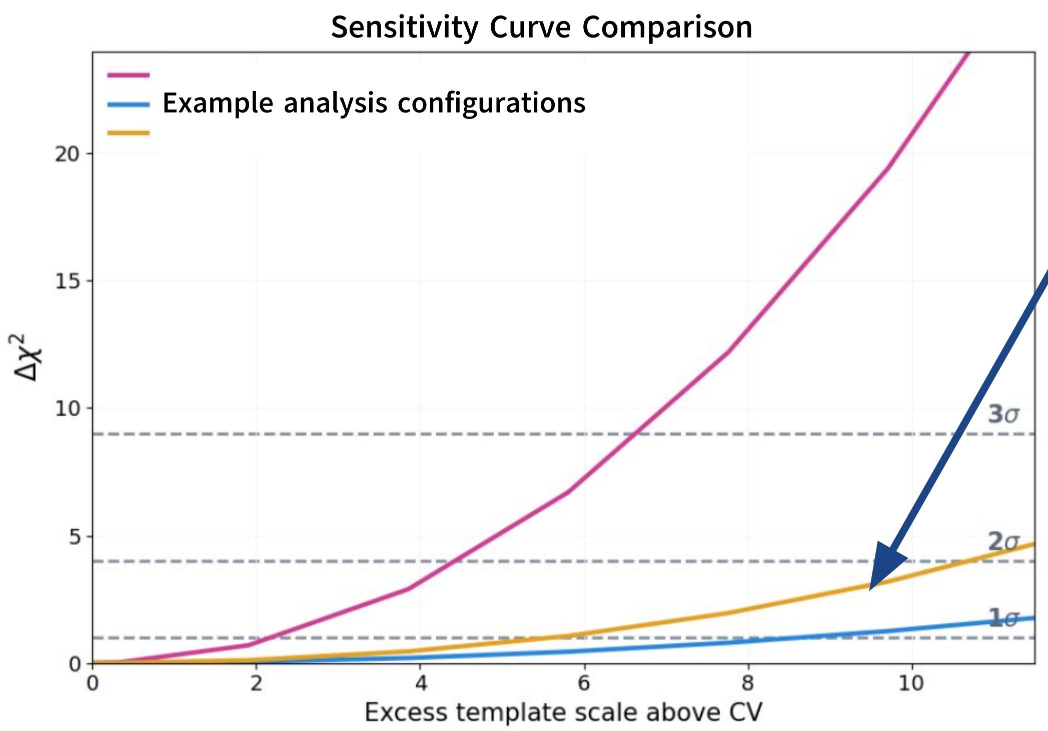
How to determine sensitivity?

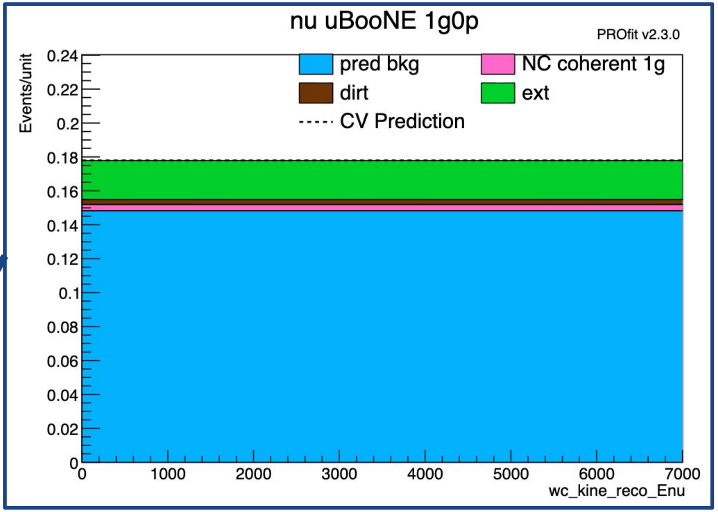


This is the sensitivity curve plot with three different analysis configurations:

- The pink configuration beats the yellow and blue (steeper is better)
- Ex: The pink analysis can distinguish an excess of ~7x the CV predicted rate of NC Coherent 1γ events at > 99% confidence level

How to determine sensitivity?

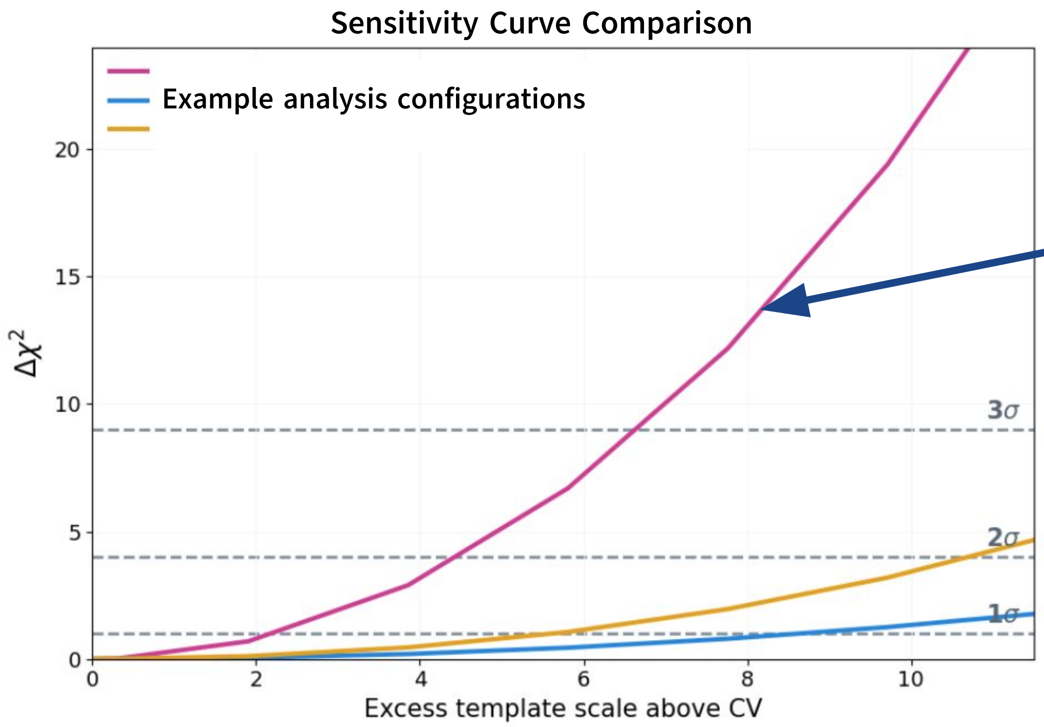


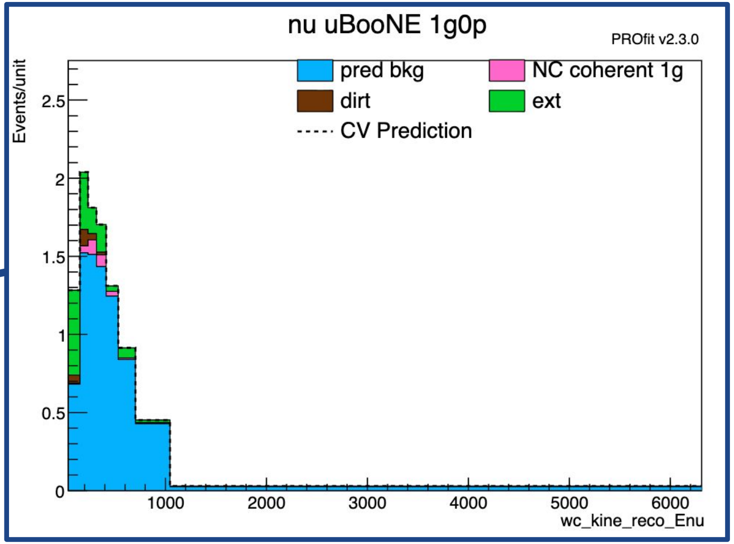


Histogram for the yellow curve

To improve sensitivity, we want binning regions that maximize signal (pink above) to background ratio (non-pink).

How to determine sensitivity?



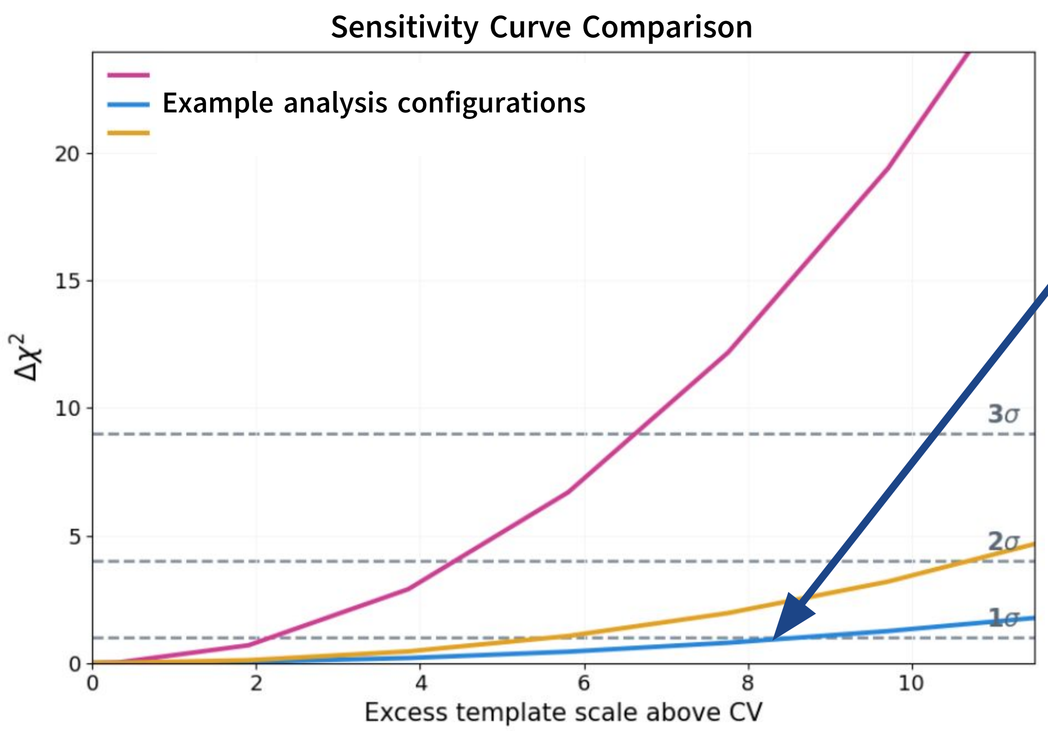


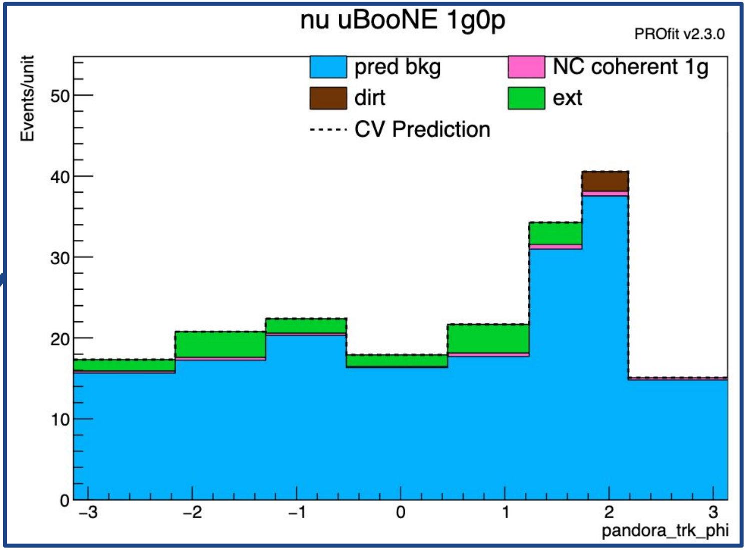
Histogram for the pink curve

Same binning variable with more bins

Bins that distinguish signal from background

How to determine sensitivity?





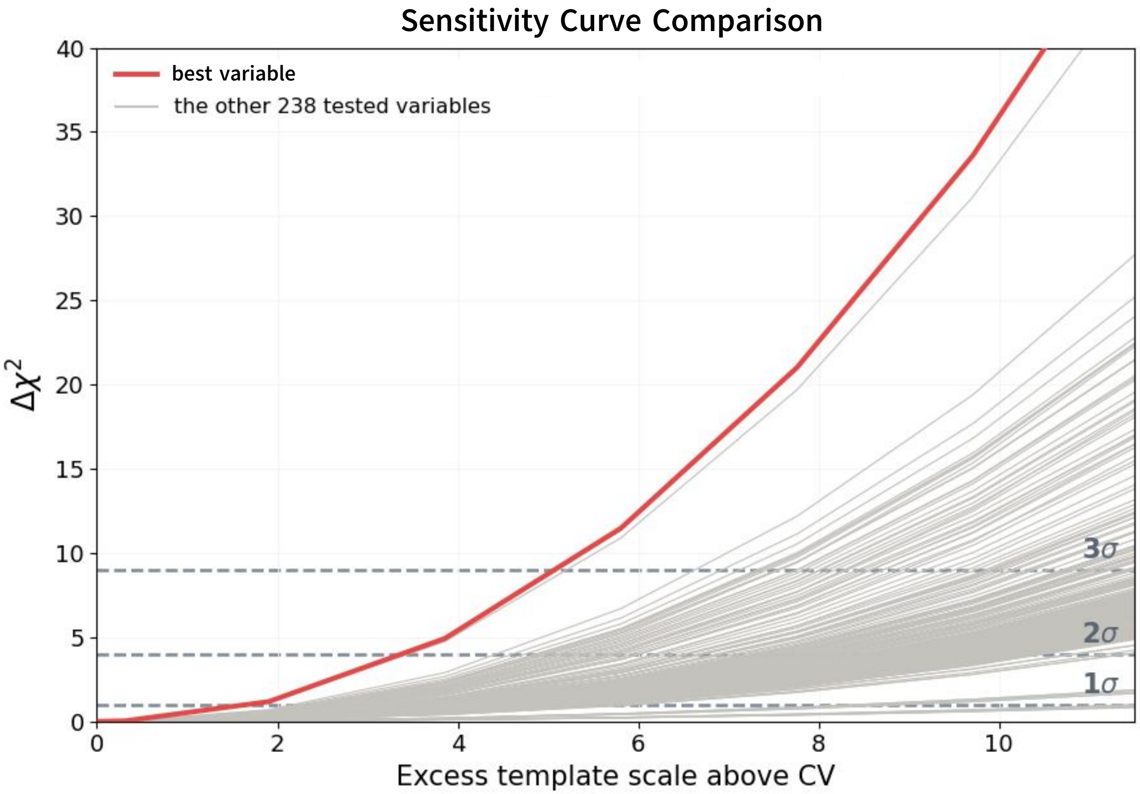
Histogram for the blue curve

Same bins with new binning variable

No distinguishing power; underperforms single bin because configuration only adds statistical noise

