Interactive talk: download scripts/code from https://github.com/kjkellyphys/neutrinou_2023

What do we do
with neutrino data?

Kevin J. Kelly, Texas A&M University
Neutrino University, August 16 2023
kjkelly@tamu.edu
[2007.08526] & [2106.06548] with P.A.N. Machado (x2), S.J. Parke, Y.F. Perez-Gonzalez, and R. Zukanovich-Funchal

Outline

- BSM signals in detectors
  - MicroBooNE search recast
- Three-flavor oscillation fit
  - NOvA + T2K “tension”

Recasting MicroBooNE

[2106.06548] with P.A.N. Machado

MicroBooNE Search for Higgs-Portal Scalars

- Inspired by Batell et al [1909.11670], MicroBooNE sought a BSM signature in a particular dataset in 2021:

$$K^+ \to \pi^+ S, \quad S \to e^+ e^-$$

- These kaons are produced in the NuMI beam line or absorber, and decay within the absorber.

- The absorber is 100 m from MicroBooNE — the S must be moderately long-lived to reach MicroBooNE and decay inside.

MicroBooNE [2106.00568]

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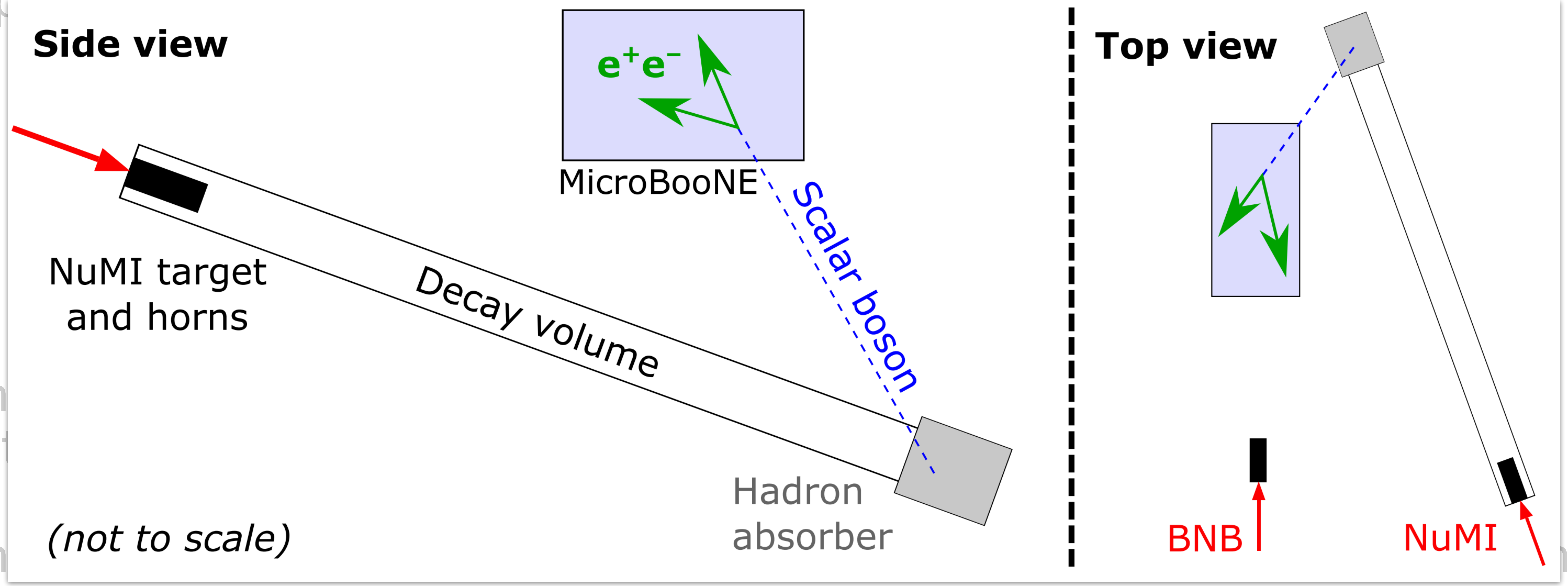

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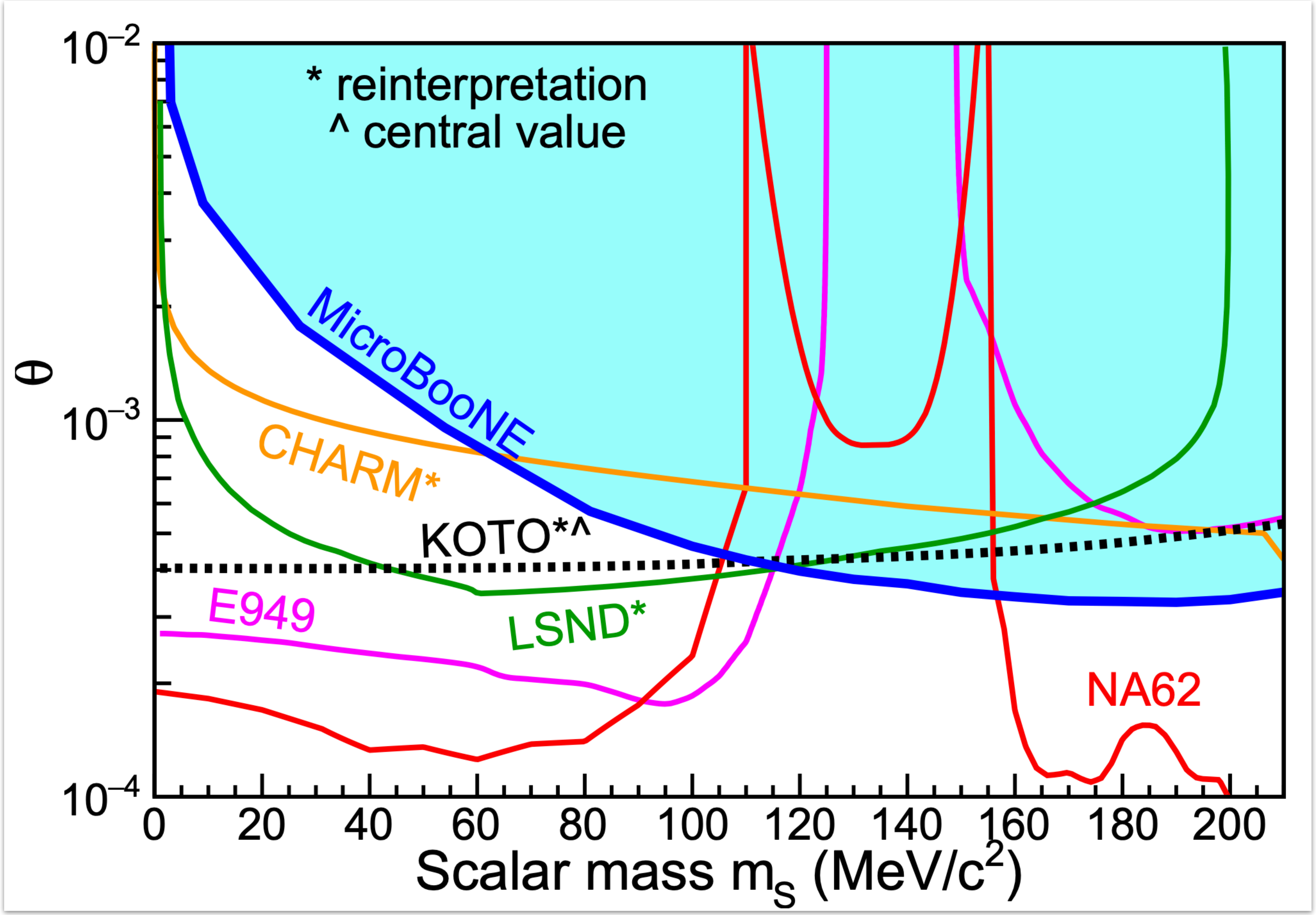
MicroBooNE [2106.00568]

MicroBooNE Constraint

MicroBooNE [2106.00568]



Signal Rate from KDAR BSM

signal rate

$$R_X = \Phi_X A_{\mathrm{det.}} P\left(X \to e^+e^-\right) \varepsilon(m_X)$$

Signal Rate from KDAR BSM

signal rate

detector area

$$R_X = \Phi_X A_{\text{det.}} P\left(X \to e^+ e^-\right) \varepsilon(m_X)$$

signal efficiency

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flux of new particles

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Signal Rate from KDAR BSM

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$$R_X = \Phi_X A_{\mathrm{det.}} P\left(X \to e^+e^-\right) \varepsilon(m_X)$$

probability of decay happening in detector

signal efficiency

$$\Phi_X = \frac{N_{\mathrm{KDAR}} \mathrm{Br}\left(K^+ \to X\right)}{4\pi D^2}$$

$$P \approx \frac{L_{\mathrm{det.}}}{\gamma} \Gamma\left(X \to e^+e^-\right)$$

Flux Example

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Scalar Model

$$\mathrm{Br}(K^\pm \to \pi^\pm \varphi) = 2 \times 10^{-3} \sin^2 \vartheta \, \rho_\varphi \left(\frac{M_\varphi^2}{m_{K^\pm}^2}, \frac{m_{\pi^\pm}^2}{m_{K^\pm}^2} \right)$$

HNL Model

$$\mathrm{Br}(K \to \mu N) \simeq \mathrm{Br}(K \to \mu \nu) |U_{\mu 4}|^2 \rho_N \left(\frac{m_\mu^2}{m_K^2}, \frac{m_N^2}{m_K^2} \right)$$

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- This included a boosted decision tree (BDT) trained on signal and background Monte Carlo.

