Muon reconstruction in JUNO

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JUNO

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on behalf of the JUNO Collaboration

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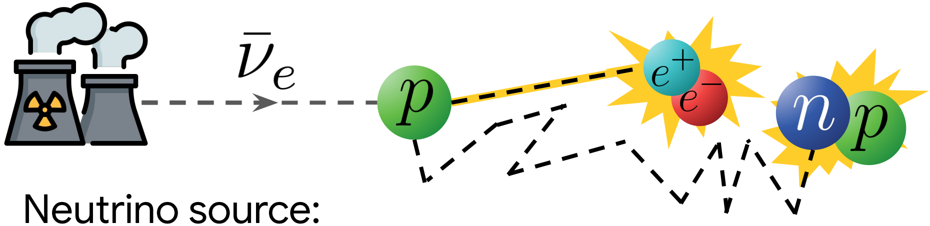
Cosmogenic background in JUNO



Neutrino source:

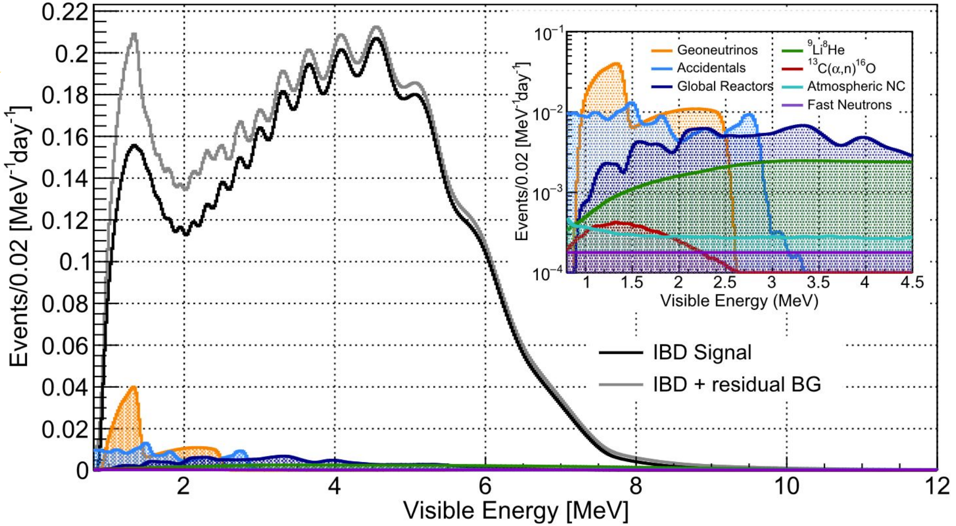
- Reactor electron antineutrino.
- IBD interaction.

Challenge: cosmogenic isotopes $^9\mathrm{Li}/^8\mathrm{He}$

- Produced by atmospheric muons.
- β-n decay.

Cannot be suppressed using IBD-like cuts (fiducial volume, prompt-delayed coincidence, etc.) ⇒ Indistinguishable.

Correlated with parent muon ⇒ use muon track information.



Current veto status:

- Spallation neutron-based ✅.
- No track-based yet ❌.

Residual cosmogenic: 3.9 ± 0.6 cpd ⇒ dominant background.

Track-based muon veto

Temporal veto

Reject events within a time window based on cosmogenic lifetimes $\tau_{1/2}(^{9}\mathrm{Li}) \sim 178\ \mathrm{ms}$

⇒ Reliable muon identification.

Spatial veto

Reject events within a cylinder around muons.

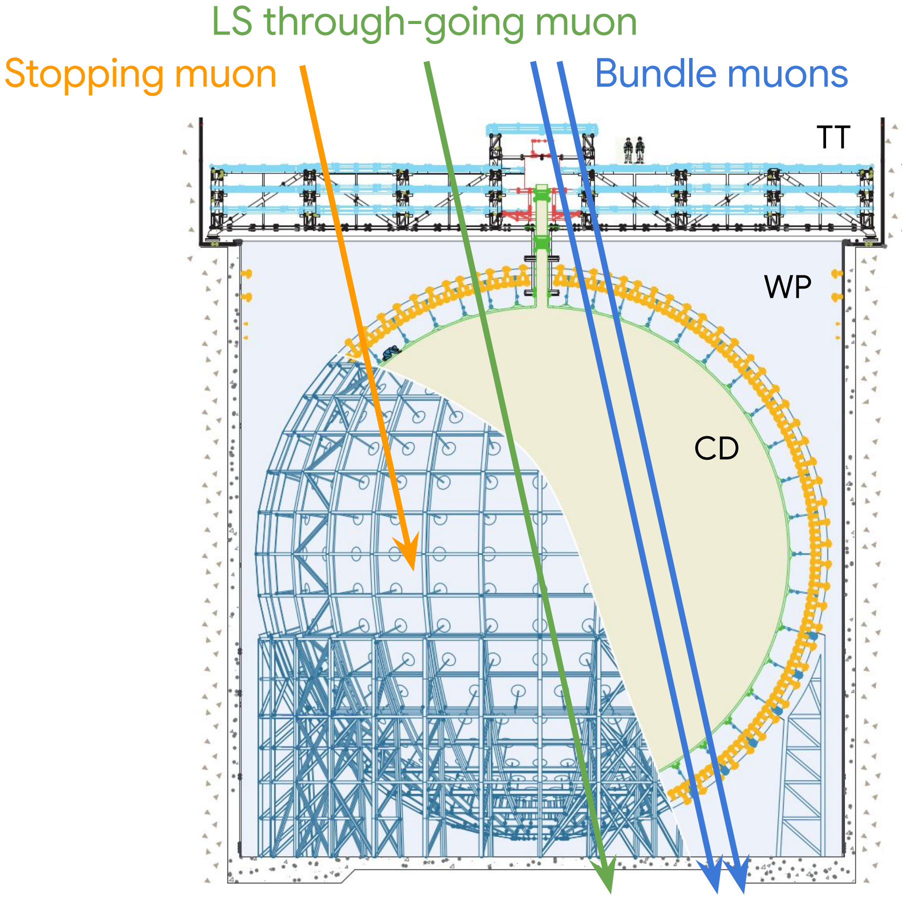
⇒ Accurate track reconstruction ⇒ veto radius depends on reconstruction resolution.

Muon topologies

Through-going, stopping, bundle, etc.

⇒ Requires event classification.

Track-based veto ⇒ limiting unnecessary dead time.



Detector observables

Central Detector (CD)

Scintillation light ⇒ high light yield.

Dense PMT coverage, hit times, charges.

Water Pool (WP)

Cherenkov detector, and covered by Tyvek.