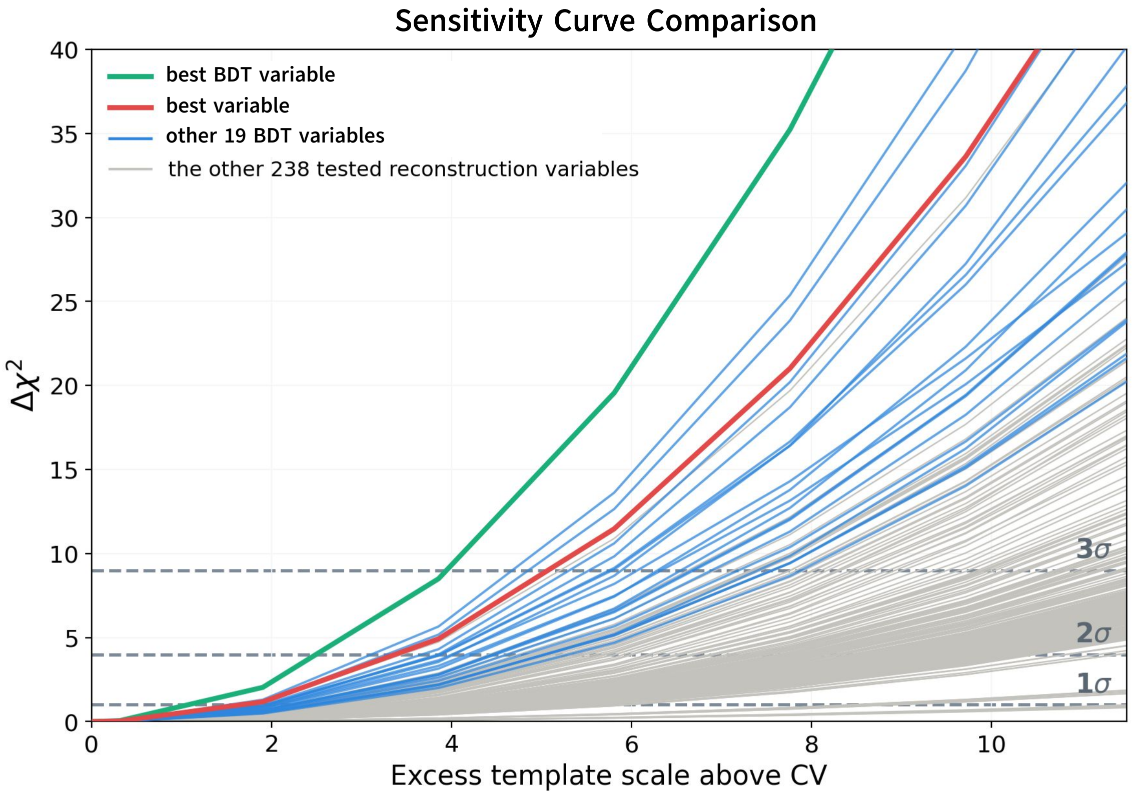
NC Coherent 1γ: Binning Variables

- Binning controlled each run
- If only there was a way to capitalize on information from all of these variables…



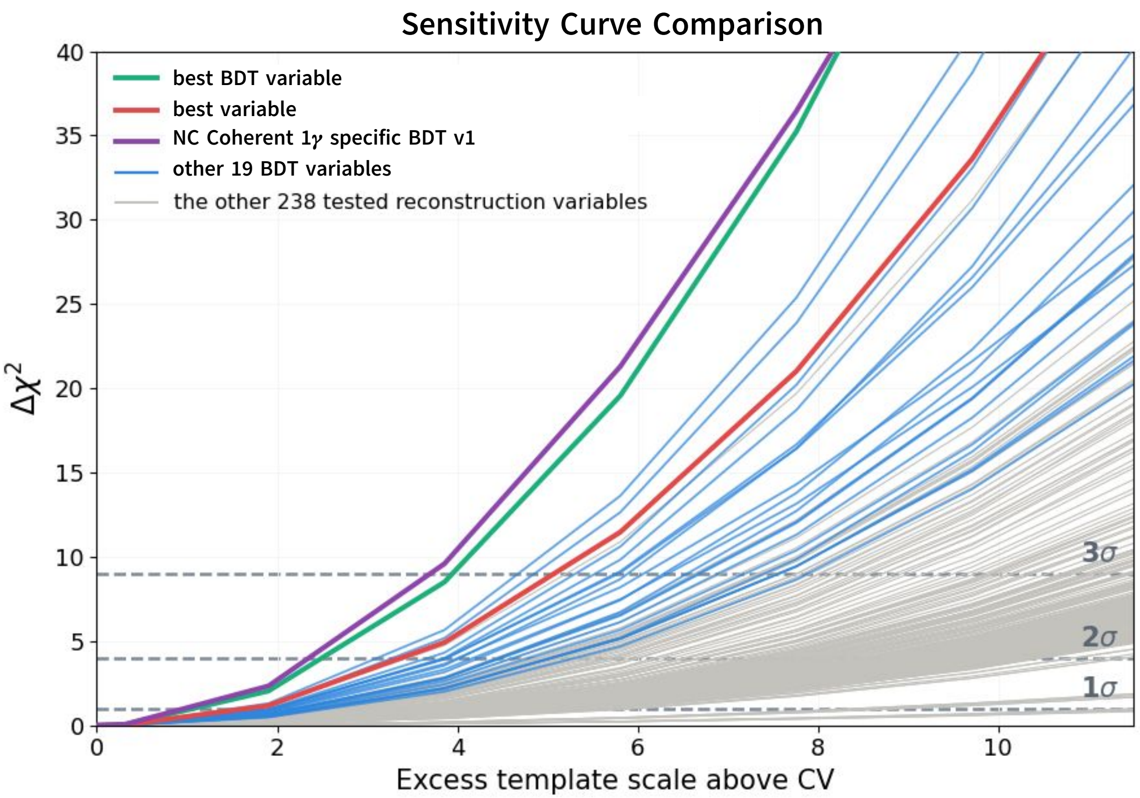
NC Coherent 1γ: Binning Variables

- BAGELS BDT!
- BDT variables outperform single variables on average
- But BAGELS does not select for NC Coherent 1γ…



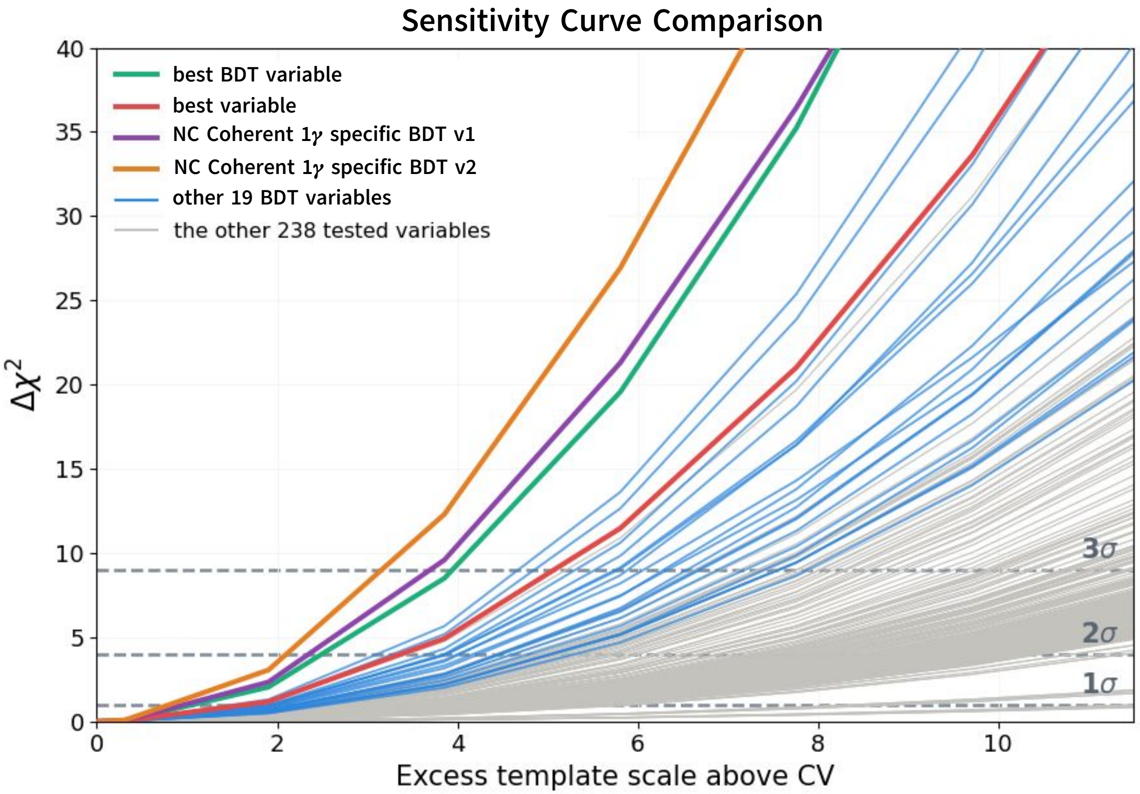
NC Coherent 1γ: Binning Variables

- Specifically designed BDT!
- But who says this BDT is optimized itself…



NC Coherent 1γ: Binning Variables

- Hyperparameter tuned BDT
  - Try different criteria for BDT and see which works best



NC Coherent 1γ: Binning and Sidebands Optimization

Choosing Bin Edges

- Previous runs sorted into eight bins with equal events
- Optimized by testing multiple binning algorithms
- Imposed minimum of 10 events per bin to avoid:

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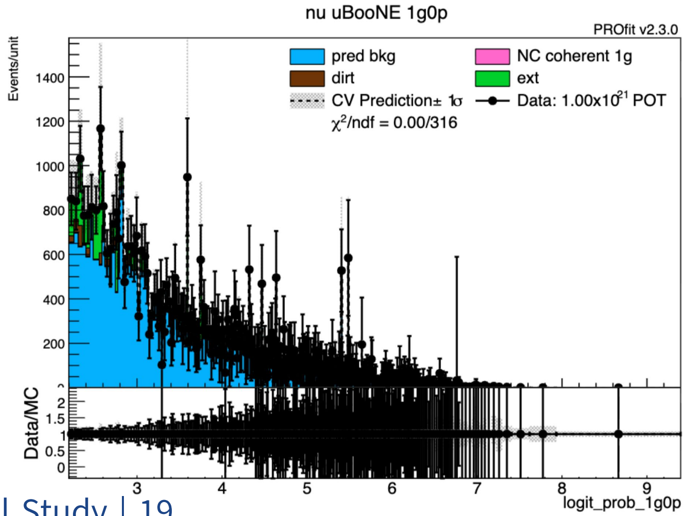

NC Coherent 1γ: Binning and Sidebands Optimization

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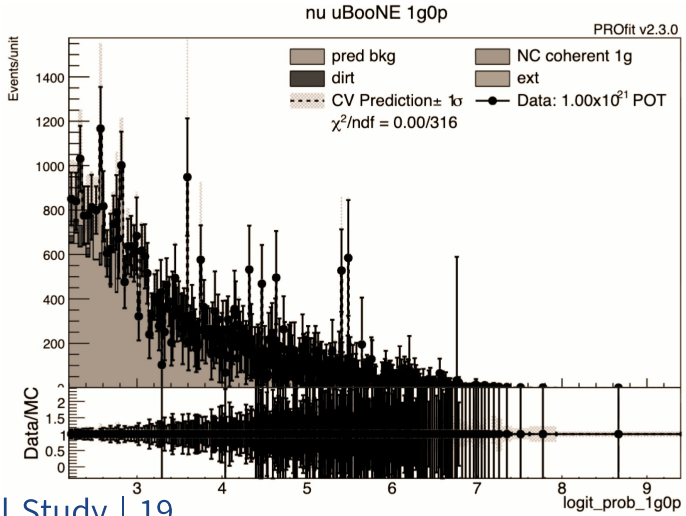
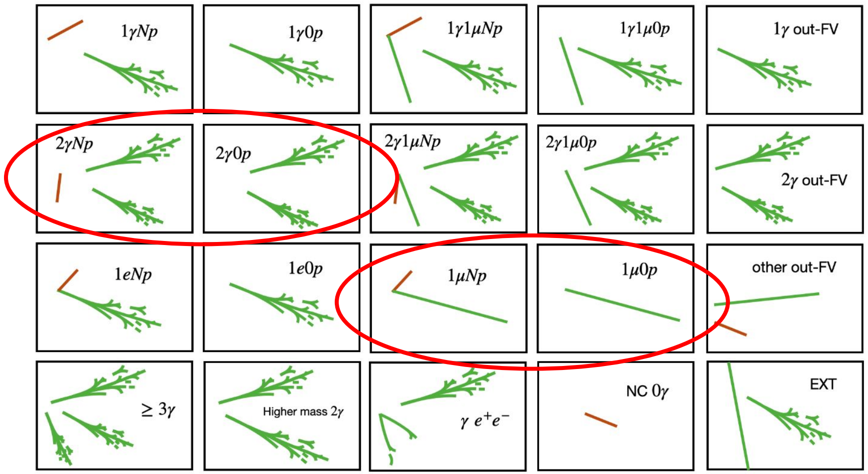
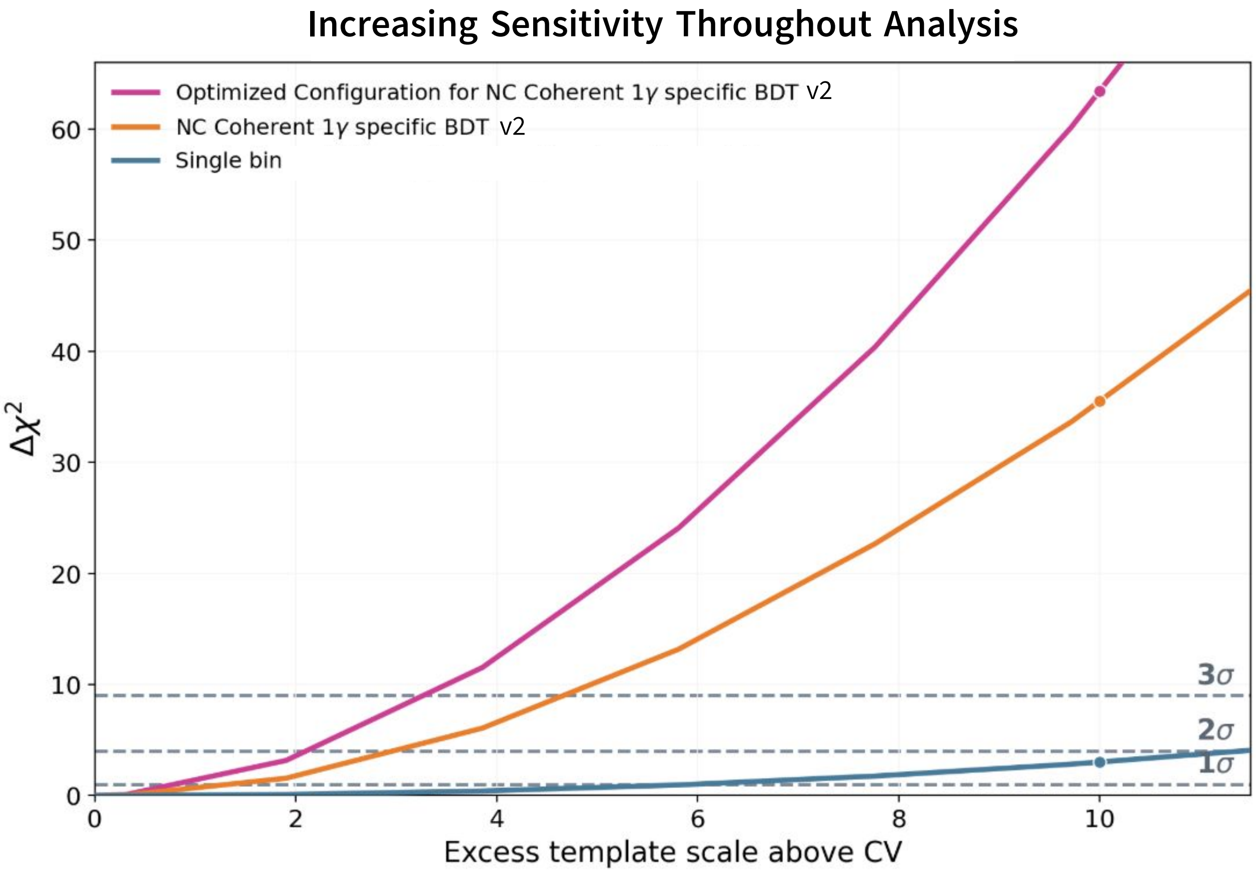