TABLE II. Estimated signal selection efficiency (eff.) for a scalar boson decay inside the TPC, and event yield [unweighted (unwt.) and beam-on exposure-weighted (exp. wt.), with the expected signal for θ_{KCV}].

Category	Eff. (%)	Event count	
		Unwt.	Exp. Wt.
Beam-off dataset		10	1.1 ± 0.4
Neutrino simulation		16	0.8 ± 0.7
Signal (120 MeV/c^2)	14.0 ± 0.8	7268	4.9 ± 1.5
Signal (160 MeV/c^2)	14.9 ± 0.9	7654	12.2 ± 3.6

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- After cutting on the BDT score, two* candidate events pass, on a background expectation of 1.9 ± 0.8 events.

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Goal: as a function of mass, determine the HNL model parameters that predict the *same* signal rate that MicroBooNE has excluded for the Higgs-portal scalar model.

Same Rate?

$$R_X = \Phi_X A_{\text{det.}} P\left(X \to e^+e^-\right) \varepsilon(m_X)$$

$$\frac{R_N}{R_S} \approx \frac{\text{Br}(K \to \mu N)}{\text{Br}(K \to \pi S)} \frac{m_N E_S \Gamma(N \to \nu e^+ e^-)}{m_S E_N \Gamma(S \to e^+ e^-)} \frac{\varepsilon(m_N)}{\varepsilon(m_S)}$$

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Given or Calculable

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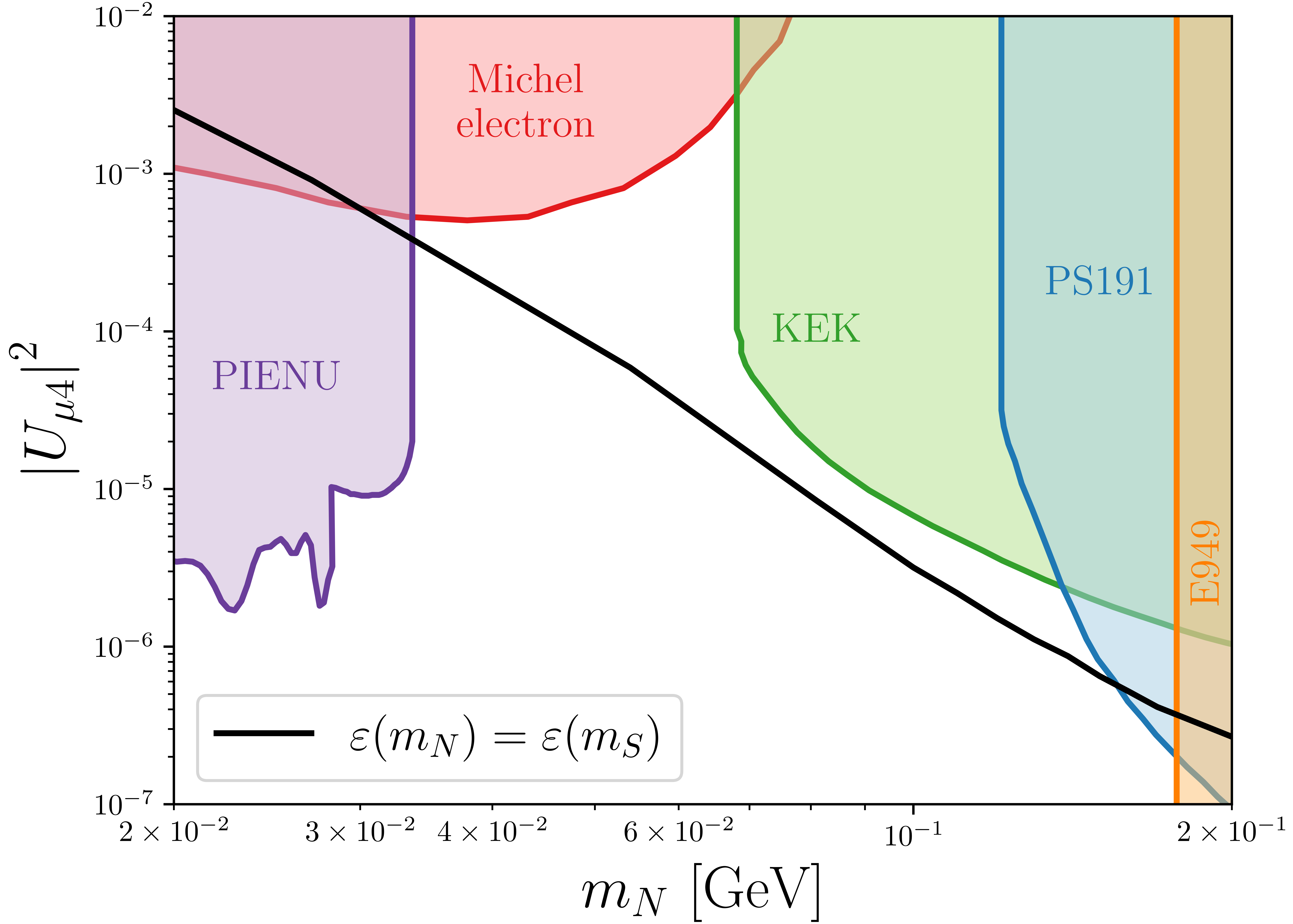
Pretend it's equal to $\varepsilon(m_S)$ for now

HPSRecast.ipynb



Michel electron
PIENU
KEK
PS191
E949
$\varepsilon(m_N) = \varepsilon(m_S)$
$|U_{\mu 4}|^2$
m_N [GeV]
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
2×10^{-2}
3×10^{-2}
4×10^{-2}
6×10^{-2}
10^{-1}
2×10^{-1}

OK, what about efficiency?

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What goes into signal efficiency?

Training Information from MicroBooNE

MicroBooNE [2106.00568]

We apply two different BDTs to the preselected candidates: one trained against cosmic backgrounds and one trained against neutrino interactions simulated inside the cryostat. Each BDT is trained separately over the run 1 events and run 3 events, i.e., there are four BDTs in total. We split the run periods because the use of the CRT in run 3 and the differences between forward and reverse horn current operations can change the topologies and properties of the background distributions that the BDTs are trained against. We use `xgboost` [27] to train and apply the BDTs. We train the BDTs on ten input variables each. Nine of the ten input variables are the same for the cosmic-focused and neutrino-focused BDTs. These are (1) the opening angle between the two reconstructed objects; (2) the opening angle in the plane transverse to the hadron absorber direction from the detector center; (3,4) the two angles between the two objects and the hadron absorber direction; (5) the Pandora track or shower score of the larger of the two objects (when ordered by number of hits); (6) the number of hits of the larger object; (7) the total number of hits contained in other objects in the slice, not including the two objects that form the decay candidate; (8) the maximum y coordinate, relative to the decay vertex position, of shower start positions or track start or end positions, for any other objects in the slice; and (9) the minimum z coordinate, relative to the decay vertex position, of shower start positions or track start or end positions, for any other objects in the slice. The last two variables are treated as "missing" within `xgboost` if the slice contains only two objects. The tenth input variable of the cosmic-focused BDT is the length of the larger object. The tenth input variable of the neutrino-focused BDT is the number of tracks in the slice. For all