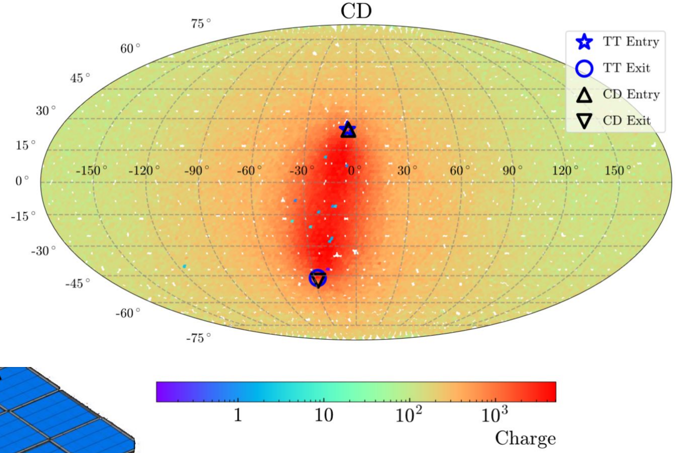
Top Tracker (TT)

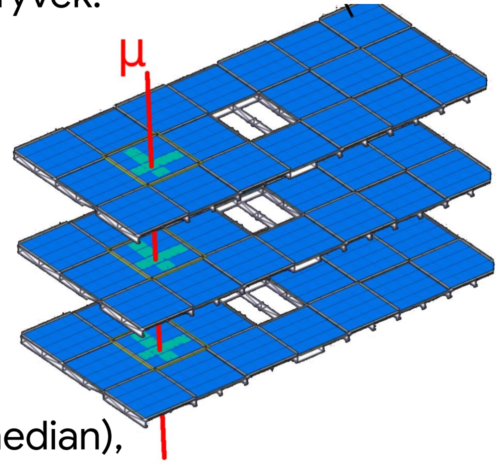
3 layers of 7 by 3 walls.

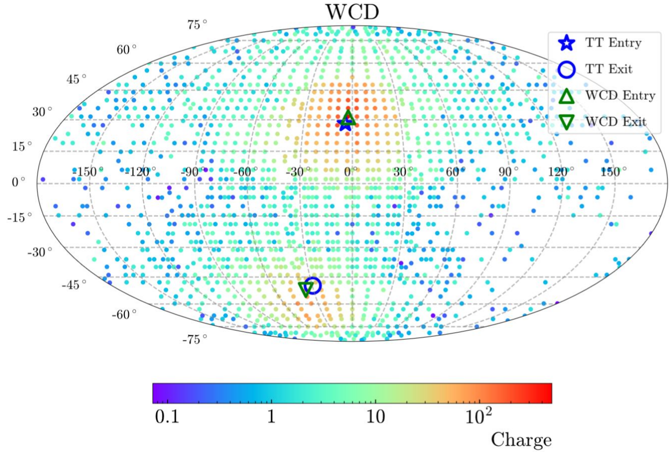
Wall composed of orthogonal plastic scintillator strips.

⇒ Discrete tracking points.

⇒ Provide clean muon sample (0.2° median), but sees only 30% of CD muons.







Approaches overview

Two main approaches to muon reconstruction

Traditional methods

⇒ Physics-driven: explicit modeling

Charge-based clustering

Timing-based reconstruction (χ^2 minimization)

Machine learning methods

⇒ Data-driven: learn from simulation/data.

Graph-based convolutional networks

Transformer-based model

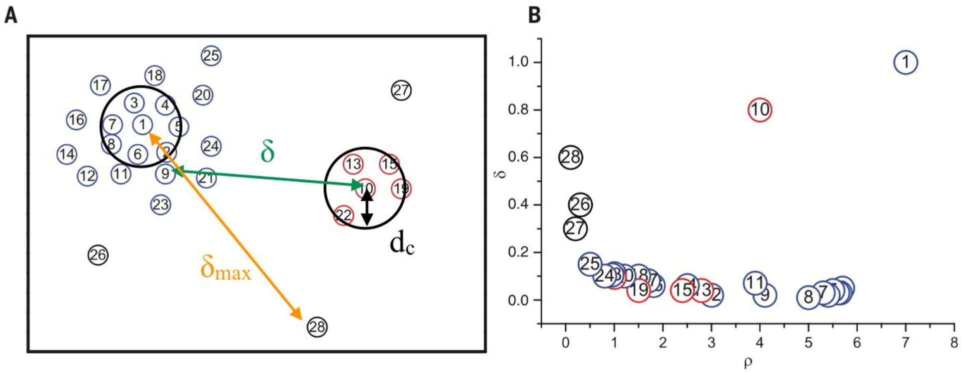
CD/WP charge cluster classification

Charge density peak algorithm.

⇒ Independently applied to the CD and the WP.

For each PMT:

- ρ is the sum of PEs within d_c.
- δ is the minimum distance to any PMT with higher density.

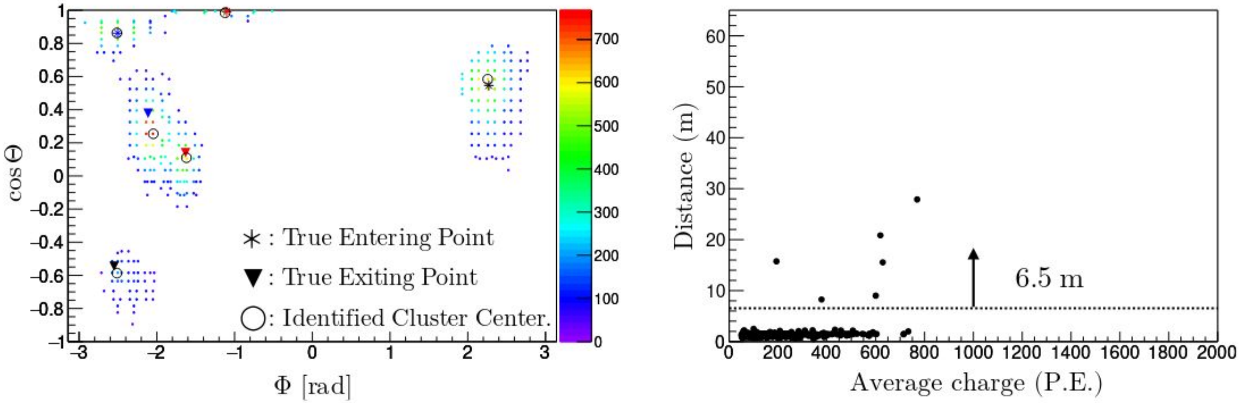


Cluster ⇒ high ρ and δ .

Identified as outliers in ρ-δ space.

Association assumptions:

- Down-going tracks
- Parallel bundle muons.