Sideband Optimization

- All 19 sidebands on always outperforms
- NCπ^0 and high stats sidebands predominantly constrain uncertainties affecting analysis

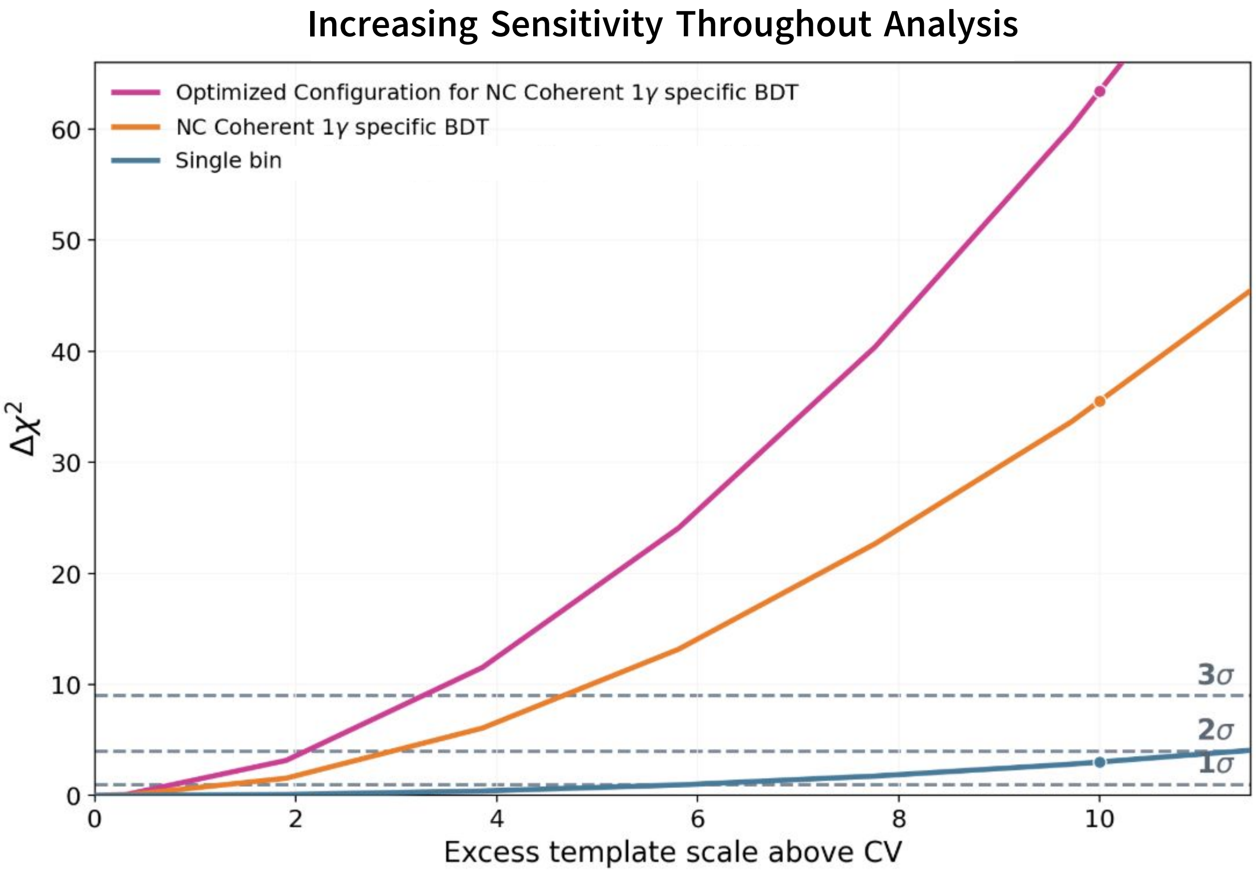


Where Does This Leave Us?



Where Does This Leave Us?

A much improved analysis!



Background

Tools

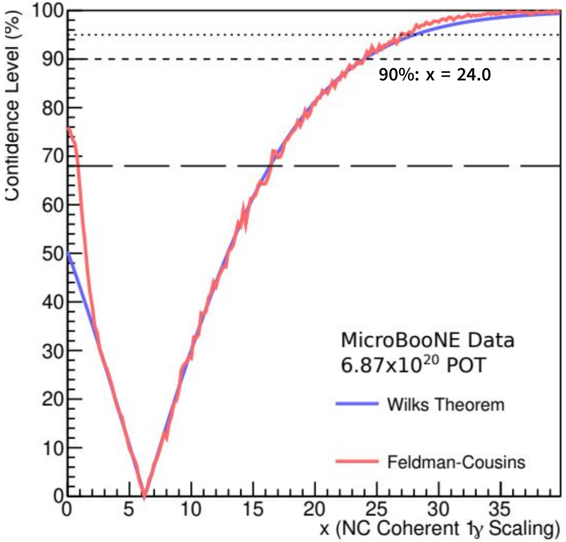
Background Studies

Signal Sensitivity Study

Takeaways

NC Coherent 1γ

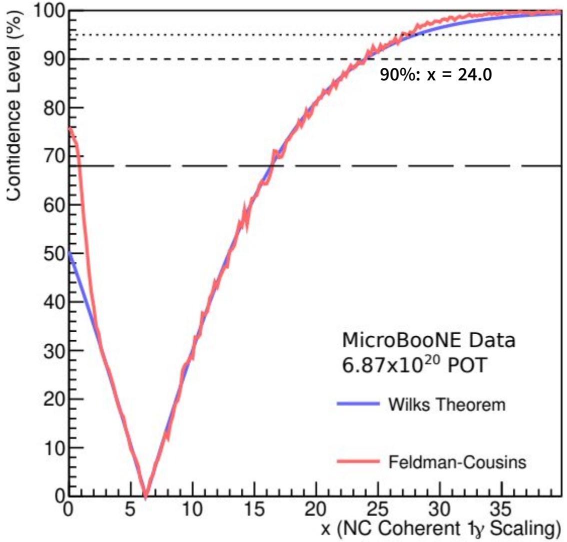
Previous MicroBooNE Analysis



https://arxiv.org/pdf/2502.06091

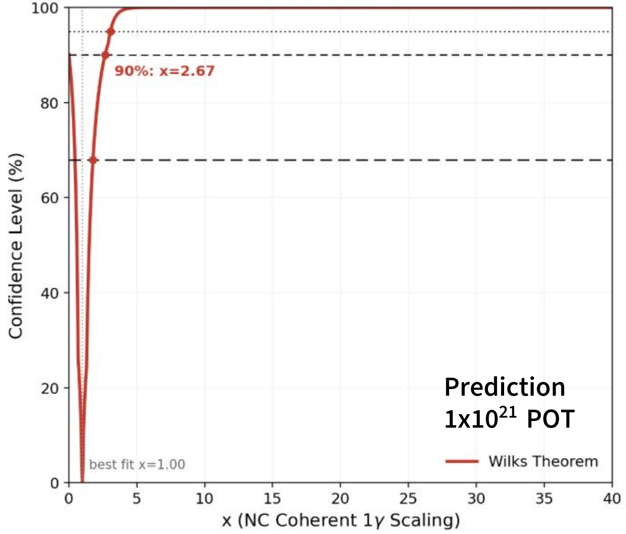
NC Coherent 1γ

Previous MicroBooNE Analysis



https://arxiv.org/pdf/2502.06091

Predicted

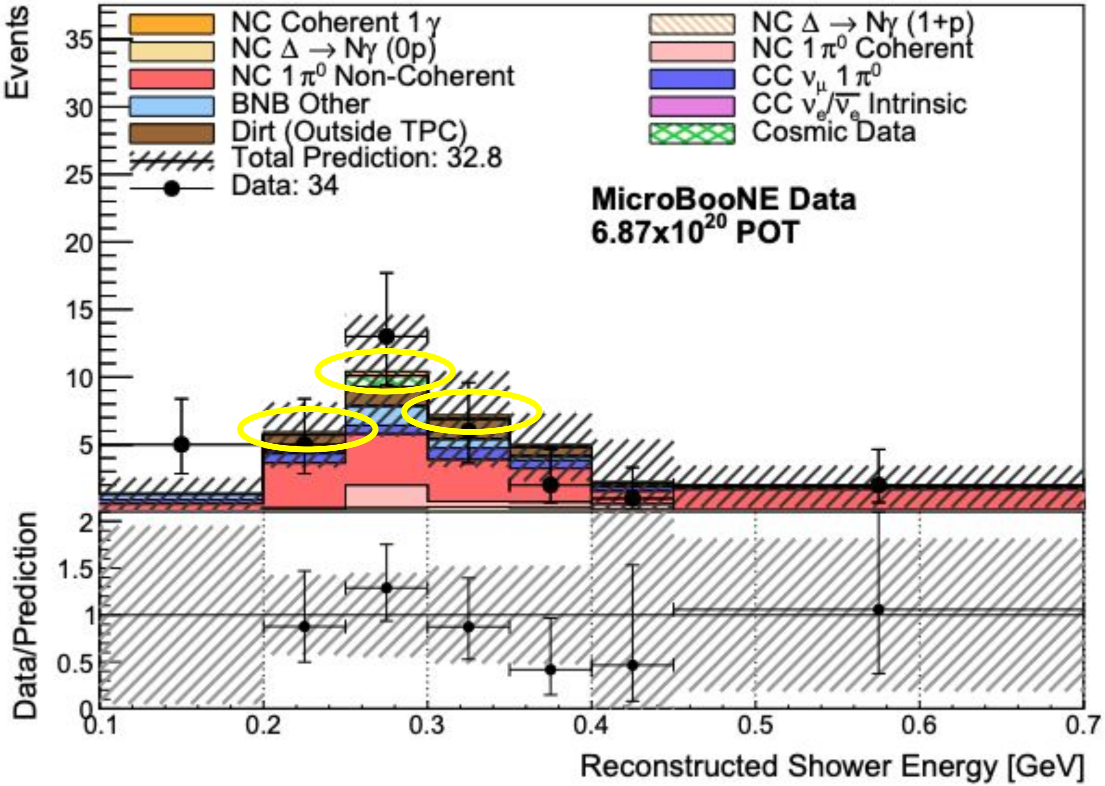


- Expected to have improved sensitivity to NC Coherent 1γ by a factor of up to 9
- Comparison is not airtight: analysis lacks some signal and detector systematics

Signal to Background

Previous MicroBooNE purity:

3.2%



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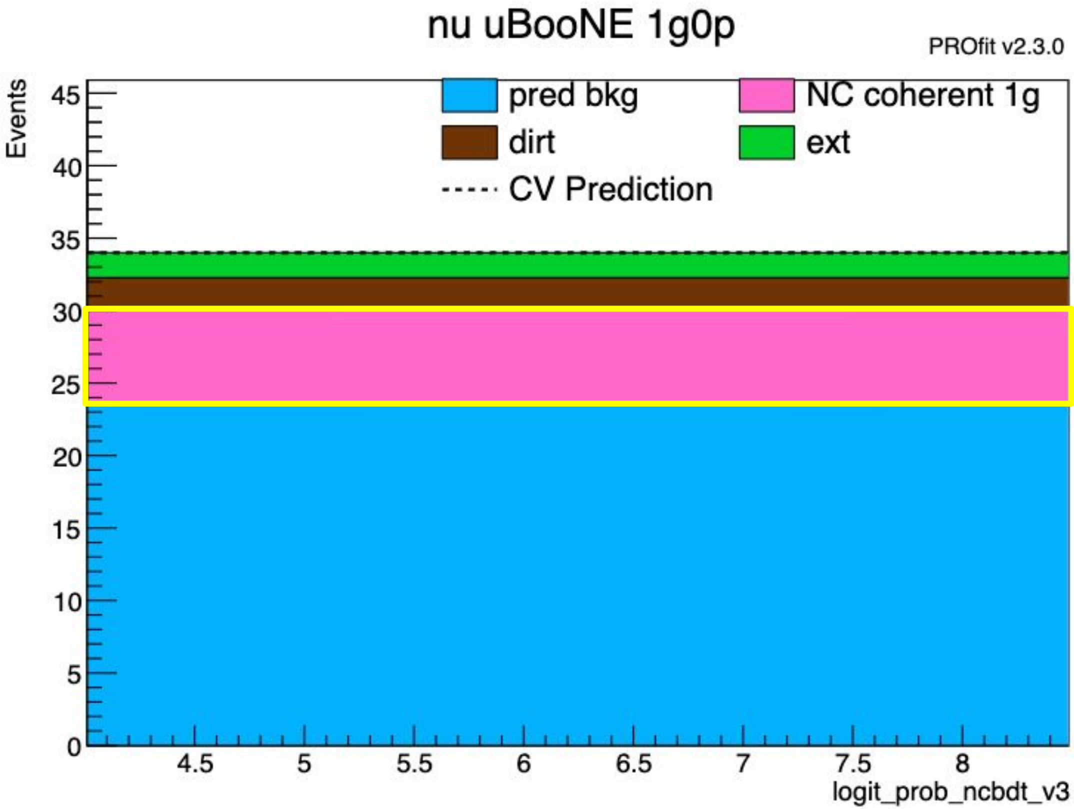
Signal to Background

Previous MicroBooNE purity:

3.2%

Purity in upper region of prediction (same number of events):

19.4%



Cross-Section Limits

Previous MicroBooNE result:

$\boldsymbol{\sigma} < \mathbf{1.49x10^{-41}\ cm^2}$

Cross-Section Limits

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σ < 1.49x10^{-41} cm^{2}

Prediction at 1x10^{21} POT:

σ < 1.66x10^{-42} cm^{2}

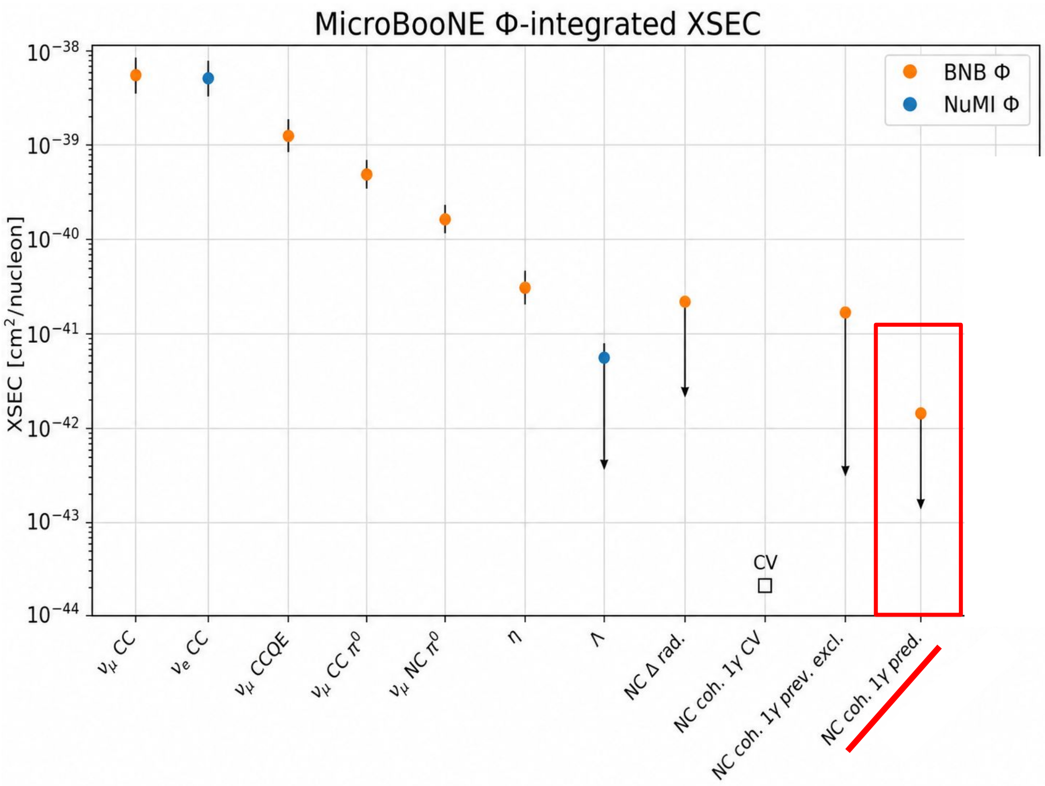
Cross-Section Limits

Previous MicroBooNE result:

$\sigma < 1.49\text{x}10^{-41}\ \text{cm}^2$

Prediction at $1\text{x}10^{21}$ POT:

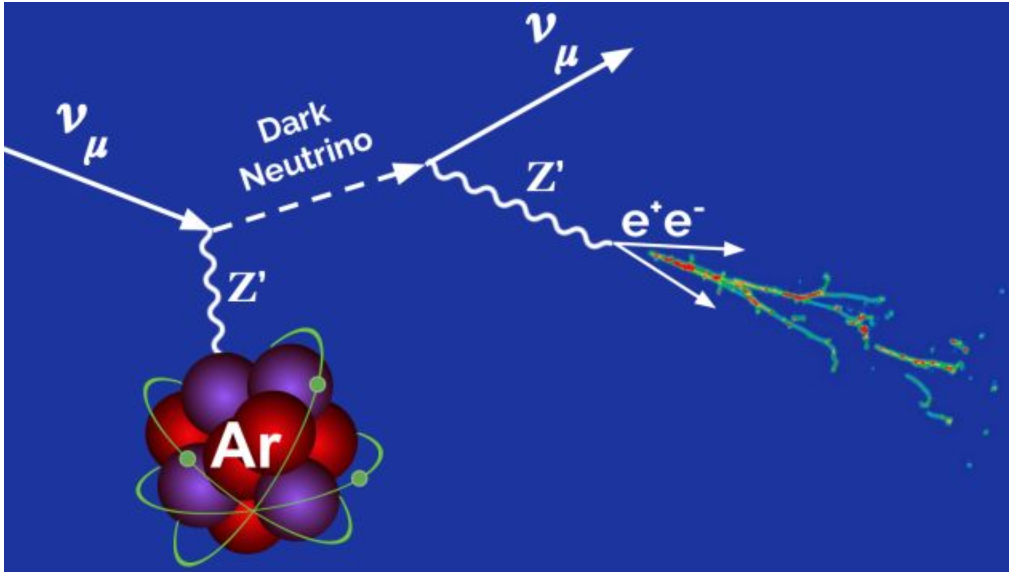
$\sigma < 1.66\text{x}10^{-42}\ \text{cm}^2$



*Analysis lacks some systematic contributions

Advancing Physics

- Being able to better distinguish NC Coherent 1γ events can lead to:
  - Proof that this process exists
  - An understanding of its role in the MiniBooNE Anomaly
  - Relevant and important for dark sector models



https://journals.aps.org/prl/abstract/10.1103/3q7x-ks7h

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Lee Hagaman

REU Program Directors
Dr. Georgia Karagiorgi & Dr. Reshmi Mukherjee

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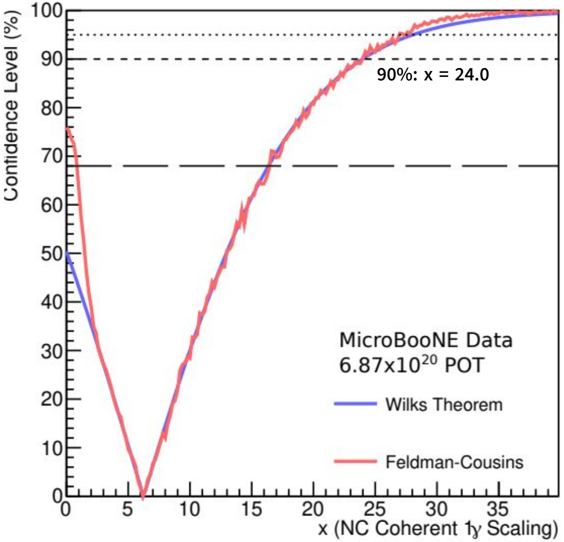
Thank you!

I am happy to take any questions!

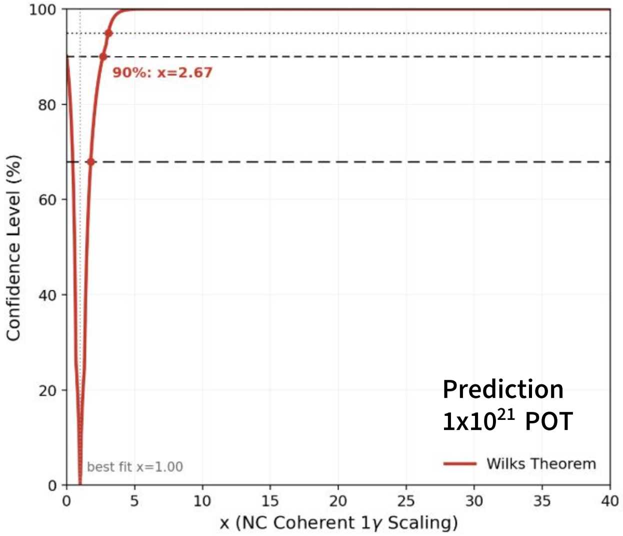
scoanderson14@gmail.com

Previous MicroBooNE Analysis



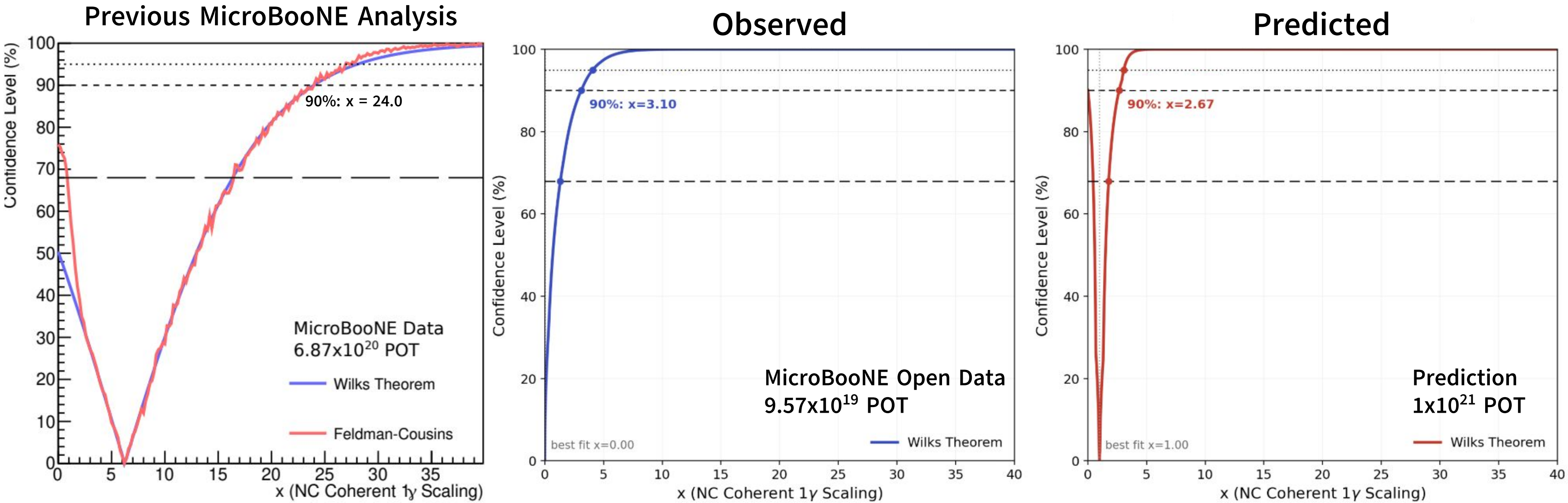
https://arxiv.org/pdf/2502.06091

Predicted



Backup

NC Coherent 1γ



https://arxiv.org/pdf/2502.06091

- Expected to have improved sensitivity to NC Coherent 1γ by a factor of up to 9
- Comparison is not airtight: analysis lacks some signal and detector systematics

Signal to Background

Previous MicroBooNE purity:

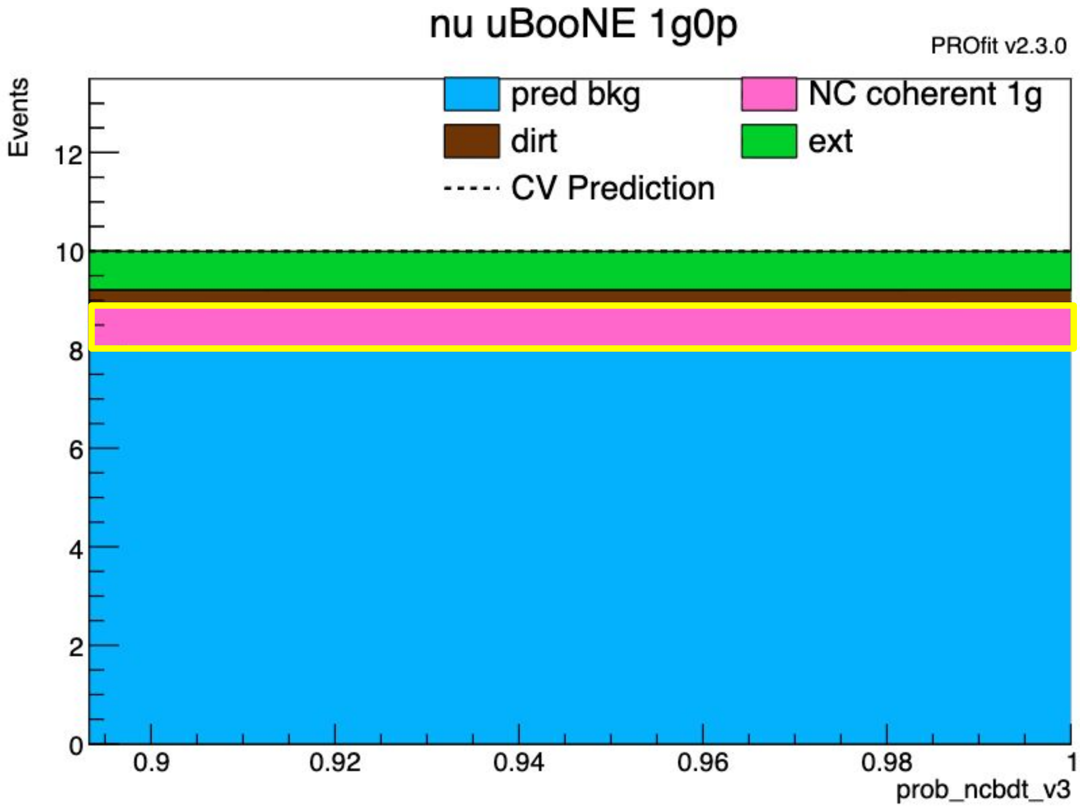
3.2%

Purity in upper region of prediction (same number of events):

19.4%

Purity in open data bin:

9.0%



Cross-Section Limits

Previous MicroBooNE result:

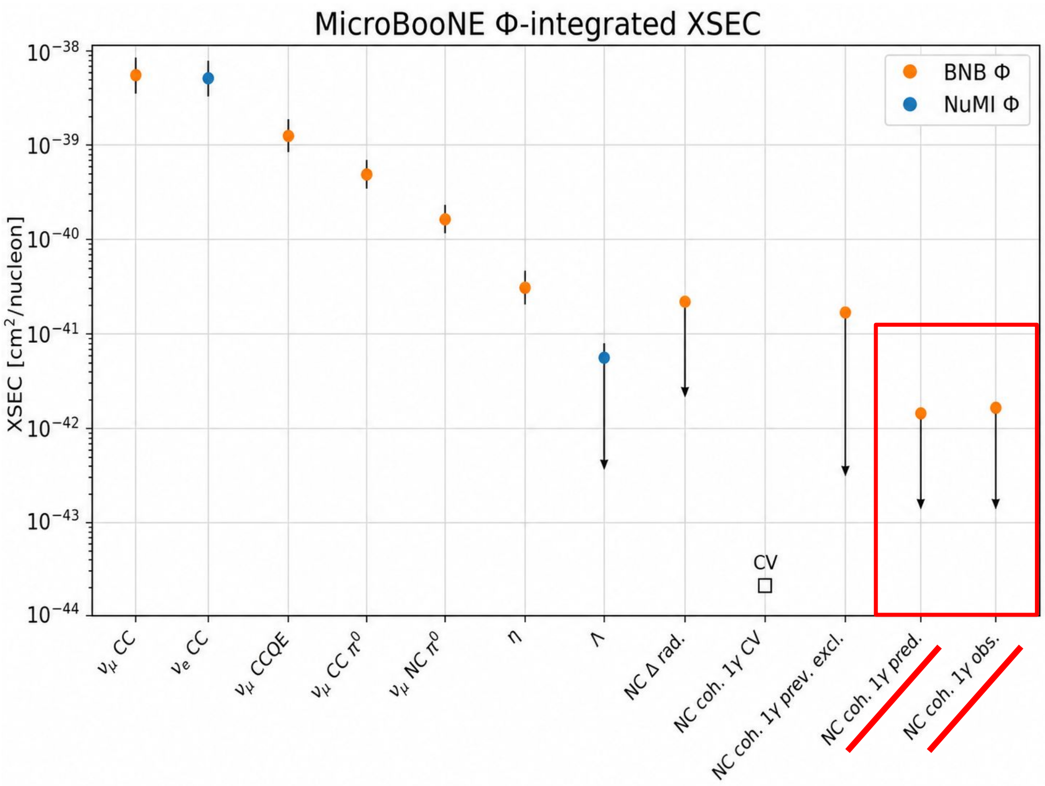
$\sigma < 1.49\text{x}10^{-41}$ cm^2

Prediction at 1x10^{21} POT:

$\sigma < 1.66\text{x}10^{-42}$ cm^2

Observed with 9.57x10^{19} POT:

$\sigma < 1.92\text{x}10^{-42}$ cm^2



*Analysis lacks some systematic contributions

Background

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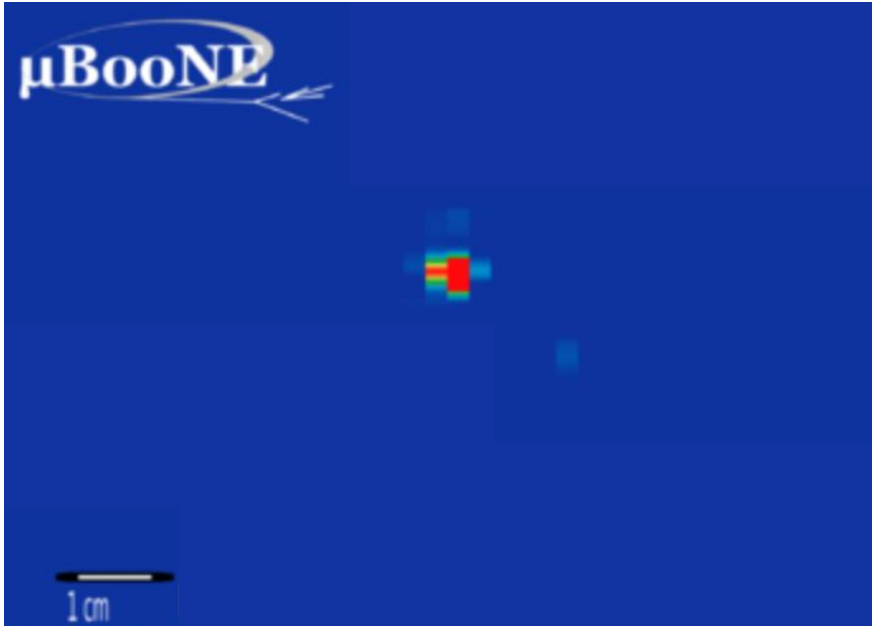
Signal Sensitivity Study

Next Steps

Takeaways

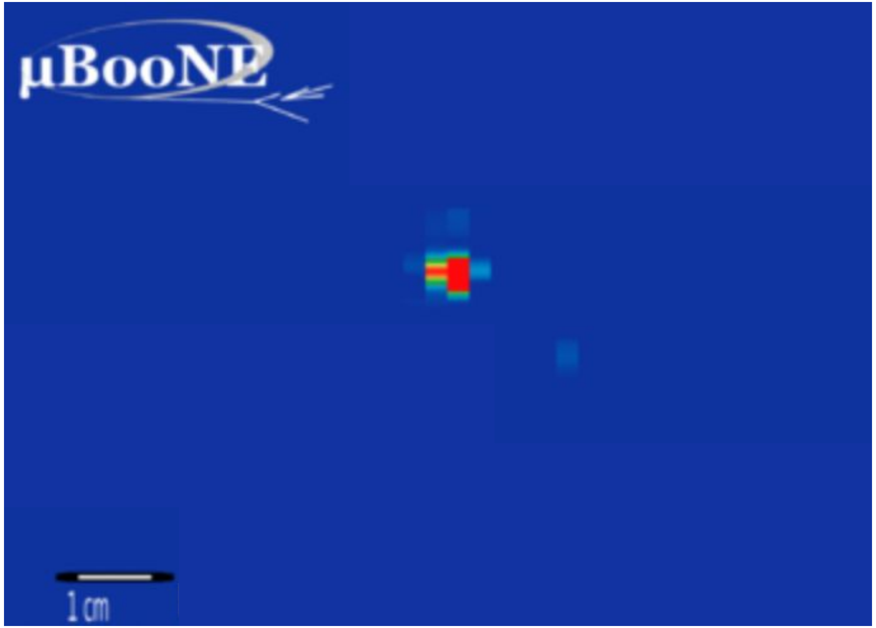
Blip Information

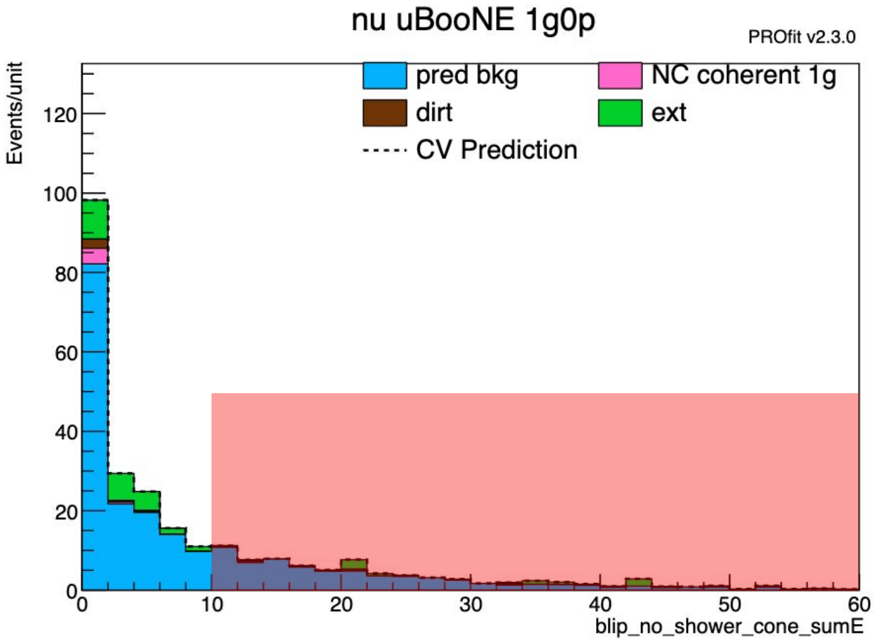
- Tiny cluster of charge



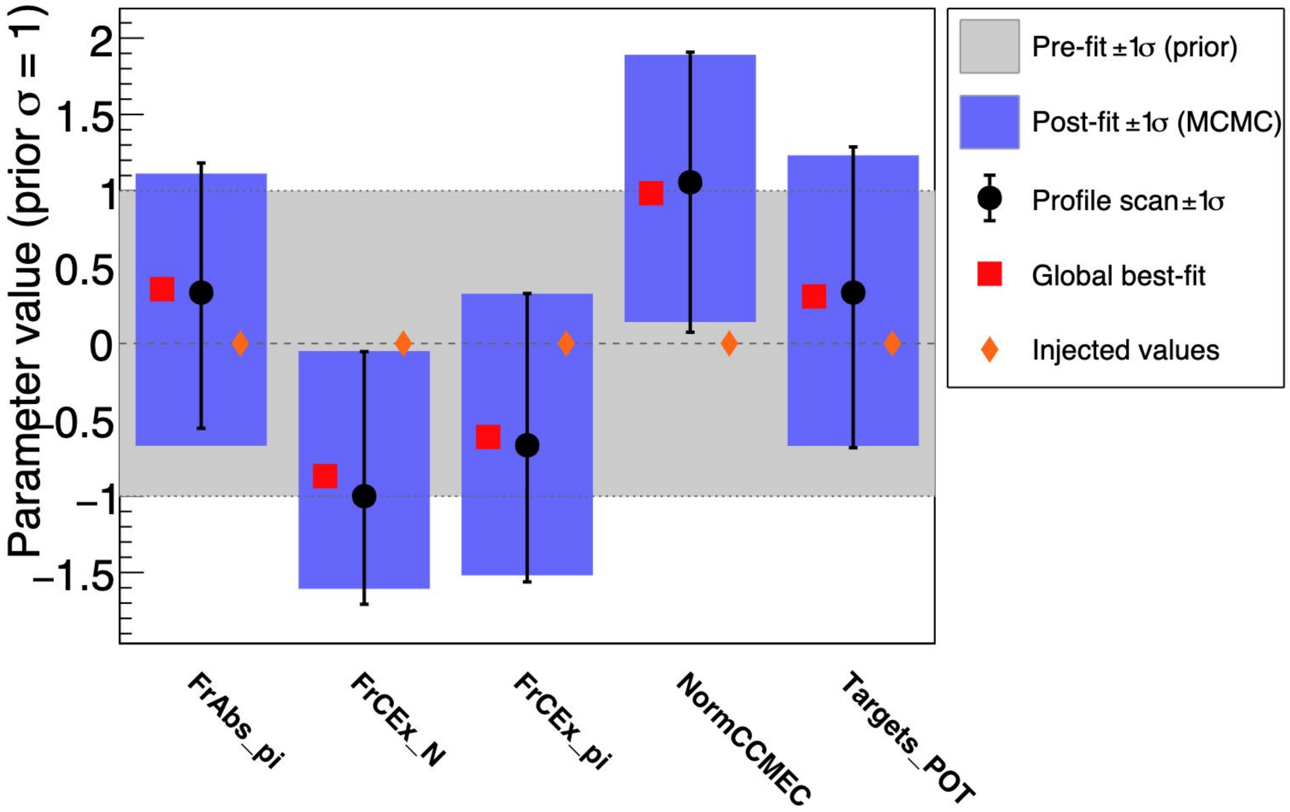
Blip Information

- Tiny cluster of charge
- Blips are not included in BDTs due to risk of mismodeling
- Evidence that imposing cut on high energy blips could increase sensitivity





Restriction Studies



- Only allow studied systematics to vary as spline knobs
- 20% NC1π^0Np deficit PROfit being used

Omission Study

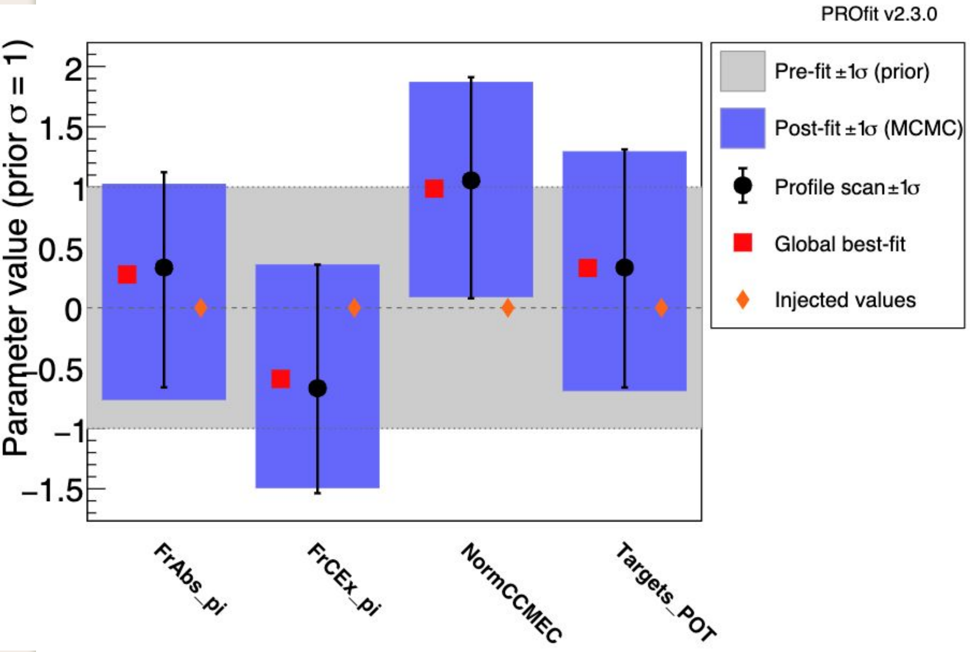
Run	χ^2/nbins
Top4 restricted	**16.36/8**
No FrAbs_pi	**15.73/8**
No FrCEx_pi	**15.79/8**
No NormCCMEC	**16.19/8**
No FrCEx_N	**16.13/8**

Only-one-spline Study

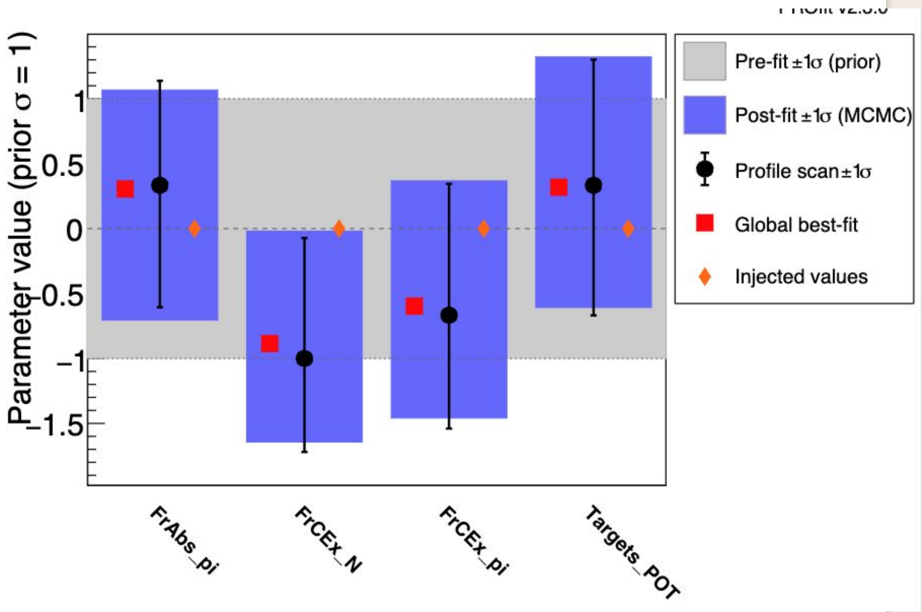
Only spline	χ^2/nbins
FrCEx_N	**14.88/8**
FrAbs_pi	**15.26/8**
FrCEx_pi	**15.18/8**
NormCCMEC	**14.87/8**

- Unrestricted $X^2 = 18.3$
- Top4 restricted = all four systematics set to “spline”
- Comparable X^2 means that no single systematic is a unique driver of the deficit

No FrCEx_pi



No NormCCMEC

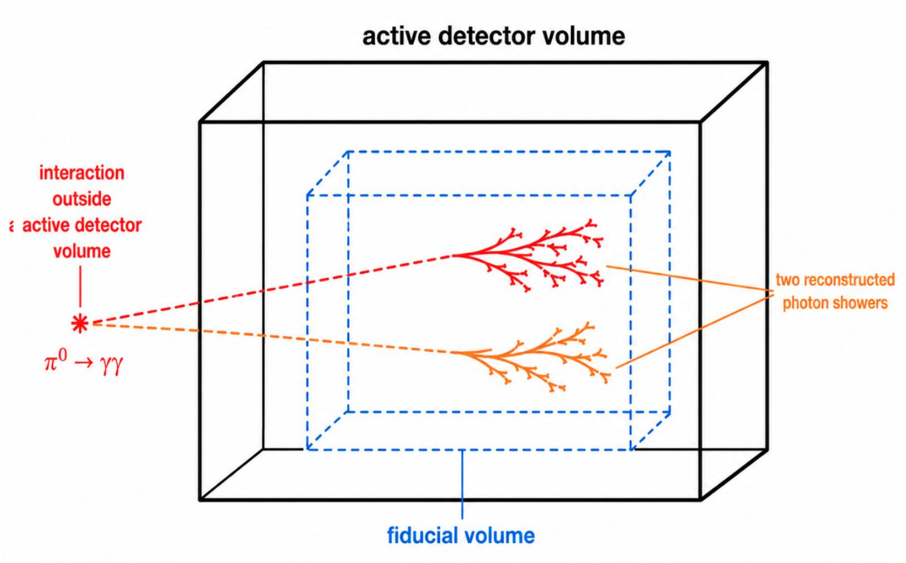


- Similar systematics are pulled about the same regardless of the omitted systematic. This is true in the runs where only one systematic is set to spline as well.

2γoutFV Excess

What is 2γoutFV?