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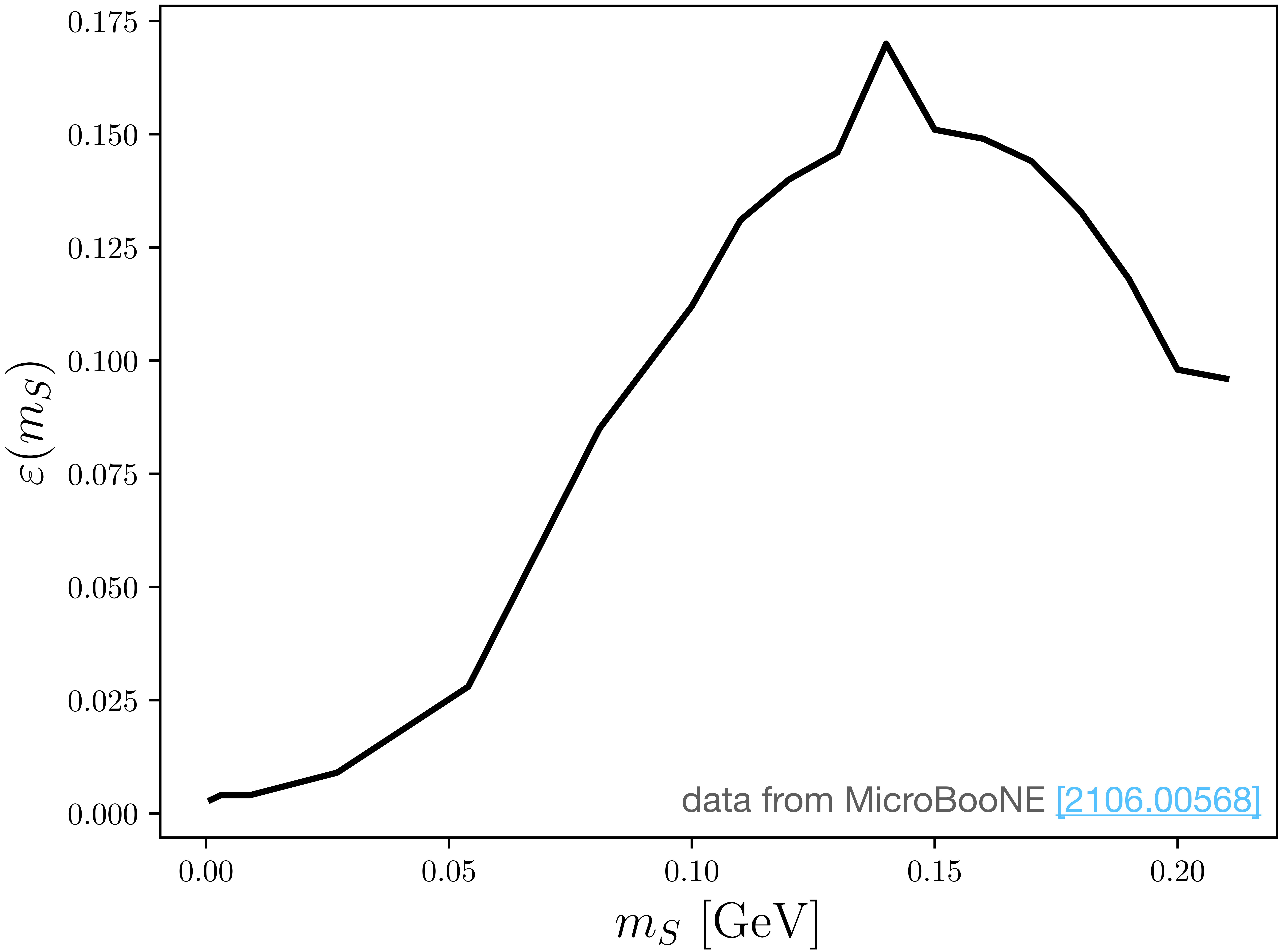
Ansatz:

(1) dominates the signal efficiency as a function of BSM particle mass

HPS Efficiency



```
RestFrame.py
LabFrame.py
```

Generate e^+e^- events in the rest-frame of the decaying HPS/HNL

(depends on `RestFrame.py` for HNL three-body kinematics and `vegas` for phase-space sampling)

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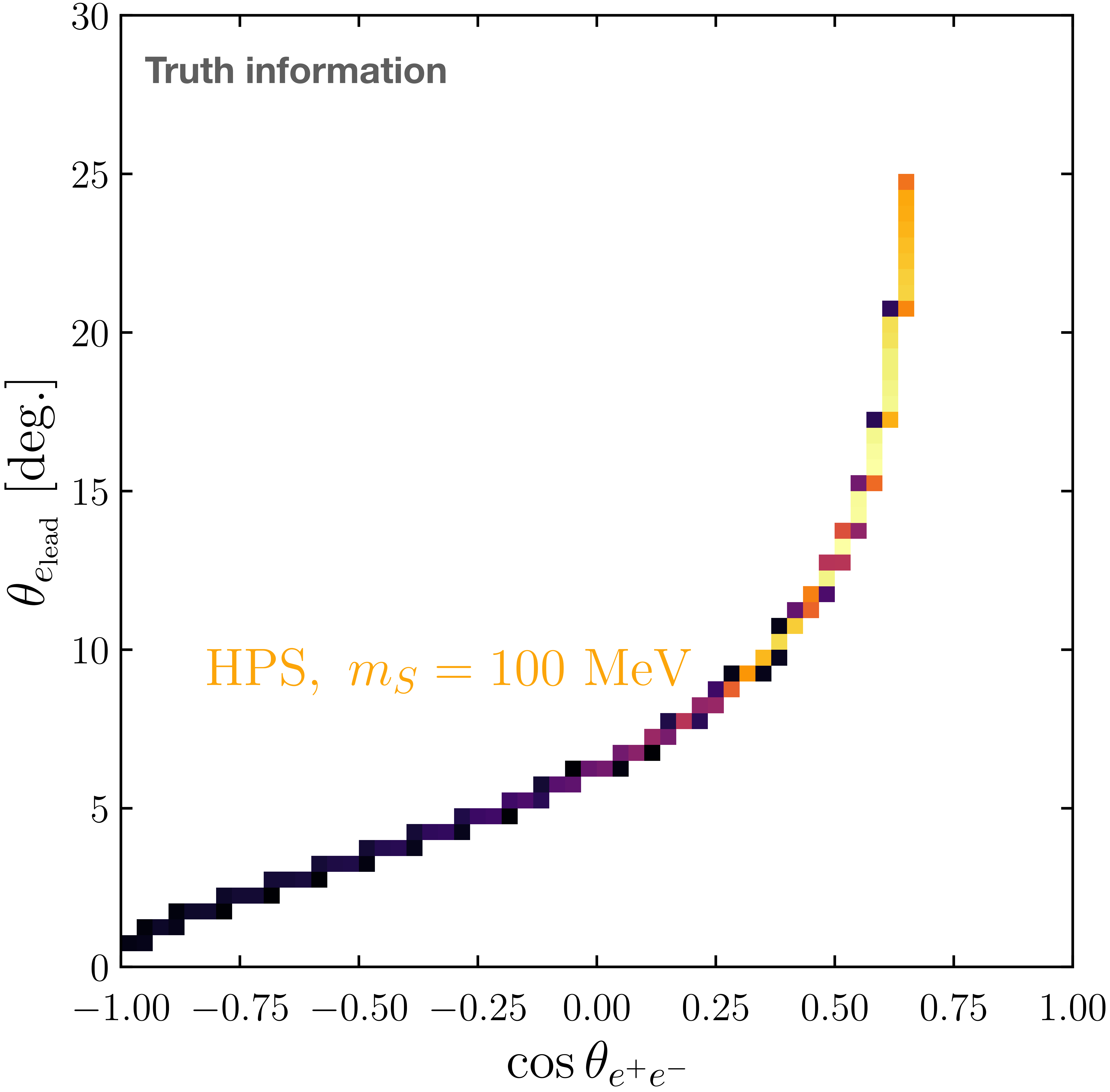
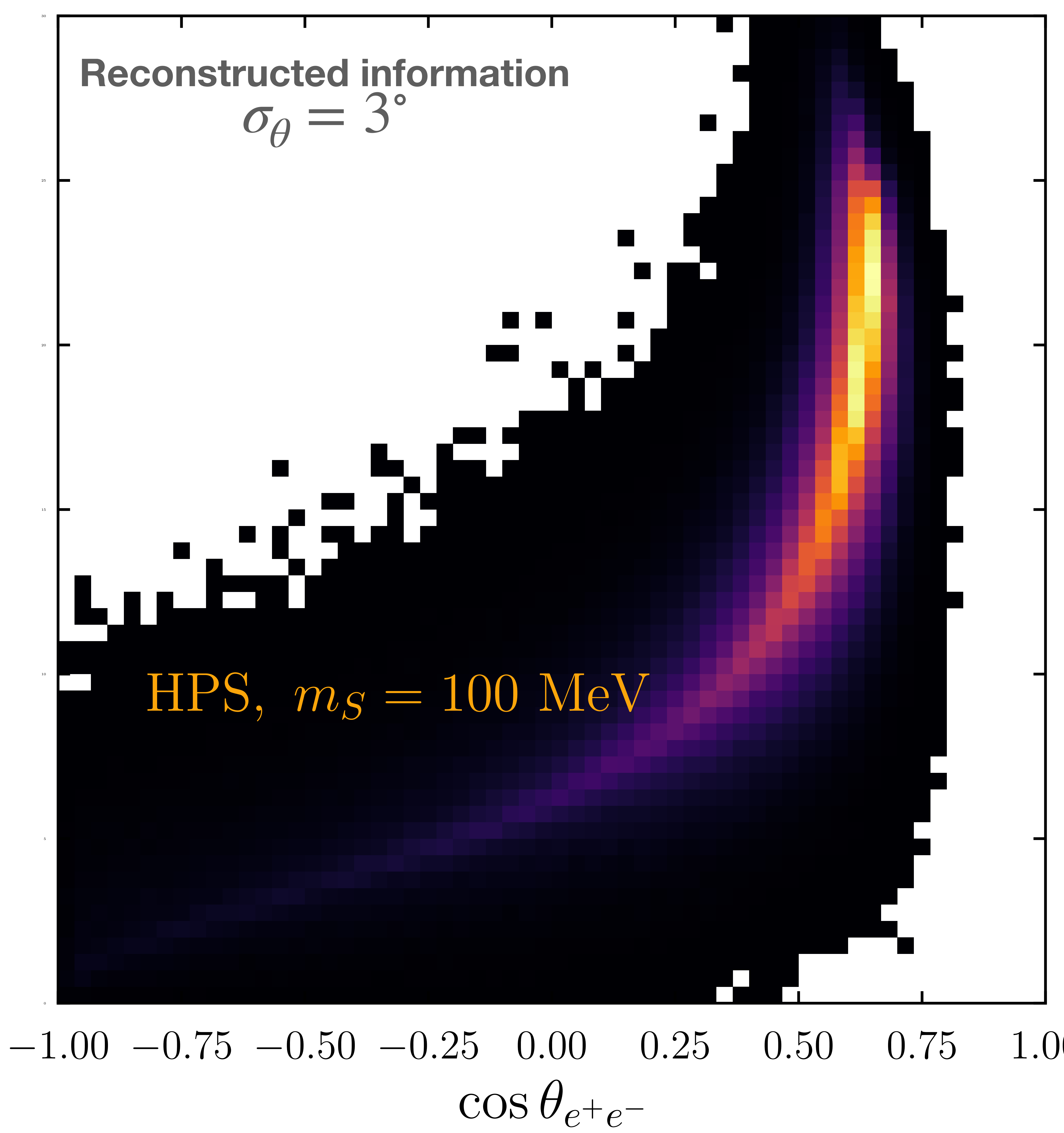
(depends on `RestFrame.py` for HNL three-body kinematics and `vegas` for phase-space sampling)