CD+WP+TT joint reconstruction

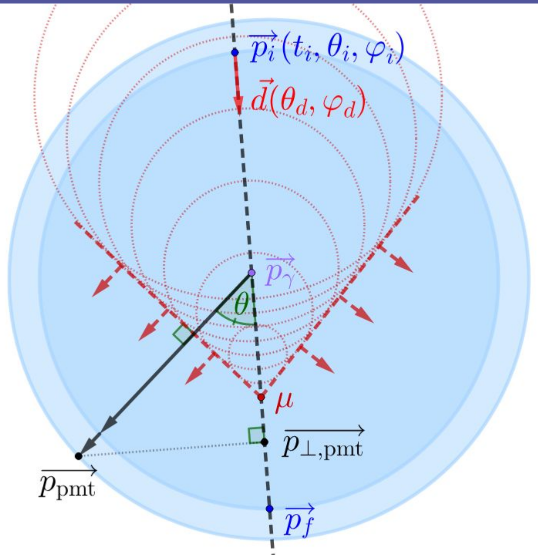
Each sub-detector contributes a chi^2 term.

Joint reconstruction ⇒ minimize the sum.

$$\chi^2 = \frac{1}{ndf_{CD}} \sum_{i=1}^{17612+25600} \left(\frac{t_{i,meas} - t_{i,theo}}{\sigma_i} \right)^2 + \frac{1}{ndf_{WP}} \sum_{j=1}^{2400} \left(\frac{t_{j,meas} - t_{j,theo}}{\sigma_j} \right)^2 + \frac{1}{ndf_{TT}} \sum_{k=1}^{3} \left(\frac{\| (\vec{p_k} - \vec{p_0}) \times \vec{d} \, \|}{\| \vec{d} \, \| \sigma_k} \right)^2$$

TT: Line fit through hit points.

⇒ Used as reference (not used in data reconstruction).



CD and WP: First Hit Time (FHT) method.

FHT: time of the earliest detected photon.

Calculate expected FHT ⇒ depends on the track parameters.

FHT residuals ⇒ χ^2 minimization.

DeepSphere-based

Large volume detector ⇒ image-like representation ⇒ CNN.

But operate on Euclidean space ≠ spherical geometry.

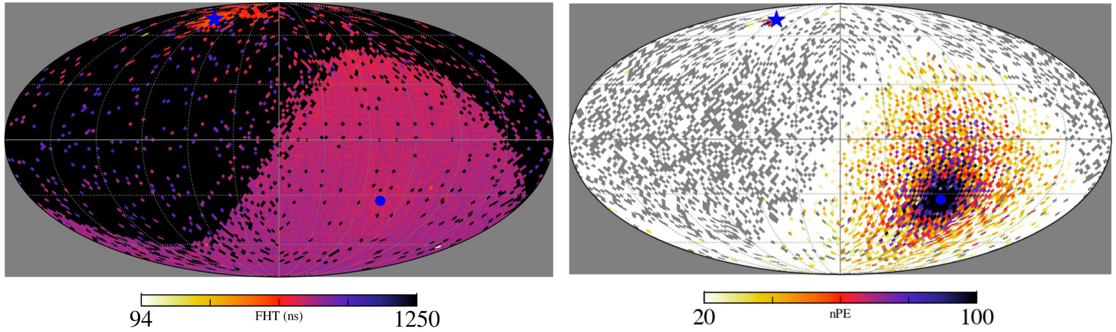
⇒ Graph-based CNN ⇒ DeepSphere framework.

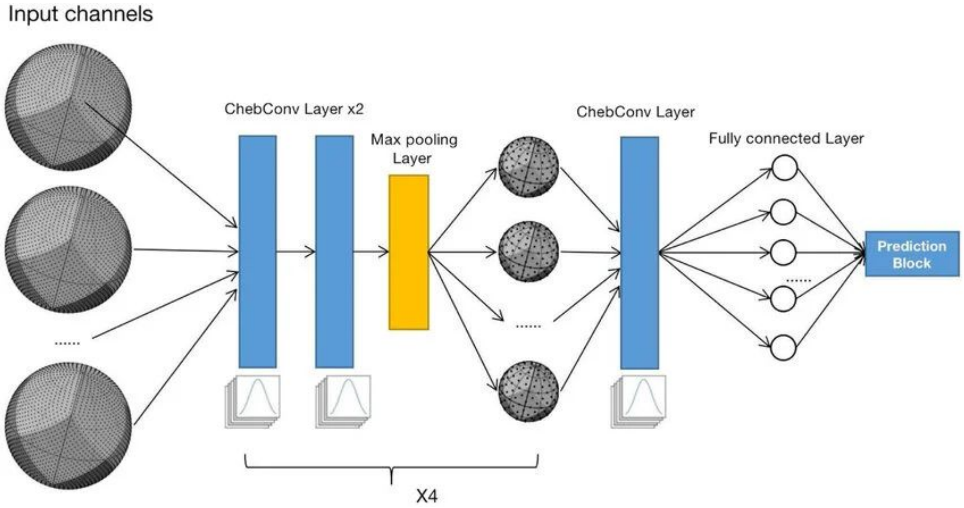
Sphere divided in pixels of equal area using HEALPix.

Input features: FHT, charge.

Convolution + fully connected layers ⇒ predicts muon entry point and direction.

⇒ Under active development and validation!





Transformer

Based on self-attention mechanism.

Each hit is treated as an input token ⇒ no need for spatial discretization.