FV meas fiducial volume: the volume actually detecting events



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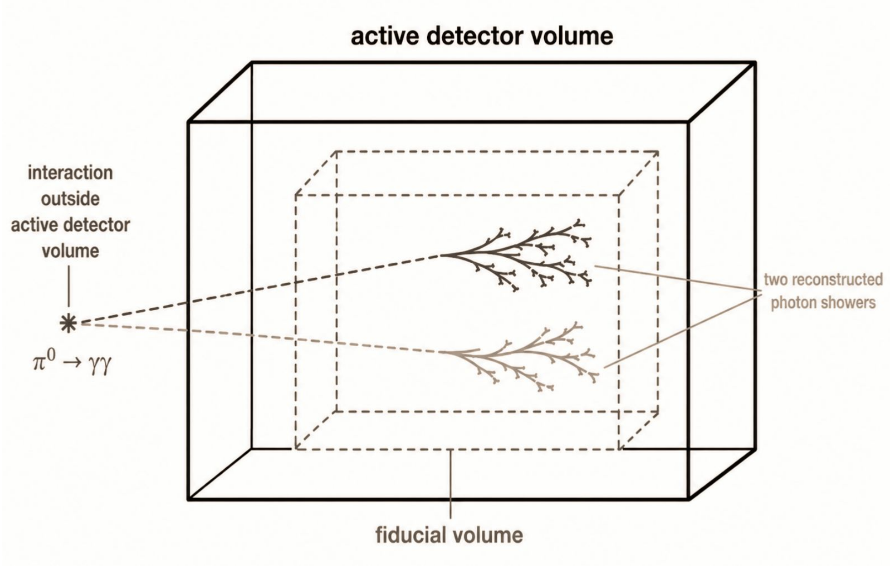

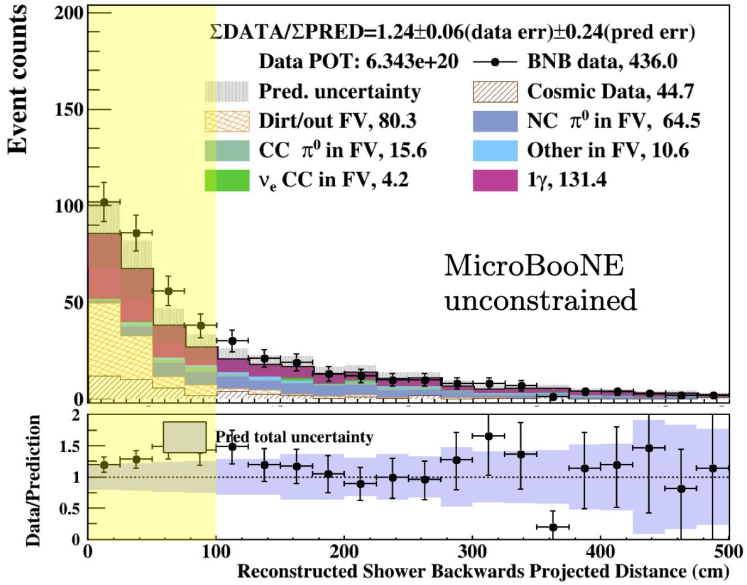

https://arxiv.org/pdf/2502.06064

Motivated by previously observed excess, we asked, “Can systematics reproduce a 30% 2γoutFV excess under 100cm without altering inFV channels?”

Can systematics reproduce a 30% 2γoutFV Excess?

- Same logic as before
- Inject excess
- Identify pulled systematics
- Heatmap of percent change of area under postfit to CV

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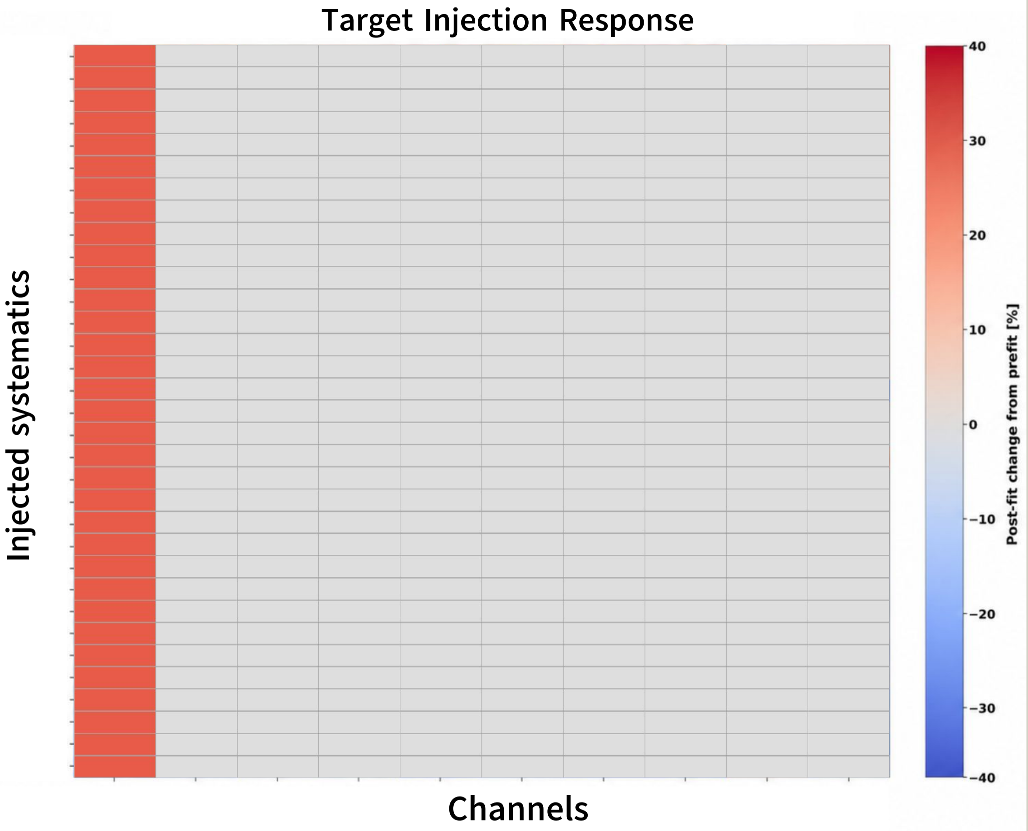
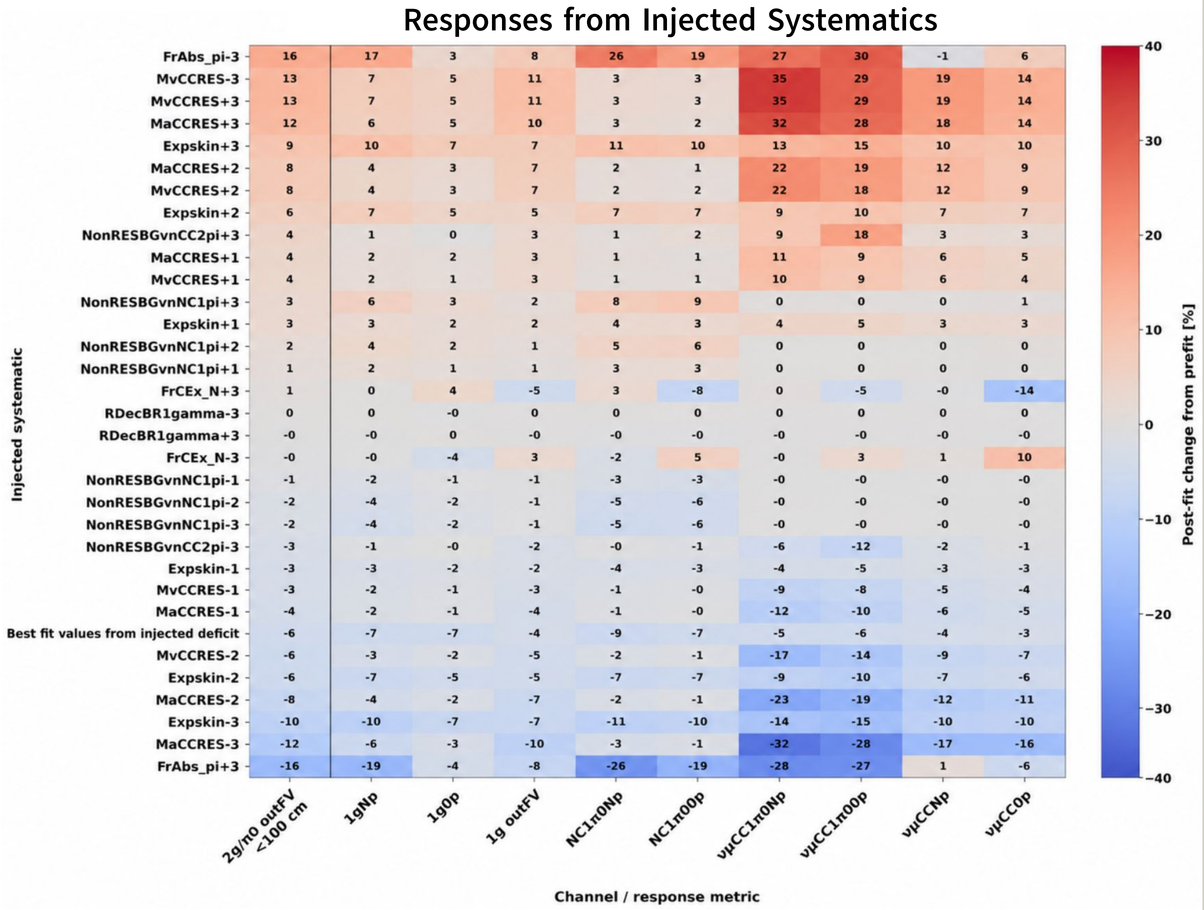


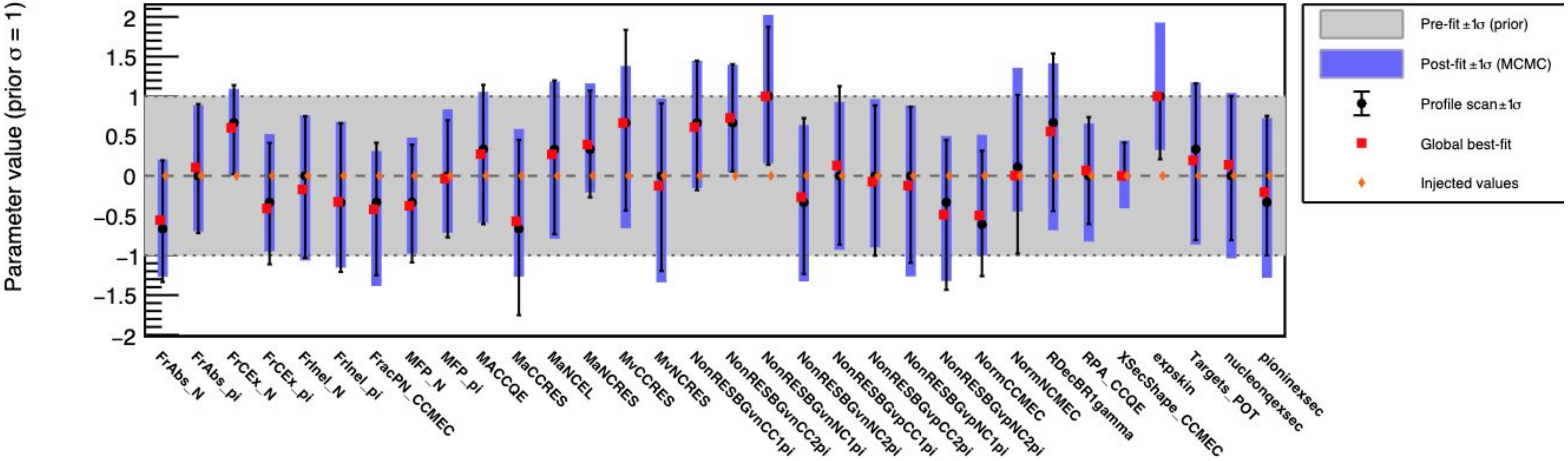
Can systematics reproduce a 30% 2γoutFV Excess?

- Same logic as before
- Inject excess
- Identify pulled systematics
- Heatmap of percent change of area under postfit to CV

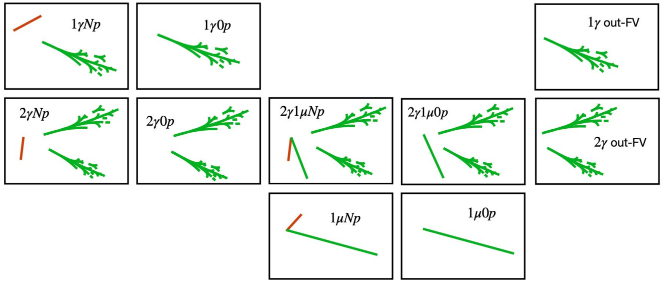
No, the excess is only partially recovered, and never in a clean outFV-only way.

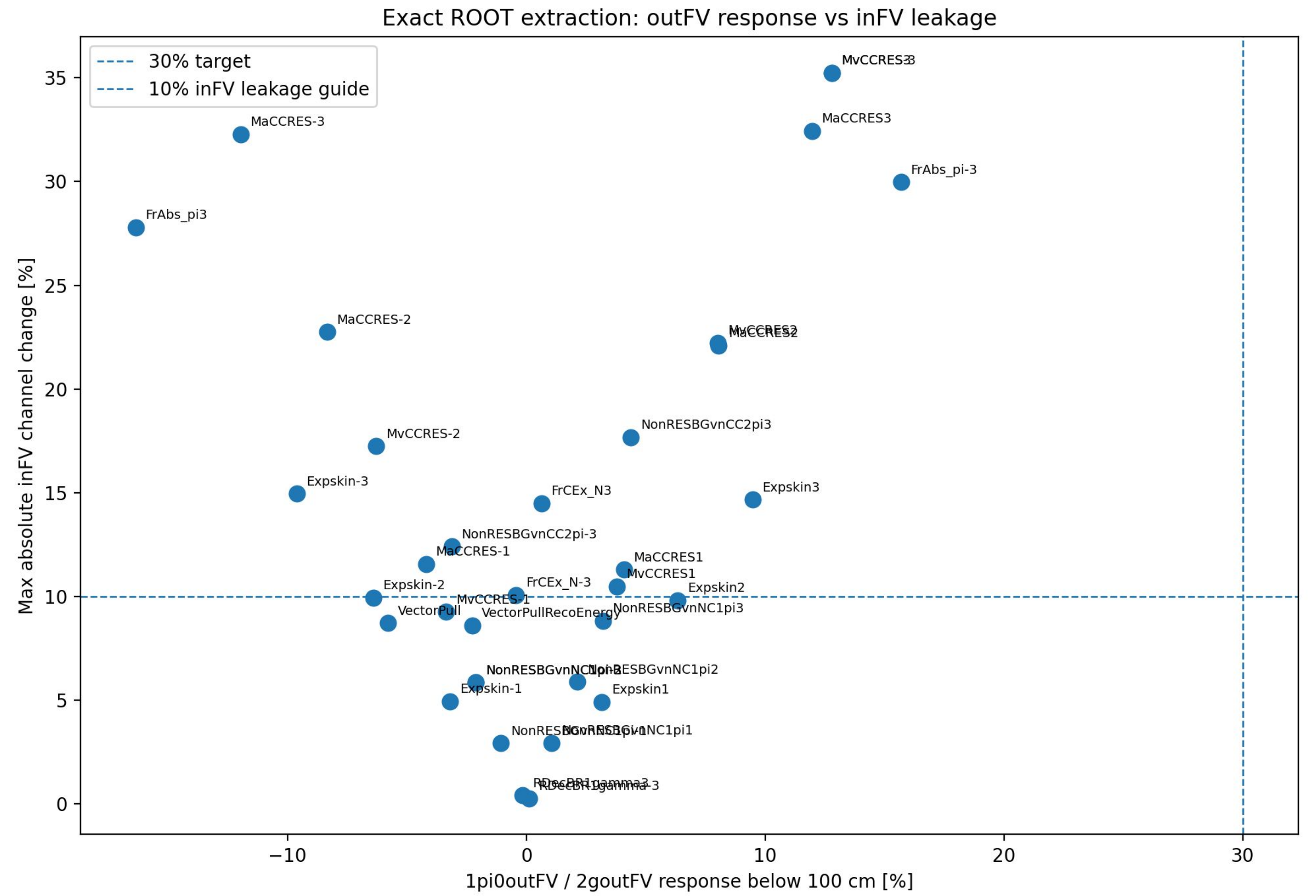


Hardcoded 30% excess in 2goutFV under 100 cm



- Interesting systematics: FrCEx_N, MaCCRES, MvCCRES, NonResBGvnCC2pi, NonResBGvnNC1pi, expskin