Transforms event to the laboratory frame, smears events, and performs different reconstruction/analyses on the events.

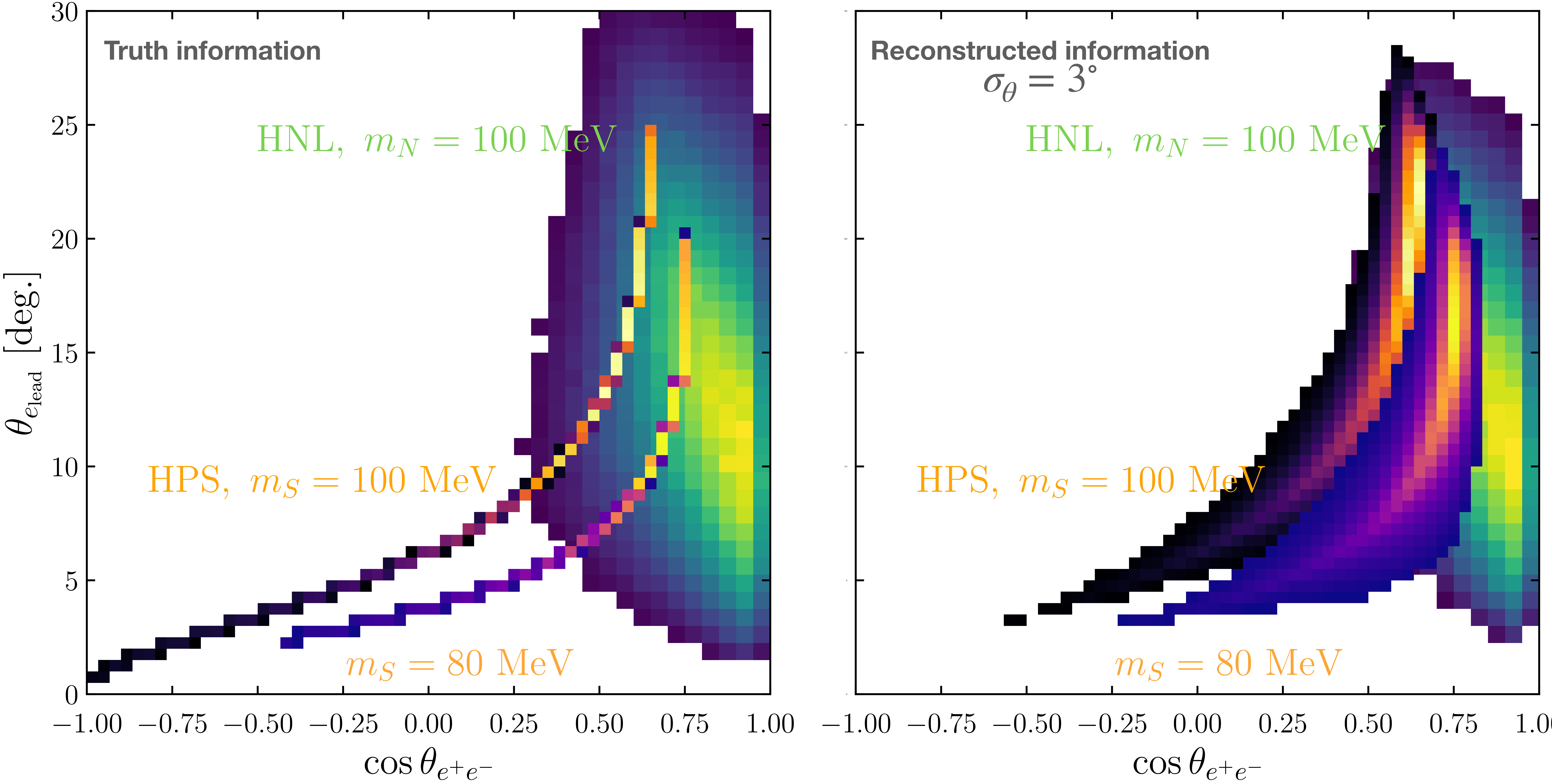
Event Distributions





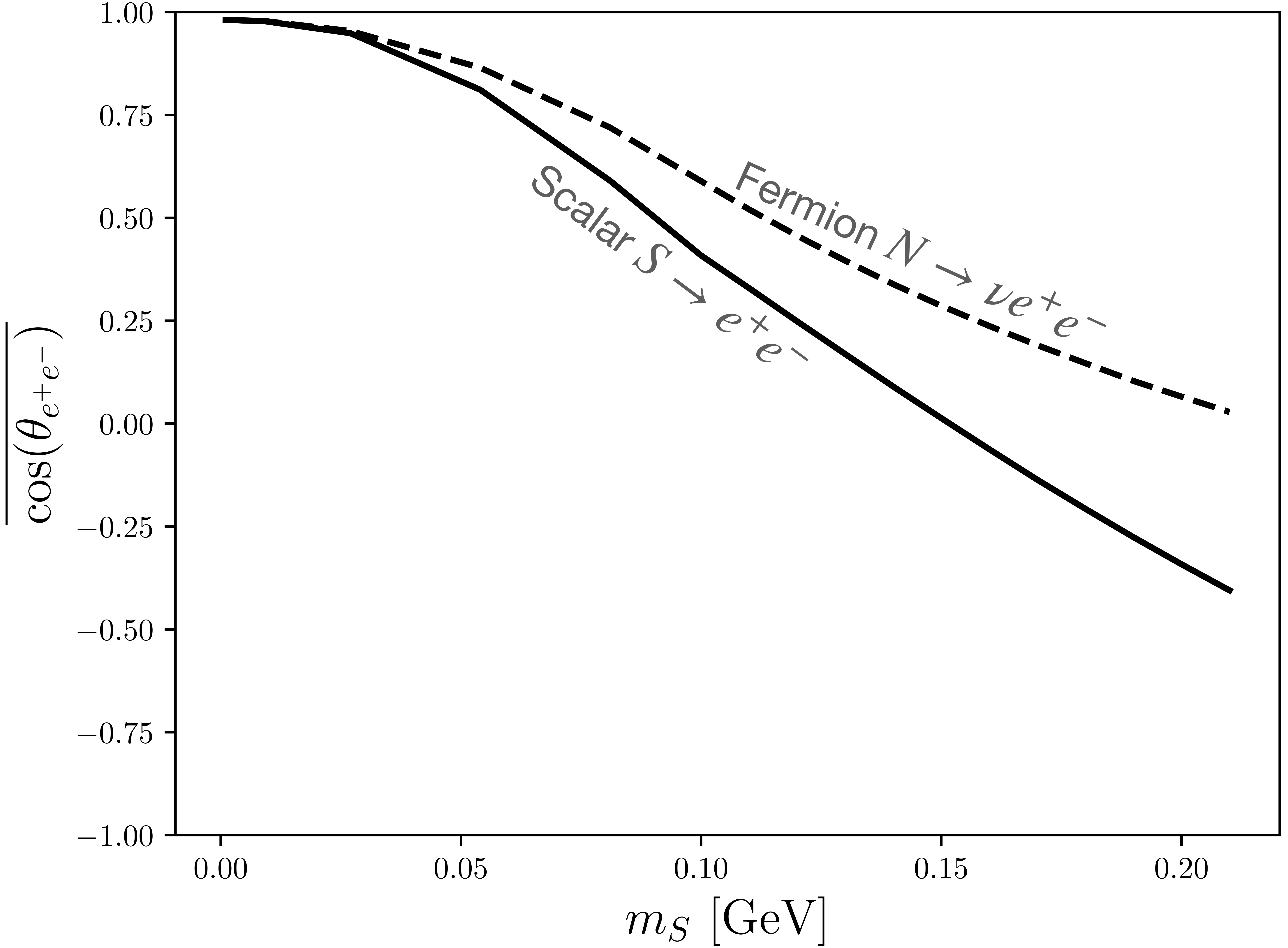
Comparison between HPS and HNL events in this kinematic space.