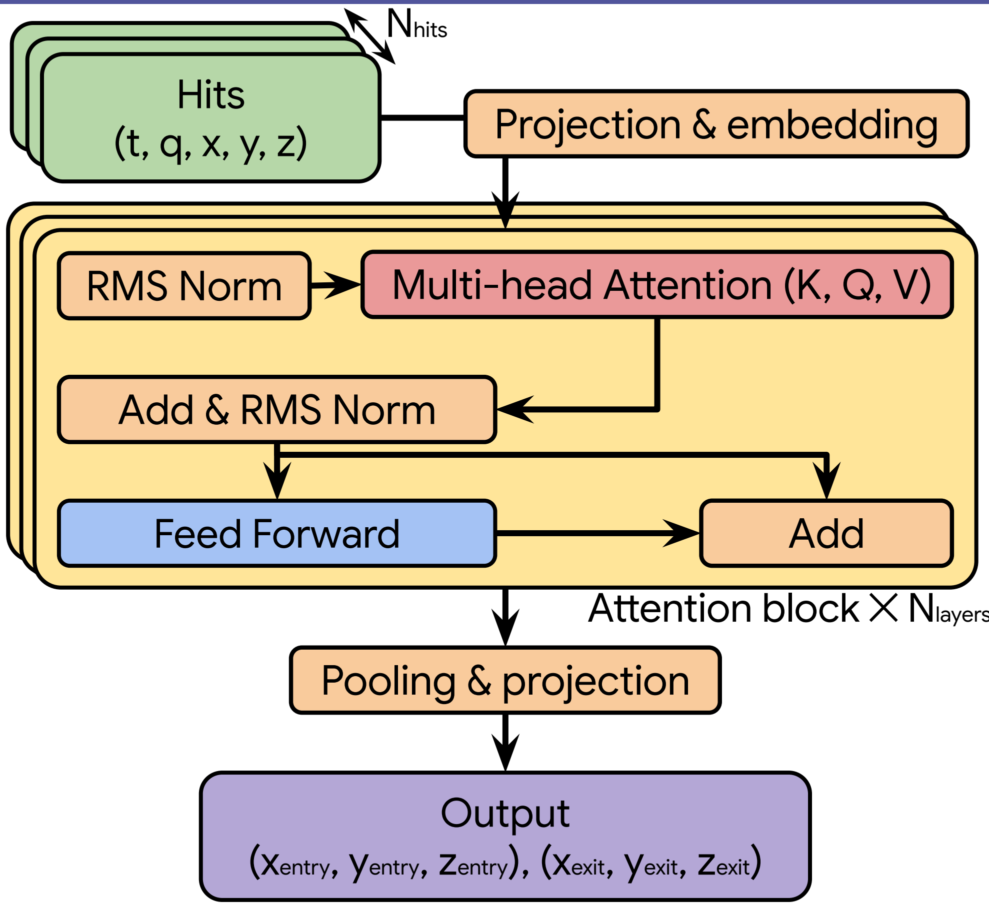
Attention mechanism learns relationships between hits ⇒ captures global event structure.

Input features: hit times and charges.

Trained using TT as reference.

Predicts muon entry and exit points.

⇒ Under active development and validation!



Methodology

Identification:

- CD/WP time correlation (muons in the CD).
- WP charge threshold (muons in the WP only).

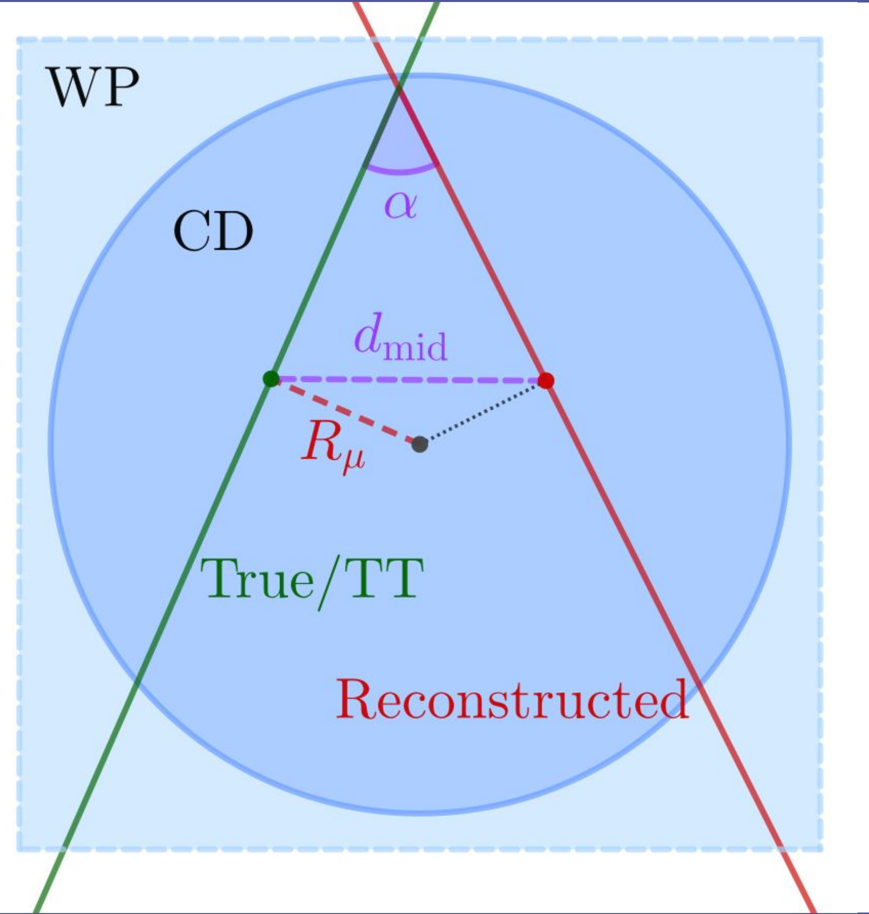
TT used as reference when available.

Metrics:

- Angle between reference and reconstructed directions.
- Distance between reference and reconstructed track midpoints.

Parameters:

- Distance between center of the CD and reference track.