Exact ROOT extraction: outFV response vs inFV leakage
30% target
10% inFV leakage guide
Max absolute inFV channel change [%]
1pi0outFV / 2goutFV response below 100 cm [%]
0
5
10
15
20
25
30
35
−10
0
10
20
30
MaCCRES-3
FrAbs_pi3
MaCCRES-2
MvCCRES-2
Expskin-3
NonRESBGvnCC2pi-3
MaCCRES-1
Expskin-2
VectorPull
MvCCRES-1
VectorPullRecoEnergy
FrCEx_N-3
FrCEx_N3
NonRESBGvnCC2pi3
MaCCRES3
FrAbs_pi-3
Expskin3
MaCCRES1
MvCCRES1
Expskin2
NonRESBGvnNC1pi3
NonRESBGvnNC1pi2
Expskin-1
Expskin1
NonRESBGvnNC1pi1

Top Variables

= BDT output

= variable catalog

Rank	Branch	ΔX^2 (x = 10)
1	prob_1g0p	58.76
2	prob_numuCC1pi0_0p	43.95
3	prob_multi_pi0	41.45
4	glee_trackstub_num_unassociated_hits	35.92
5	wc_nc_delta_score	35.90
6	prob_NC1pi0_Np	35.45
7	glee_sss_num_unassociated_hits	33.24
8	prob_numuCC1pi0_Np	32.89
9	wc_kine_reco_Enu	20.73
10	wc_reco_showerKE	18.89

Binning

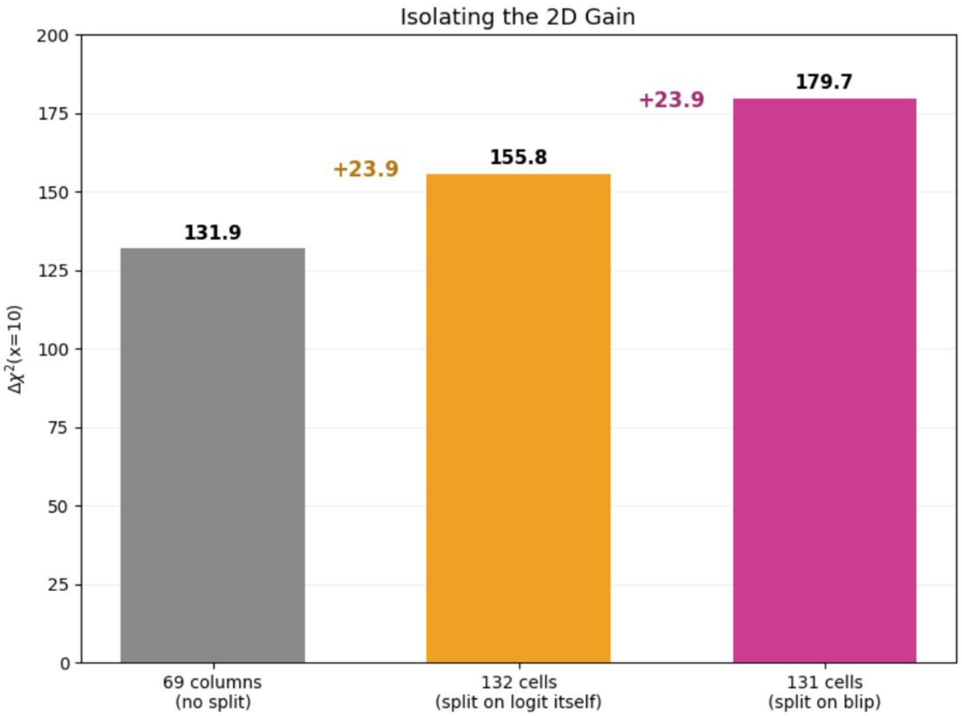
- Different formulas tested in NumPy to compute edges
- Rest of the configuration held constant
  - logit(prob_1g0p), no sidebands, target bin count of 130

Criterion	Formula	What it optimizes	ΔX^2 (x = 10)
Classic	$\frac{s^2}{b}$	Signal-to-noise ratio	159.1
Significance-weighted	$\frac{s^2}{(s+b)}$	Equal significance contribution per bin	171.7
MC-stat-aware	$\frac{s^2}{(s+b+w^2)}$	Same, with statistics penalty	172.7

S = signal
b = background
w^2 = sum of squared event weights

2D Histograms?

- Real gain
- Encounter same binning problem
- Secondary variable MC-stat-aware loses to equal content binning



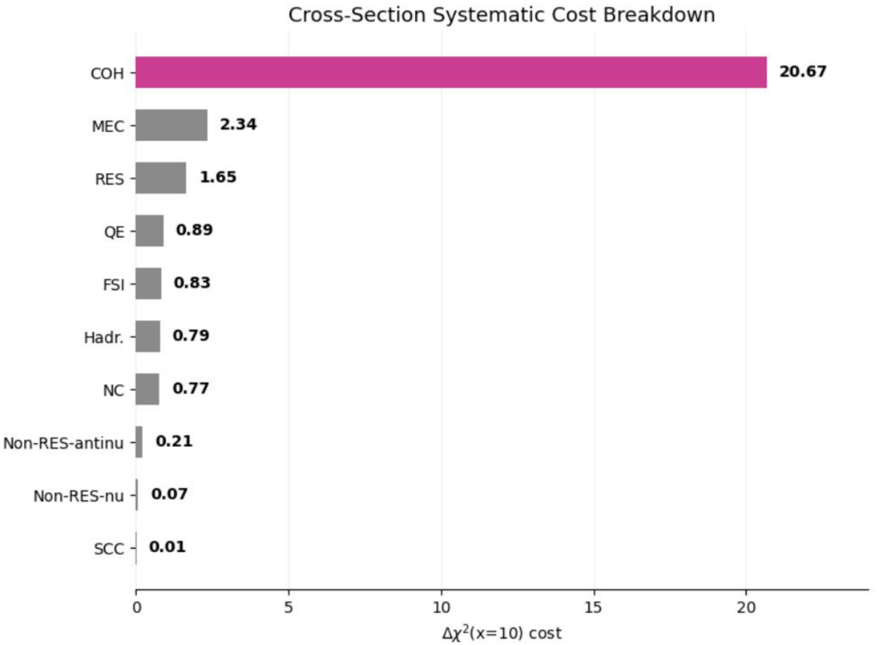
Partner	ΔX^2 (x = 10)
glee_trackstub_num_unassociated_hits	176.77
blip_no_shower_cone_sumE	178.52
lantern_blip_nWithin_100cm	179.19
pandora_NeutrinoEnergy2	179.45
blip_no_shower_cone_sumE on MC-Stat-Aware edges	179.95

Logit(p) base, SigW algorithm, Consistent number of bins ± 2

Sidebands

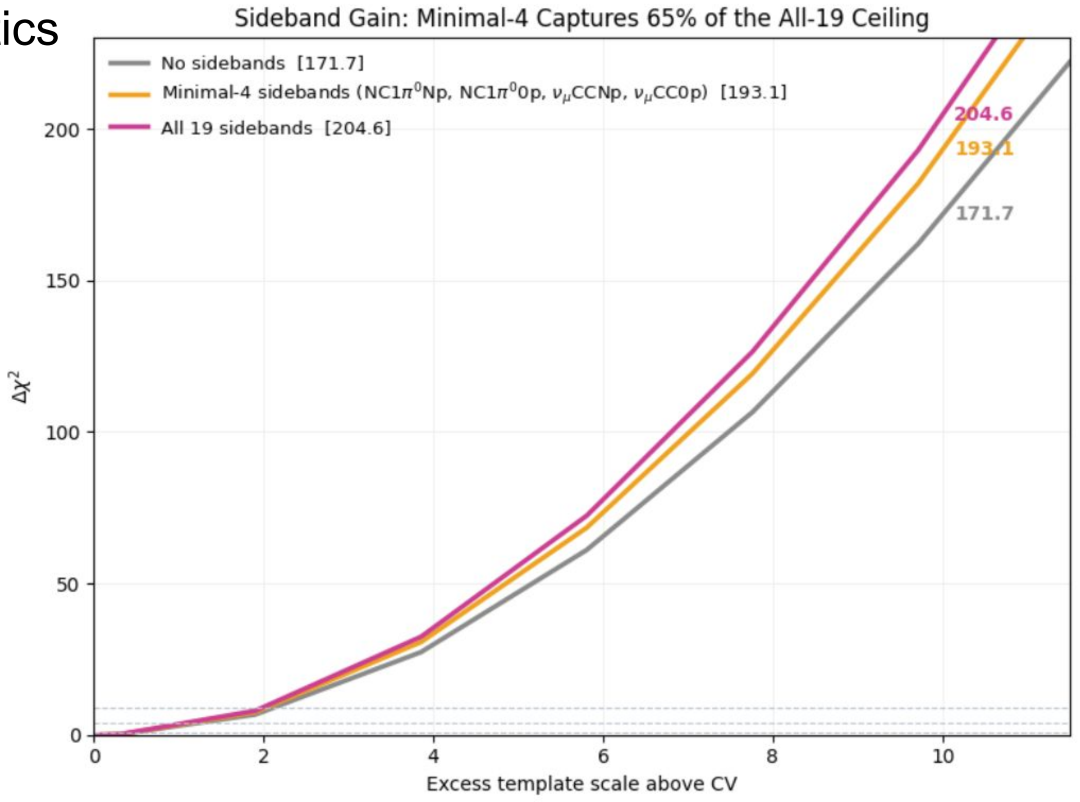
- Baseline: 1D, logit(p), significance-weighted binning
- Systematic understanding through ablation study:

Group Removed	ΔX^2 (x = 10) w/o Group	Cost (Δ vs. 171.71)
Cross-section (xsec)	207.51	35.8
Flat normalization	184.39	12.7
MC statistics	181.01	9.3
Flux	172.47	0.8
Hadron reinteraction	171.86	0.1



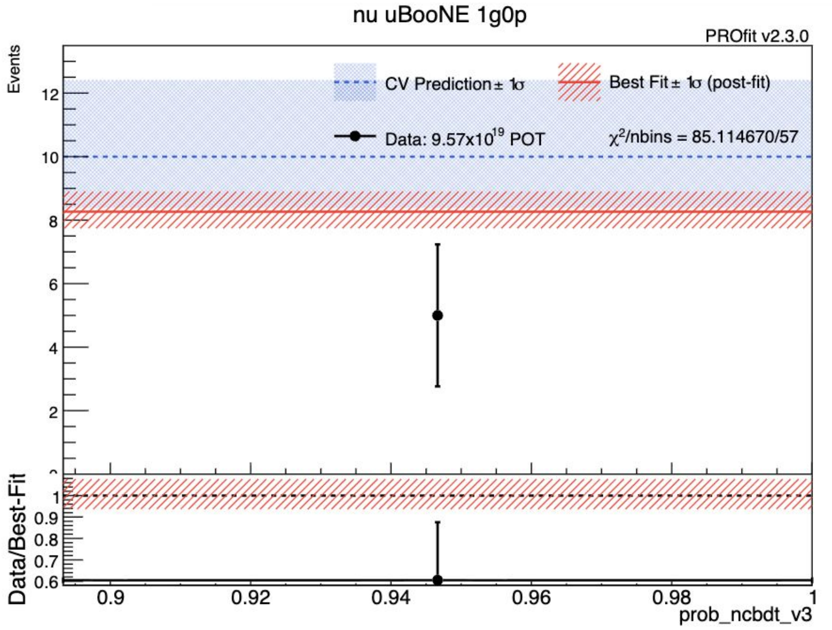
Sidebands

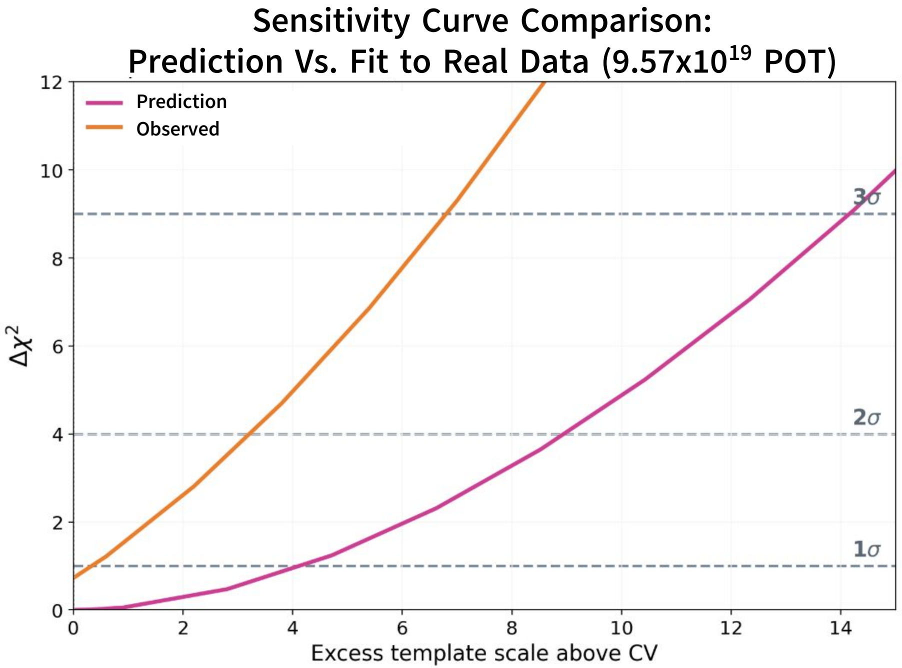
- NC1π0 → largest background
- $\nu\mu$CC → highest-statistics, constrains flux and general cross-section background systematics