HNL vs HPS



Truth information
Reconstructed information
$\sigma_\theta = 3^\circ$
HNL, $m_N = 100$ MeV
HPS, $m_S = 100$ MeV
$m_S = 80$ MeV
$\theta_{e_{\rm lead}}$ [deg.]
$\cos\theta_{e^+e^-}$

Average Opening Angles



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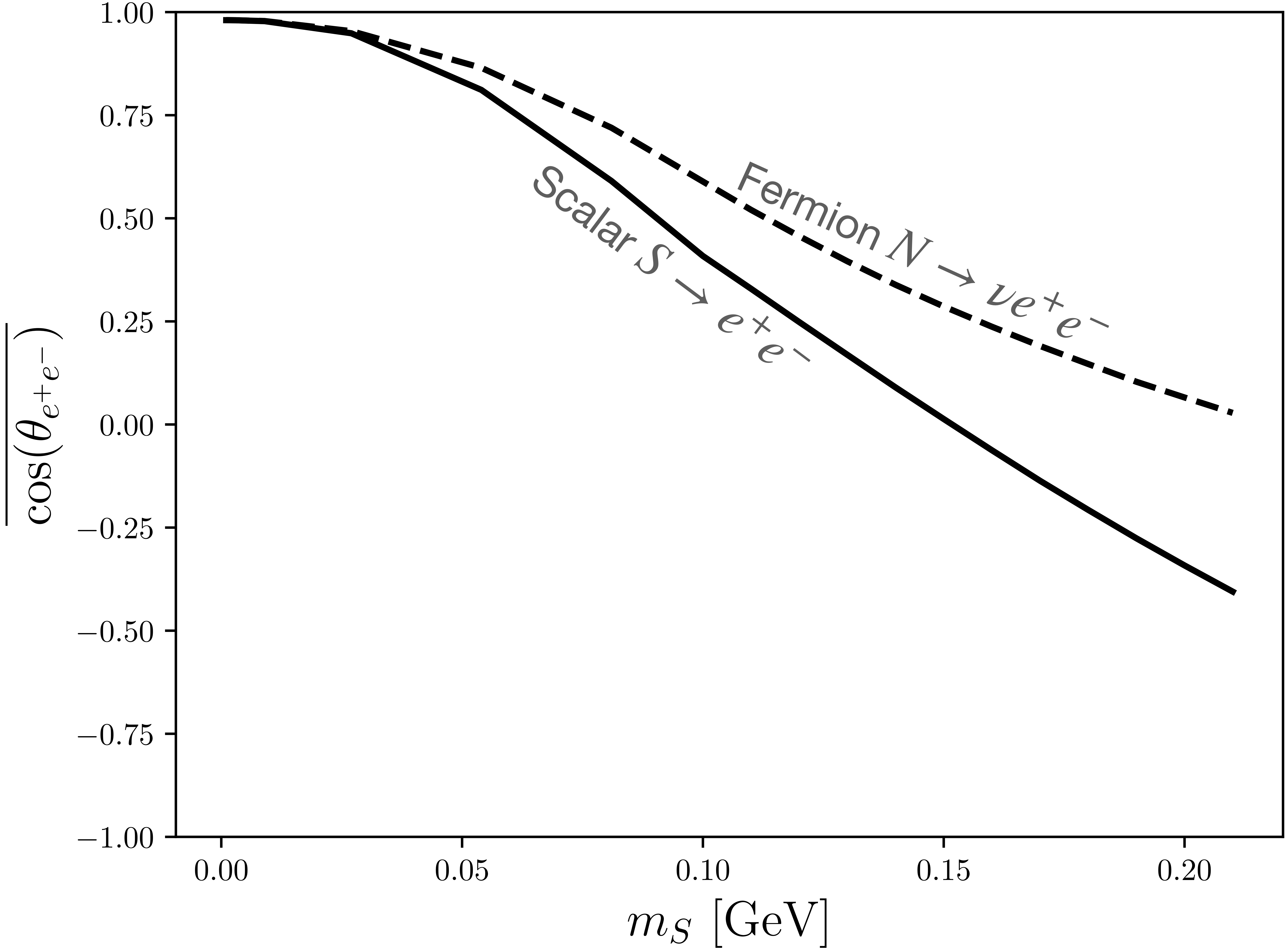
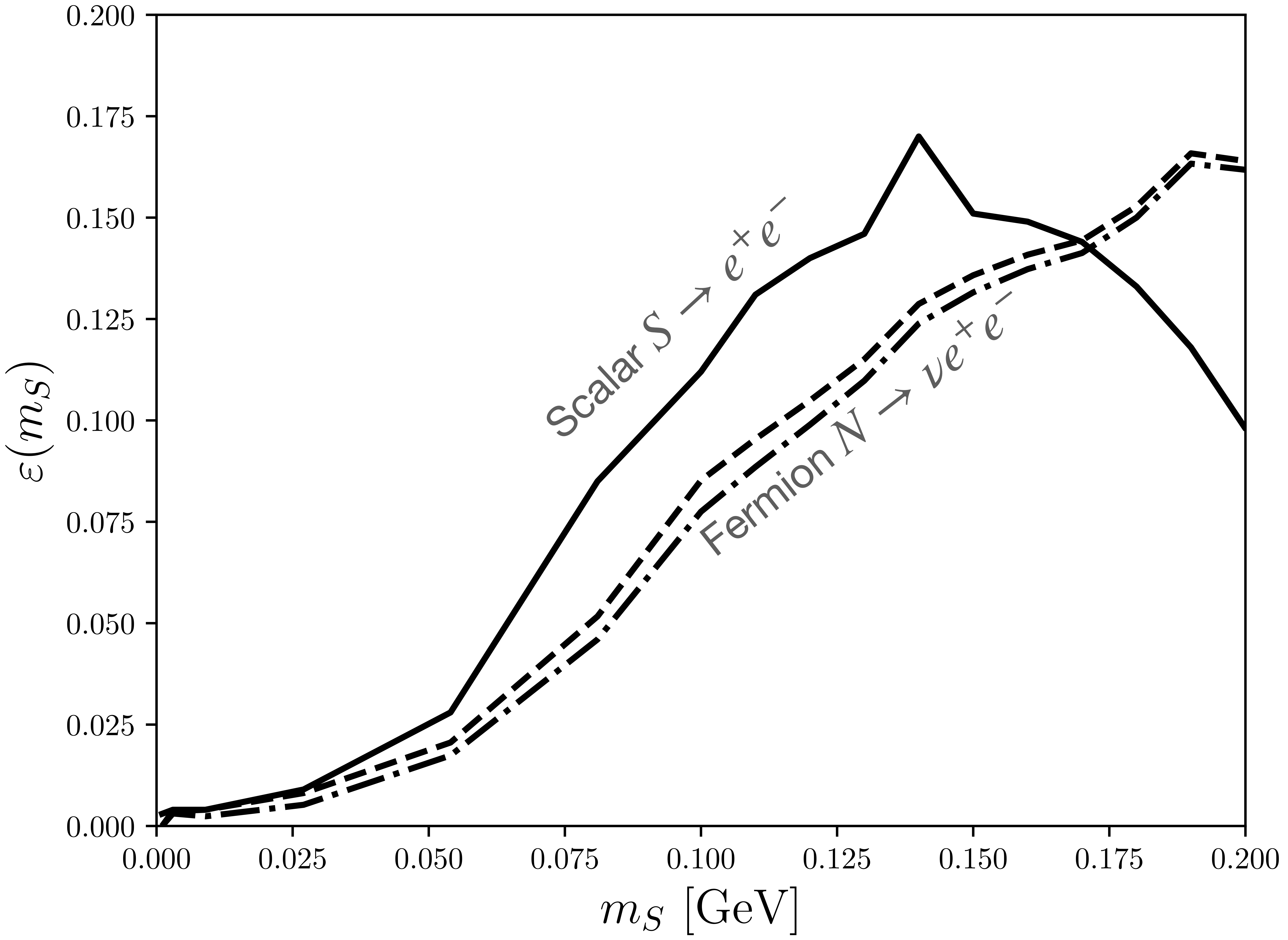