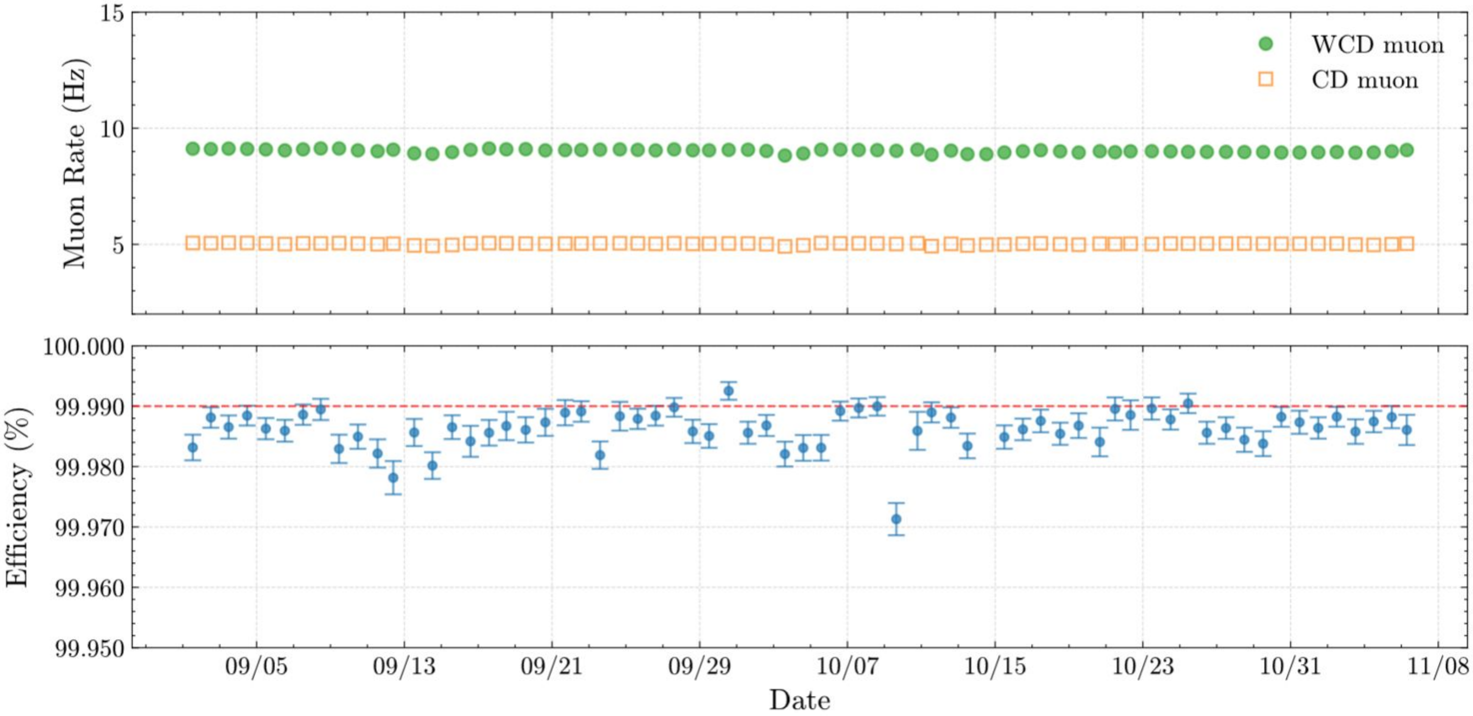
Rate and efficiency

CD rate ~ 5 cps, WP rate ~ 9 cps.

⇒ Stable over time, consistent with simulations.

WP tagging efficiency > 99.97%.

⇒ Stable.



Classification

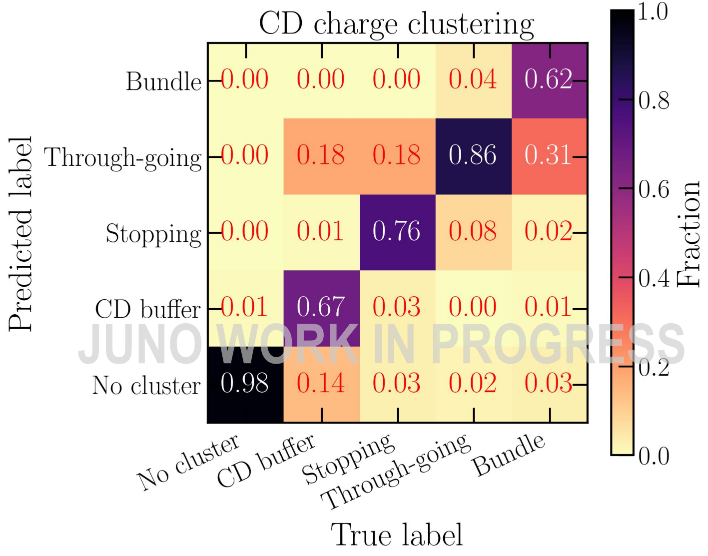
$$\text{Classification Efficiency} = \frac{(\text{Correctly classified } \mu \text{ Events})}{(\text{Total number of } \mu \text{ Events})}$$

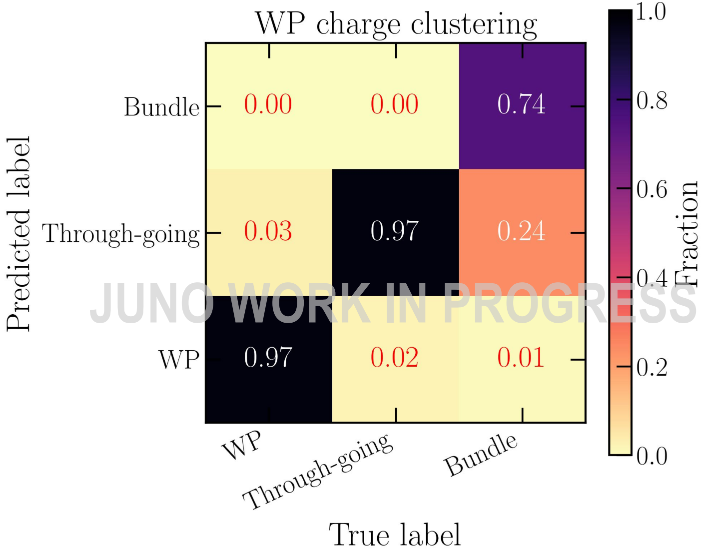
Classification efficiency (charge clustering):

- CD: 81%.
- WP: 95%.

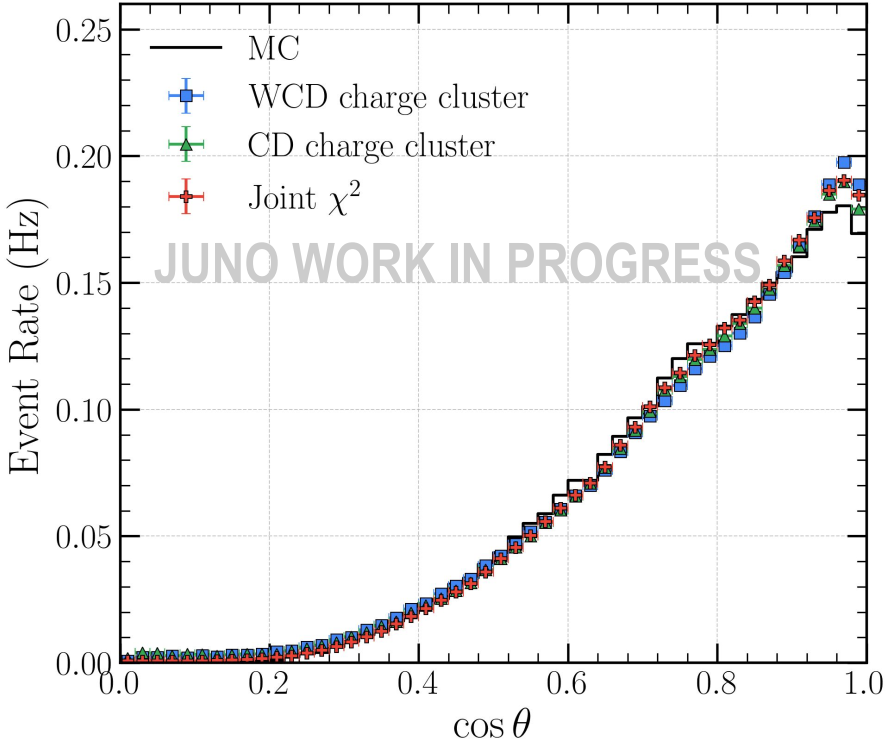
Source of inefficiencies:

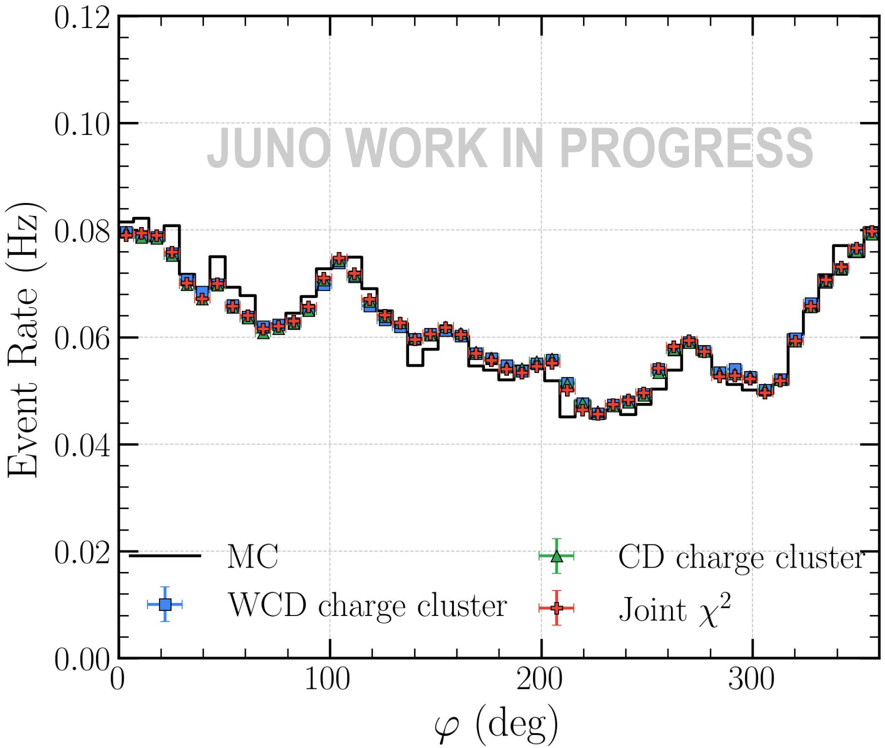
- Two close muons ⇒ single-like charge pattern.
- Stopping muons decaying before exiting ⇒ through-going-like charge pattern.





Reconstruction: muon direction

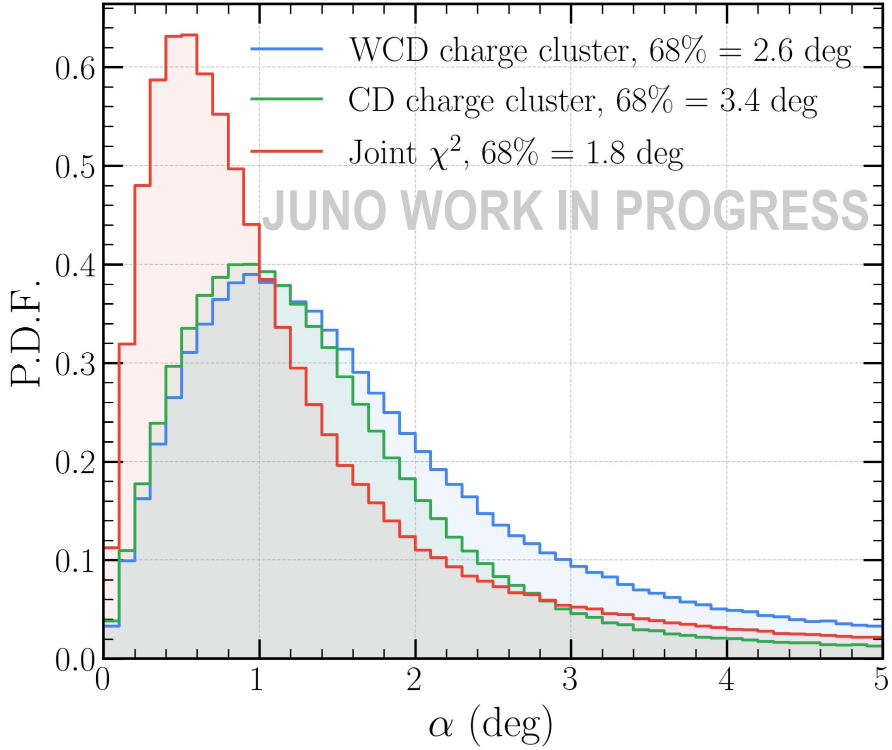


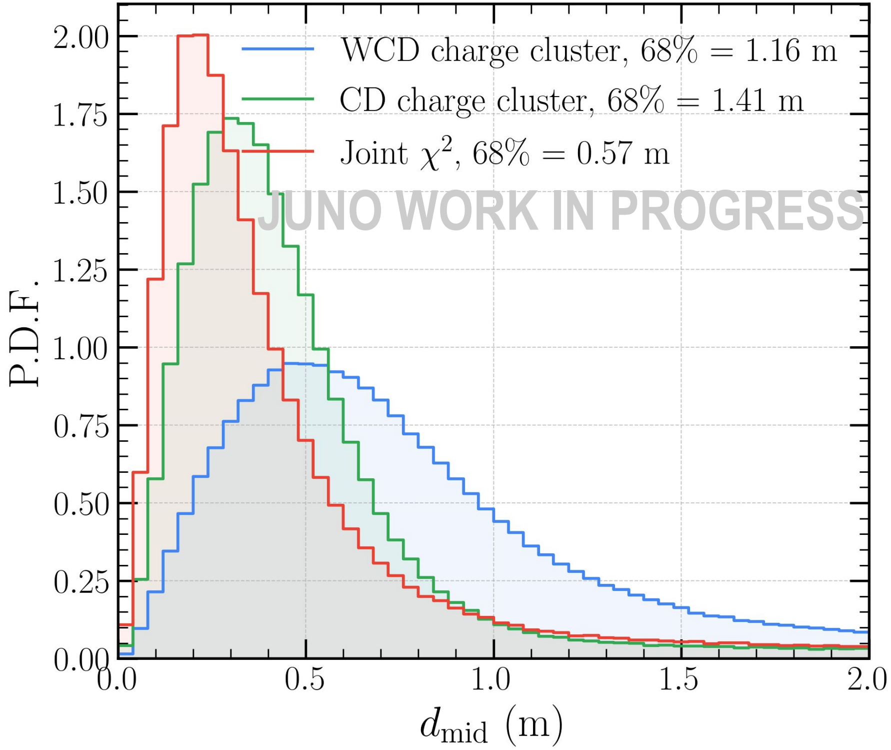


Zenith and azimuth angles of the reconstructed muons.

Good agreement between all methods and simulation ⇒ accurate mapping of the mountain profile.