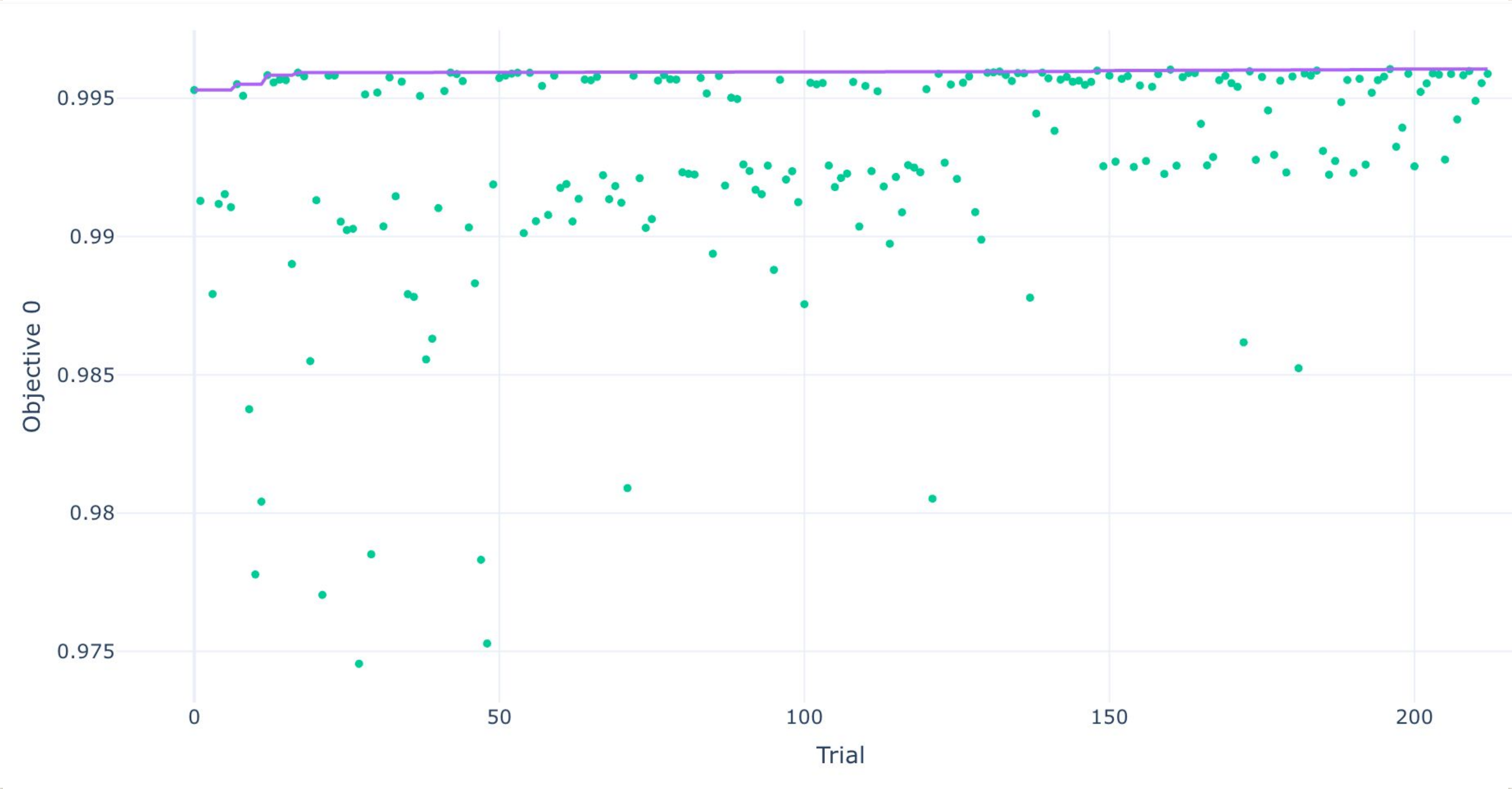


What happens when we turn the data on?

- One bin to increase stats up to 10 events
- Deficit, which shifts scale factor left

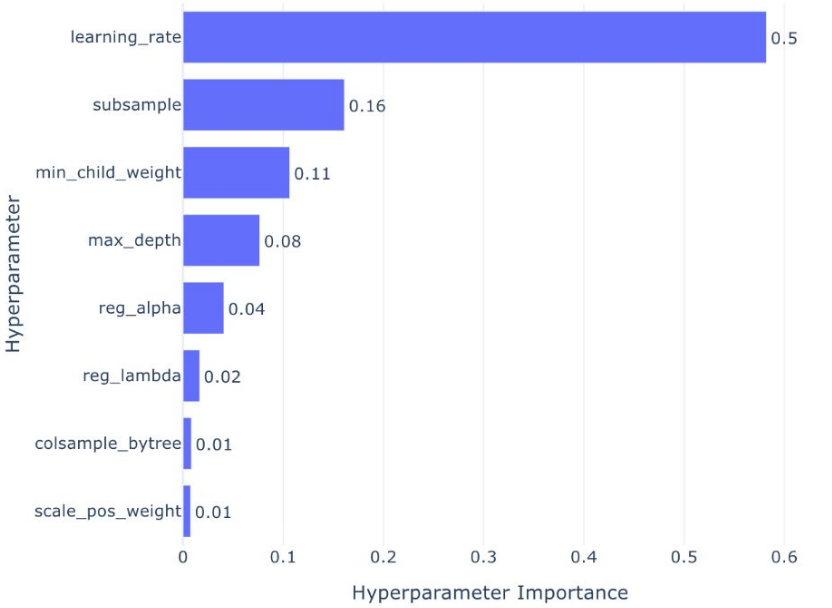




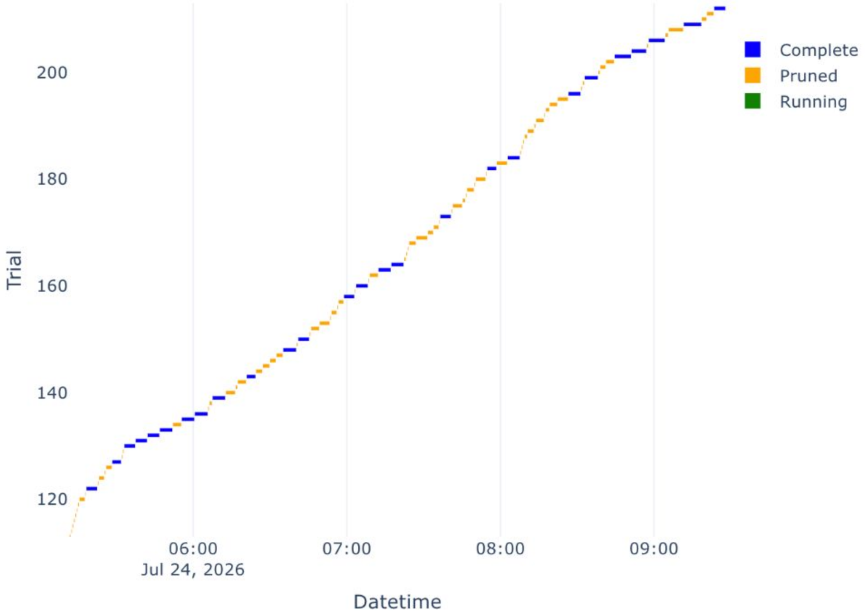


Objective 0
0.995
0.99
0.985
0.98
0.975
0
50
100
150
200
Trial

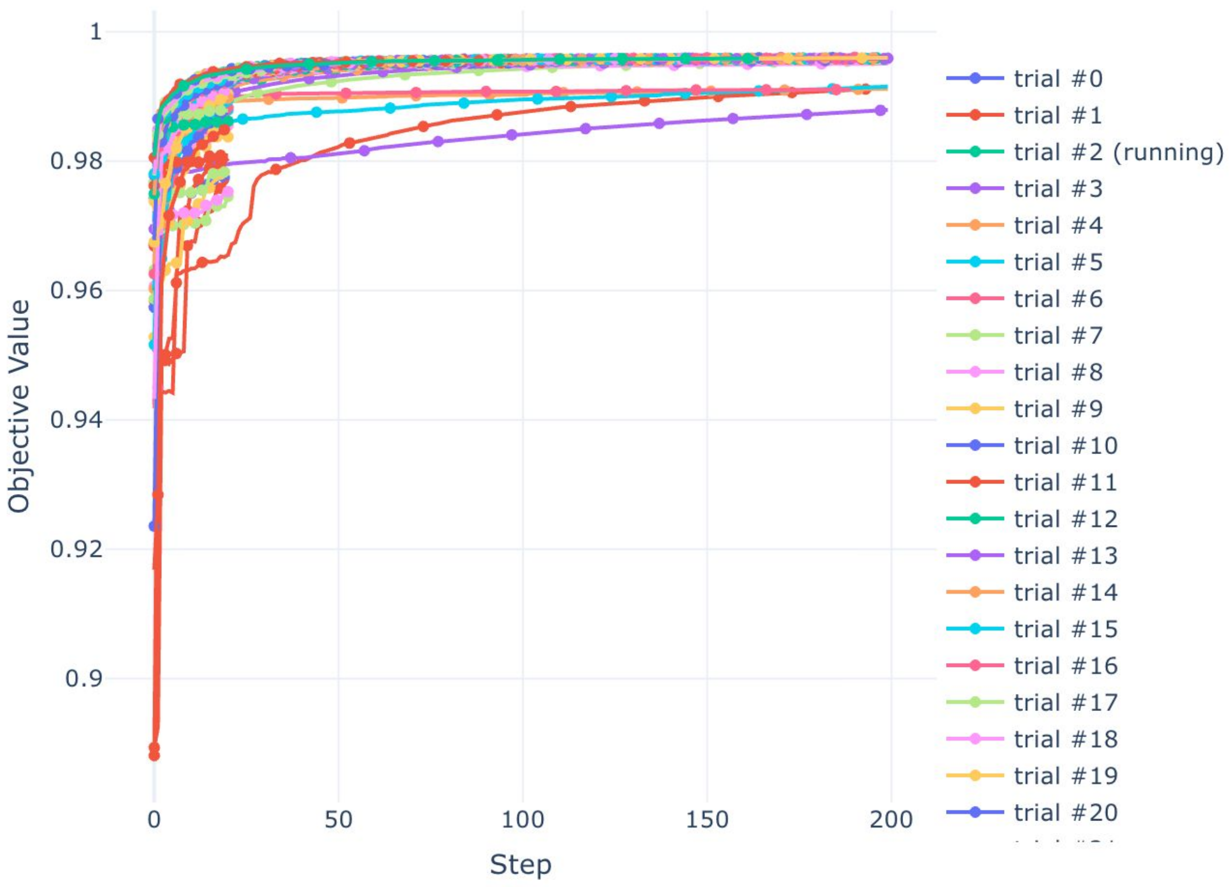
Hyperparameter Importance



Timeline



Intermediate values



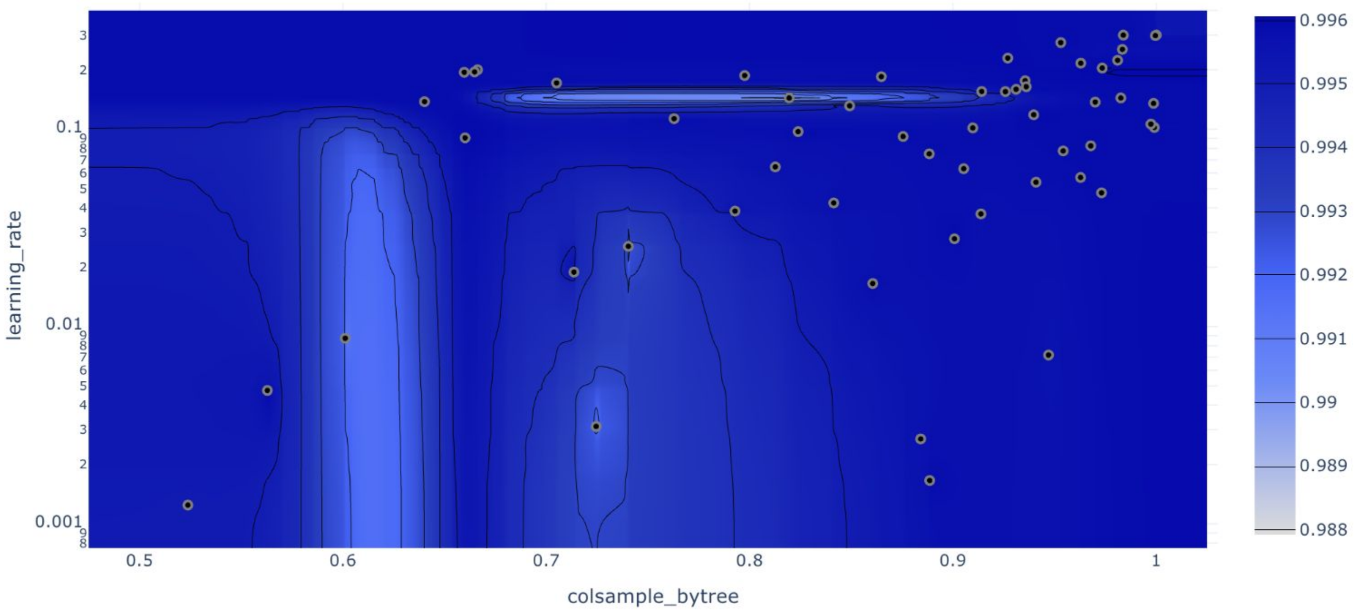
Contour

x:

colsample_bytree

y:

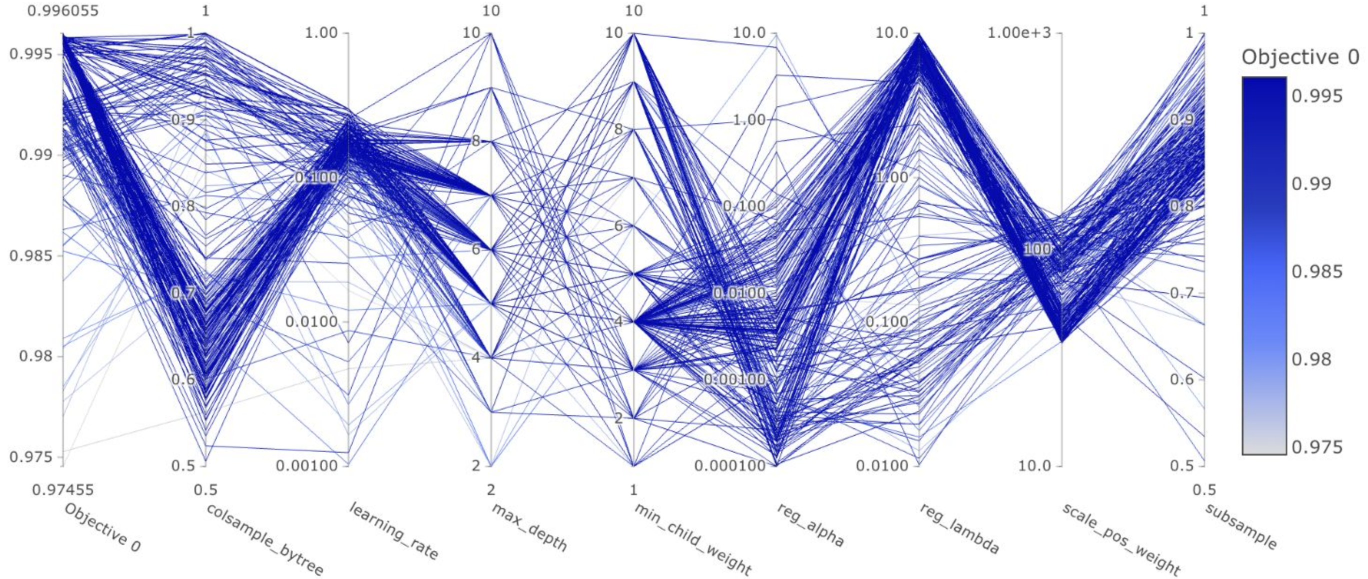
learning_rate



Parallel Coordinate

- [x] Check All

- [x] Objective 0
- [x] Param colsample_bytree
- [x] Param learning_rate
- [x] Param max_depth
- [x] Param min_child_weight
- [x] Param reg_alpha
- [x] Param reg_lambda



Rank

x:

colsample_bytree

y:

learning_rate