Updated Efficiency for HNLs



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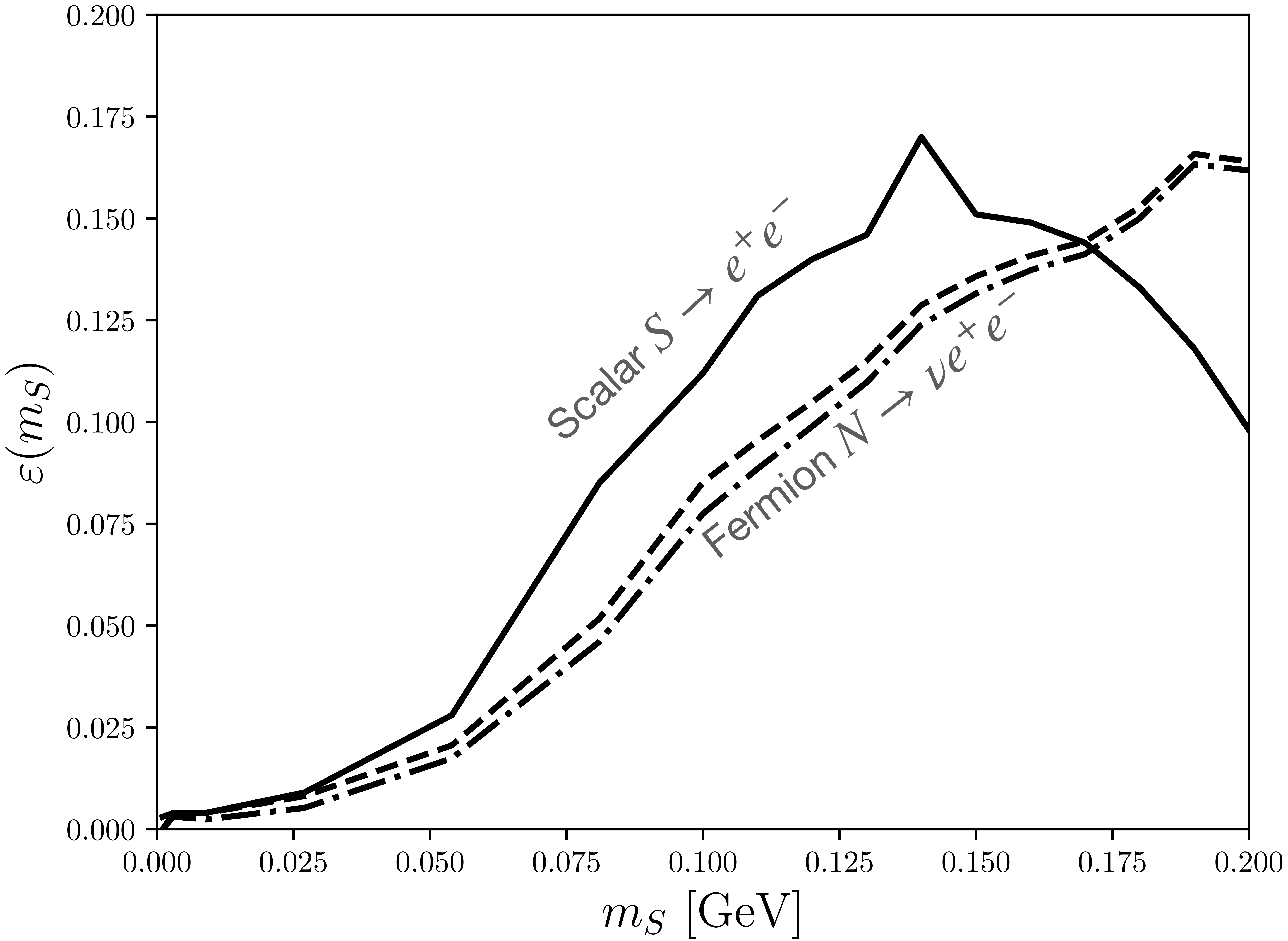
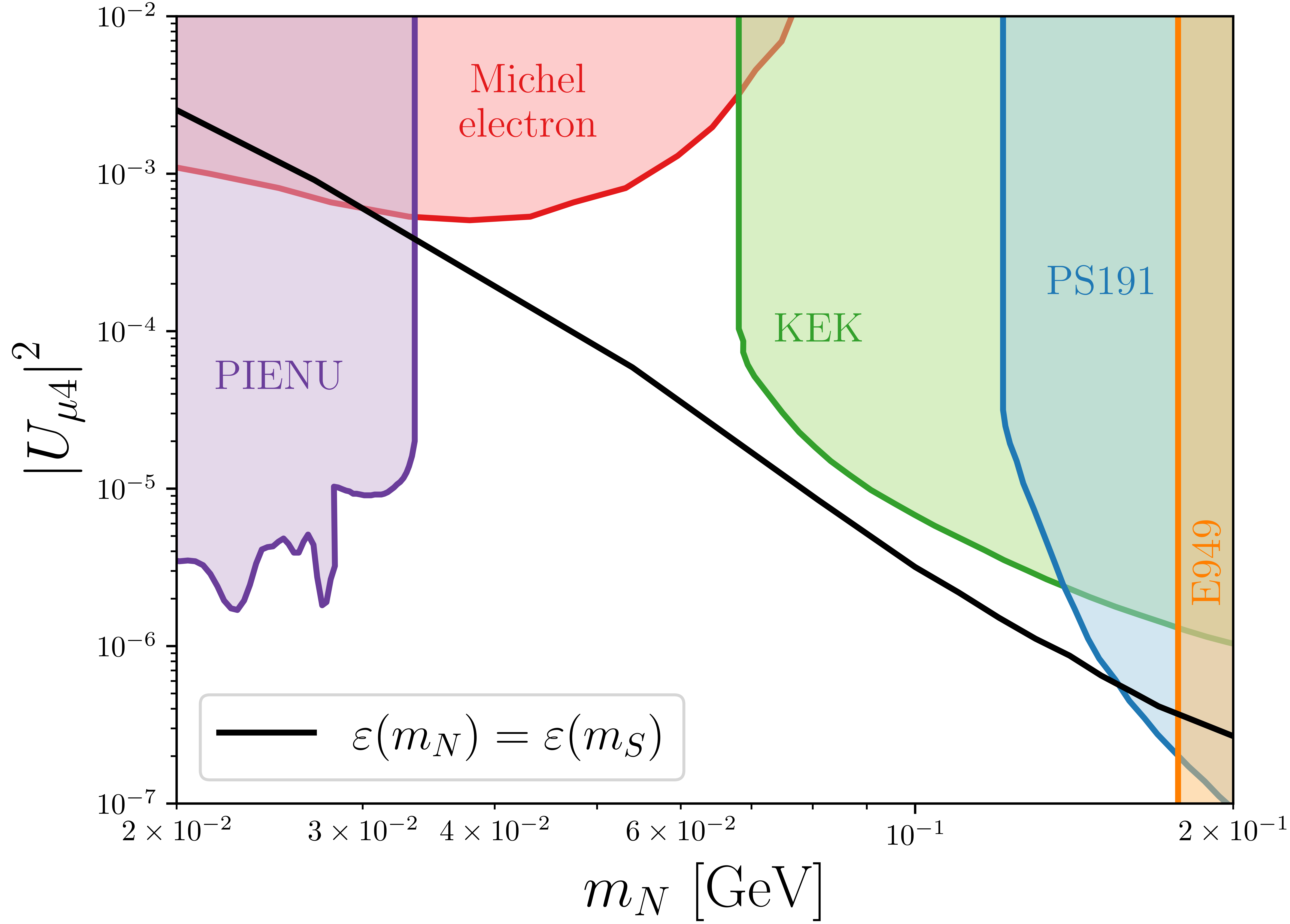