Reconstruction: performance

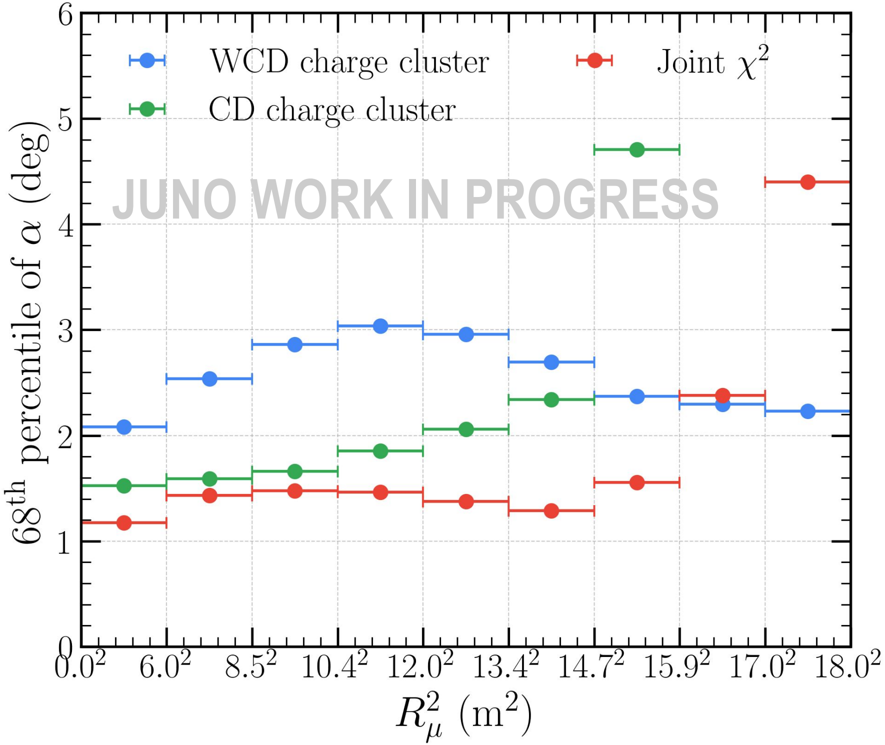


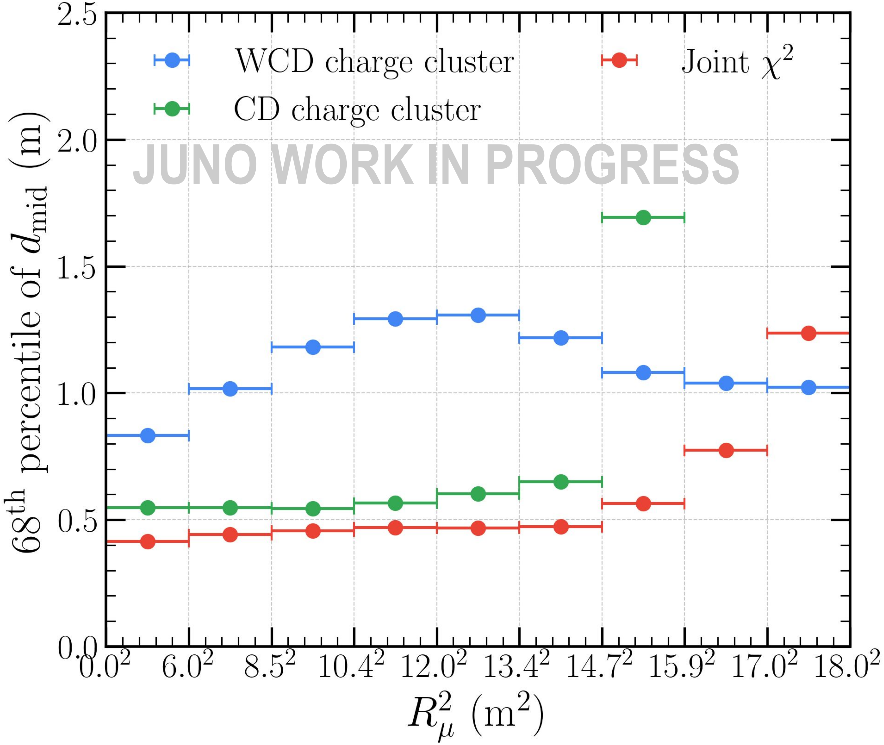


Angular and spatial differences with TT reference.

Joint reconstruction provides the best resolution for now. Note: machine learning yet not included!

Reconstruction: performance vs radial position





Resolution as a function of radial position.

Performance degrades for tracks near detector boundaries ⇒ optical effects.

Conclusion

Muon reconstruction is essential for cosmogenic background suppression.

Different approaches explored:

- Traditional methods (charge-based clustering, timing-based reconstruction).
- Machine learning (graph-based CNN, transformer).

Good consistency between reconstruction methods and simulation.

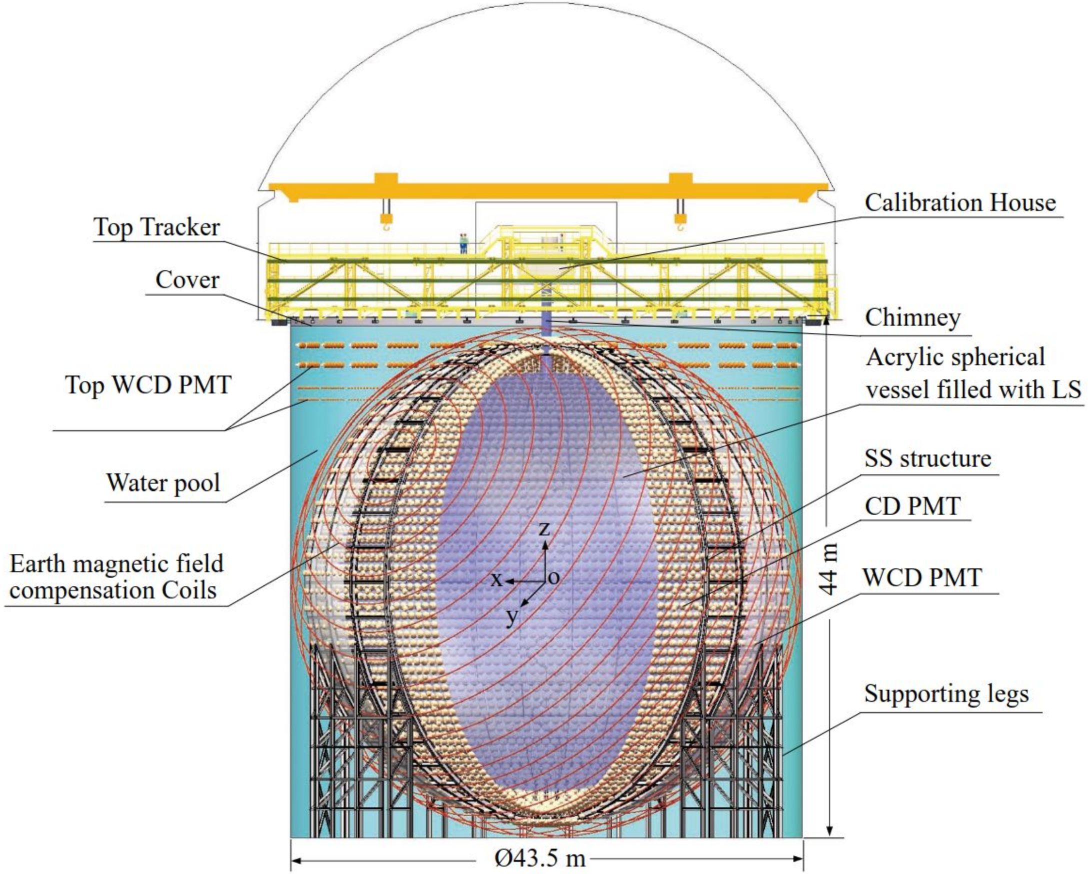
Good reconstruction performance achieved, with ongoing developments to improve resolution and integration of new methods.

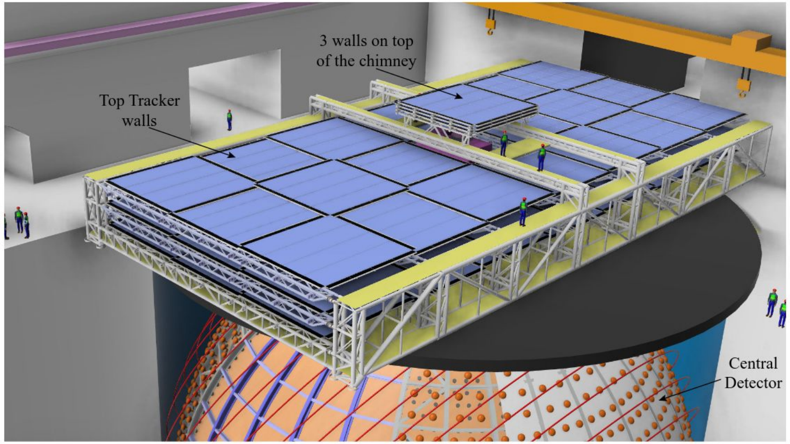
Outlook:

- Integration into physics analyses.
- Continued validation.

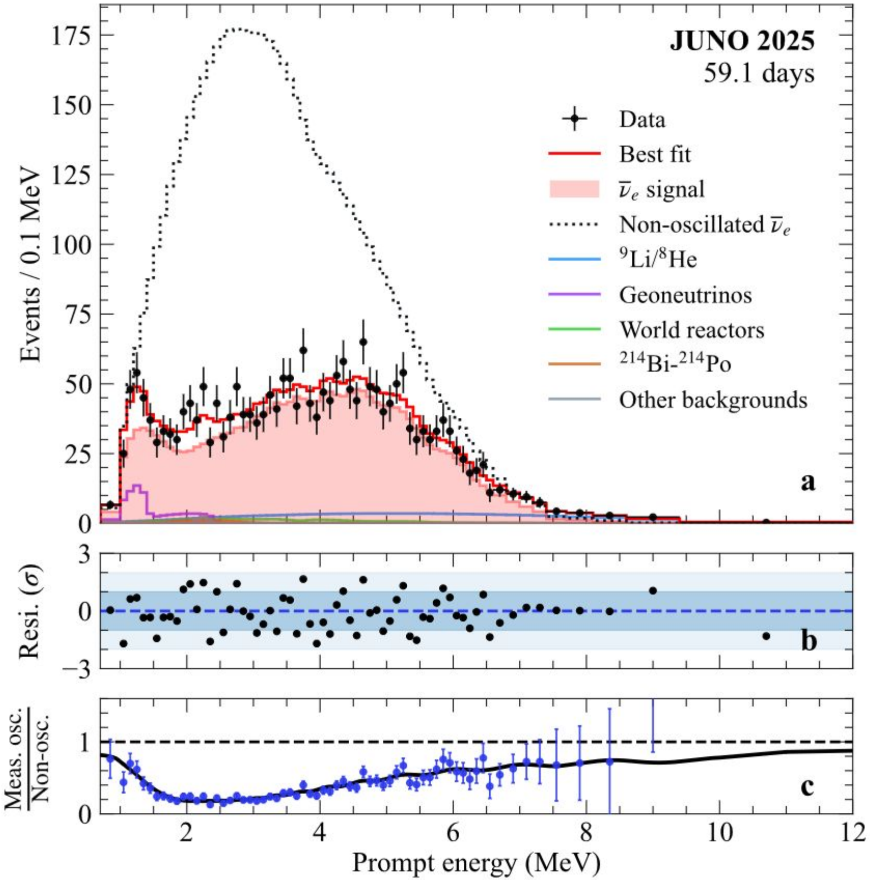
Thanks for your attention!

Backup - JUNO detector





Backup - First results and background



Antineutrinos ($\overline{\nu}_e$) Candidates Summary		
DAQ live time (days)	59.1	
$\overline{\nu}_e$ candidates	2379	
Selection Efficiencies (%)	ε	σ_{rel}
Fiducial volume	80.6	1.6
PMT flasher rejection	>99.9	negligible
μ veto	93.6	negligible
Multiplicity	97.4	negligible
Prompt-delayed coinc.	95.1	0.13
Total efficiency ($\varepsilon_{\mathrm{tot}}$)	69.9	1.6
$\overline{\nu}_\mathrm{e}$ signal (cpd[1])		
w/o $\varepsilon_{\mathrm{tot}}$ corrected	33.5 ± 1.7	
w/ $\varepsilon_{\mathrm{tot}}$ corrected	47.9 ± 2.6	
Non-oscillated $\overline{\nu}_e$	150.9 ± 2.7	
Backgrounds (cpd)	Pre-fit	Best-fit
^{9}Li/^{8}He	4.3 ± 1.4	3.9 ± 0.6
Geoneutrinos	1.2 ± 0.5	1.4 ± 0.4
World reactors	0.88 ± 0.09	0.88 ± 0.09
^{214}Bi-^{214}Po	0.18 ± 0.10	0.20 ± 0.10
^{13}C(α, n)^{16}O	0.04 ± 0.02	0.04 ± 0.02
Fast neutrons	0.02 ± 0.02	0.02 ± 0.02
Double neutrons	0.05 ± 0.05	0.07 ± 0.05
Atmospheric neutrinos	0.08 ± 0.04	0.07 ± 0.04
Accidentals ($\times 10^{-2}$)	4.9 ± 0.3	4.9 ± 0.3