New Constraint on HNLs



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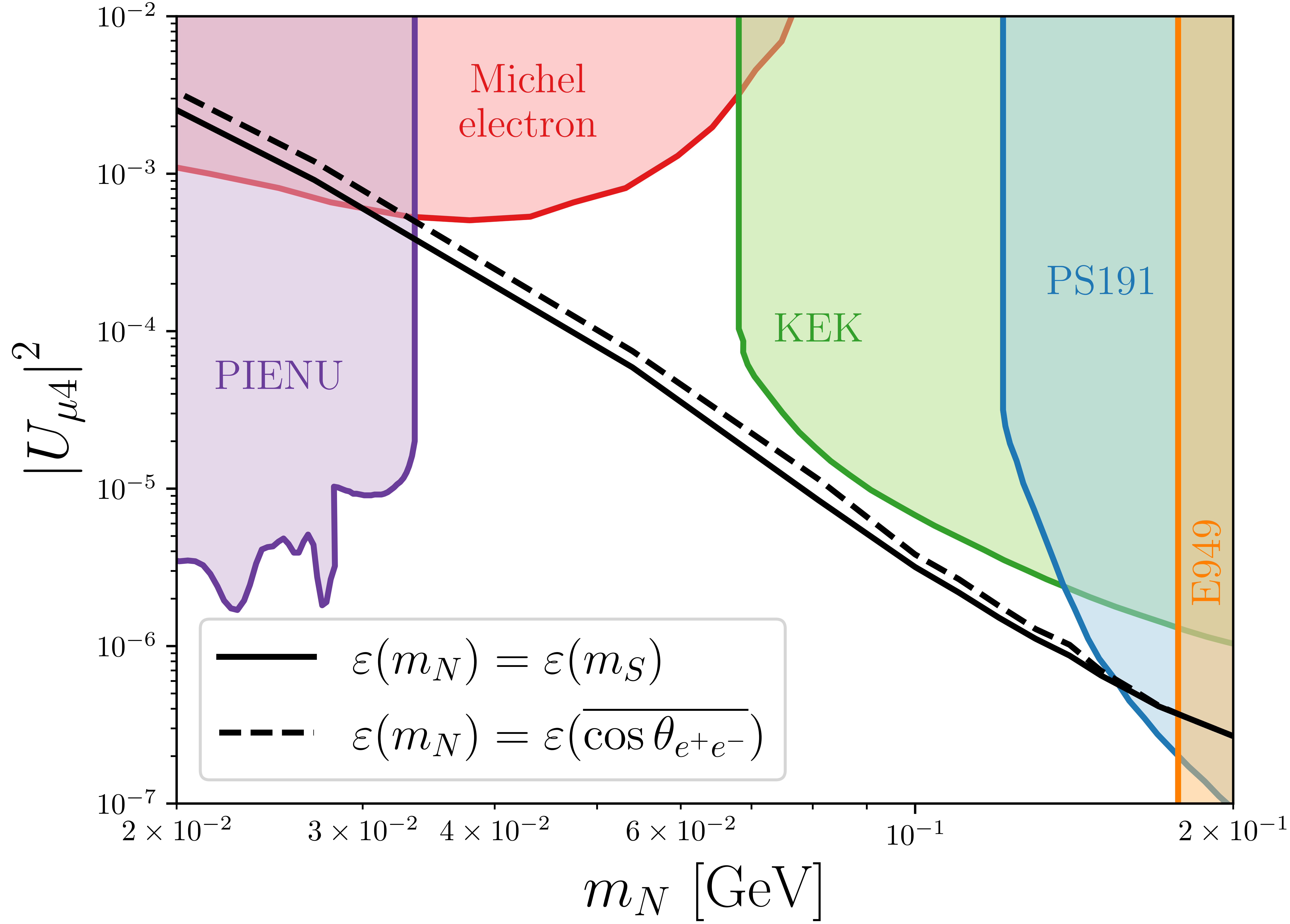
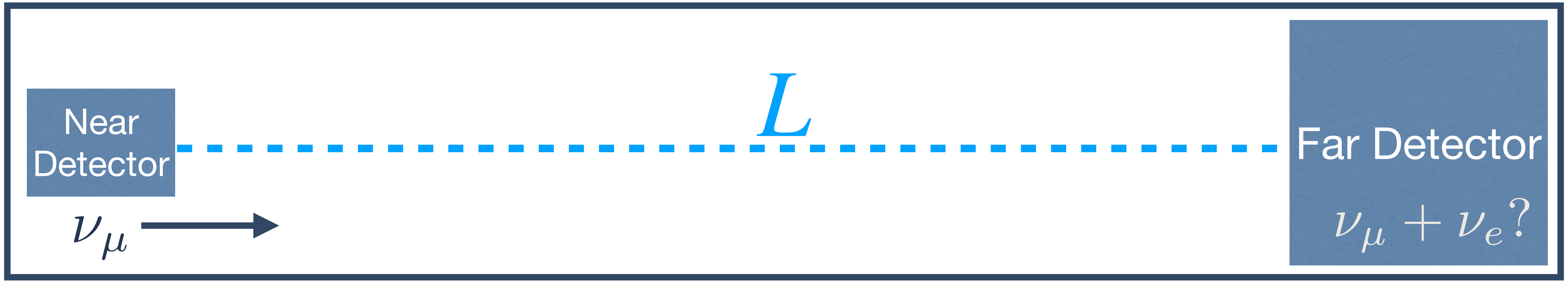


T2K & NOvA Three-flavor Oscillations

[2007.08526]

with P.A.N. Machado, S.J. Parke, Y.F. Perez-Gonzalez, and R. Zukanovich-Funchal

Long-baseline Accelerator Neutrinos in One Slide



$$\frac{\Phi_{\nu_\mu}(L)}{\Phi_{\nu_\mu}(0)} = P(\nu_\mu \to \nu_\mu)$$

"Disappearance" or "Survival" Probability

$$\frac{\Phi_{\nu_e}(L)}{\Phi_{\nu_\mu}(0)} = P(\nu_\mu \to \nu_e)$$

"Appearance" Probability

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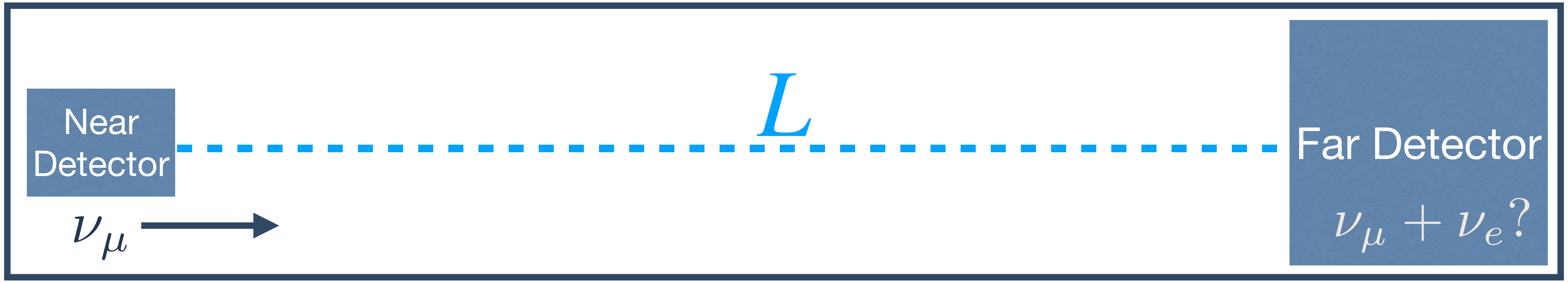

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$$\left\{ \sin^2\theta_{23}, \ \left|\Delta m^2_{31}\right| \right\}$$

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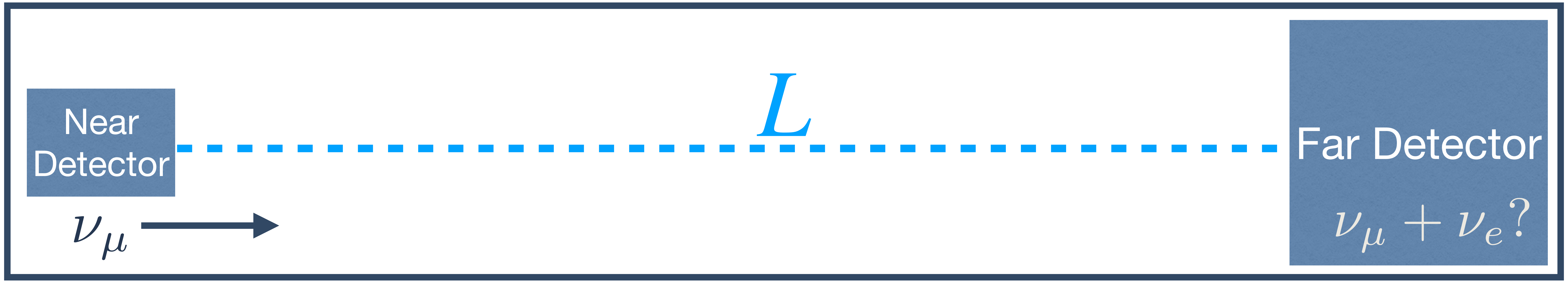

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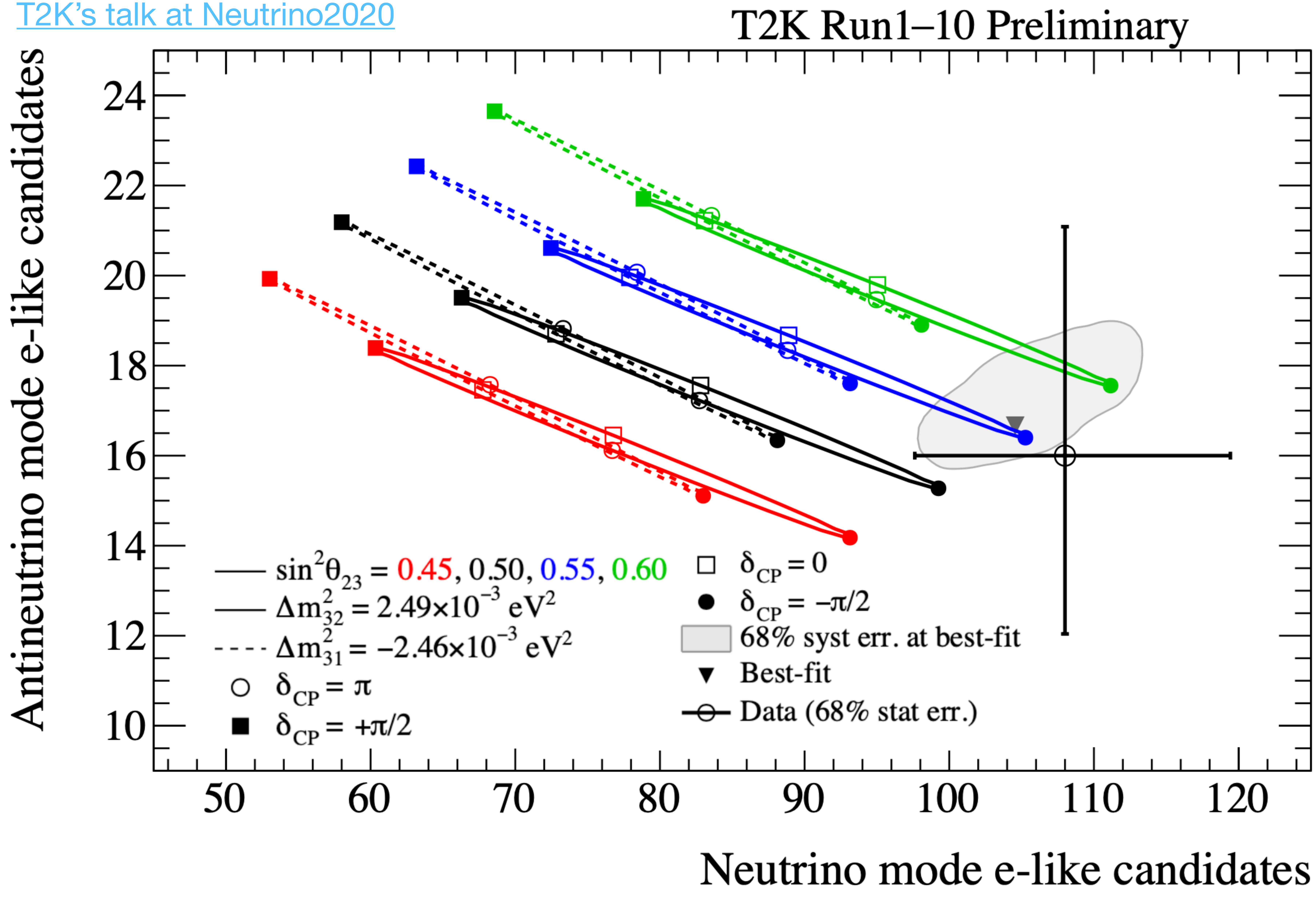
“Appearance” Probability

$$\left\{\sin^2\theta_{23},\ \left|\Delta m^2_{31}\right|\right\}$$

$$\left\{\sin^2\theta_{13},\ \sin^2\theta_{23},\ \Delta m^2_{31},\ \delta_{\rm CP}\right\}$$

Example: “fitting” T2K Expected Event Rate

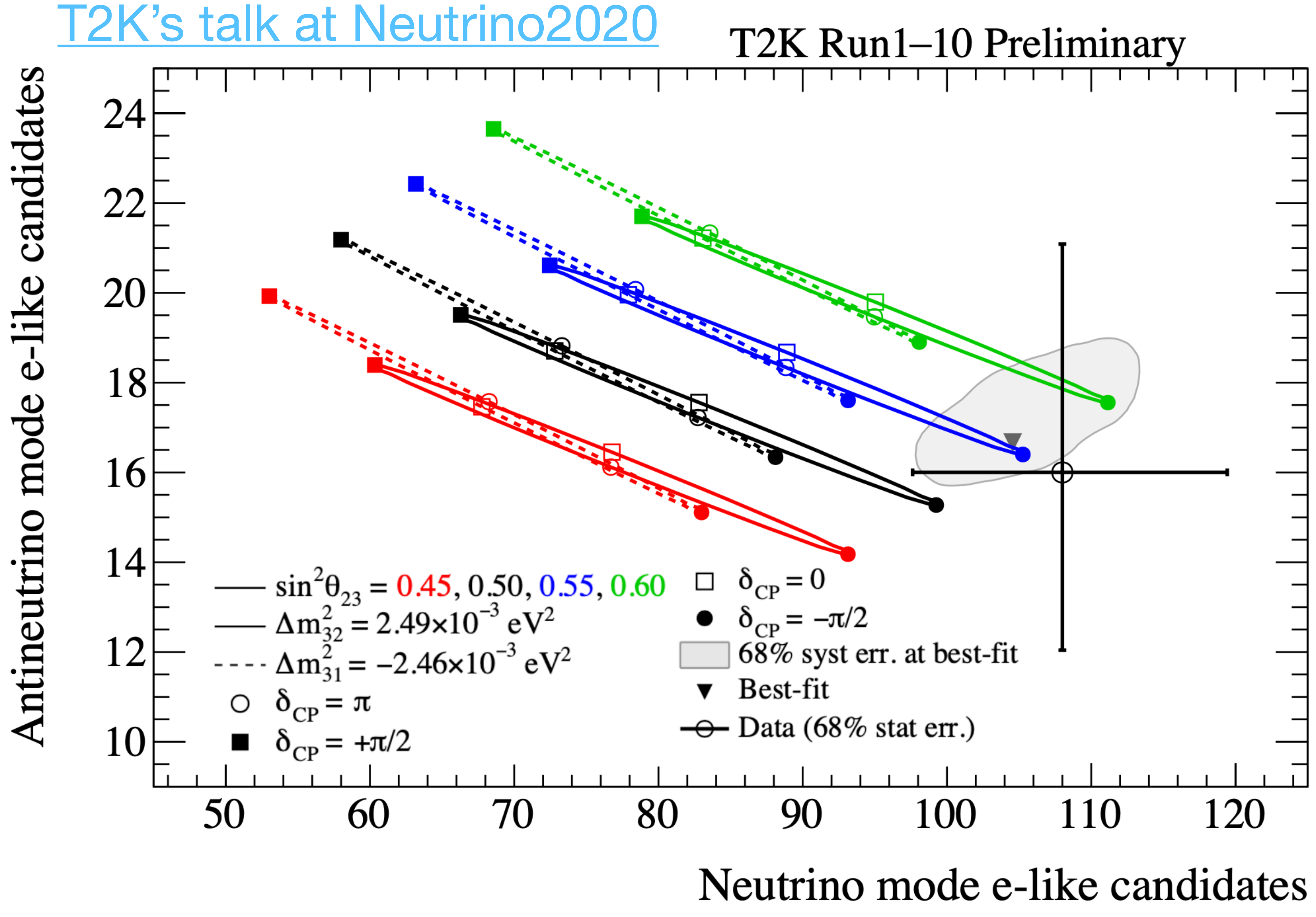
T2K’s talk at Neutrino2020



$$L_{\mathrm{T2K}} = 295 \text{ km}$$
$$E_{\mathrm{T2K}} = 600 \text{ MeV}$$
$$\rho_{\mathrm{T2K}} = 2.6 \text{ g/cm}^3$$

Goal: Reproduce such a prediction

T2K's talk at Neutrino2020



(Dominant) contribution to electron-like events in neutrino/antineutrino modes

- True signal arising from $\nu_\mu \to \nu_e$ oscillations
- Beam-contamination of $\bar{\nu}_\mu$ subject to $\bar{\nu}_\mu \to \bar{\nu}_e$ oscillations
- Backgrounds that are (predominantly) oscillation-indepenedent

Ansatz (Denton et al [2008.01110]):

$$\boxed{n(\nu_e) = xP(\nu_\mu \to \nu_e) + yP(\bar{\nu}_\mu \to \bar{\nu}_e) + z}$$

(Probabilities evaluated at $L = L_{\mathrm{T2K}}$, $E = \langle E_{\mathrm{T2K}} \rangle$, $\rho = \rho_{\mathrm{T2K}}$)

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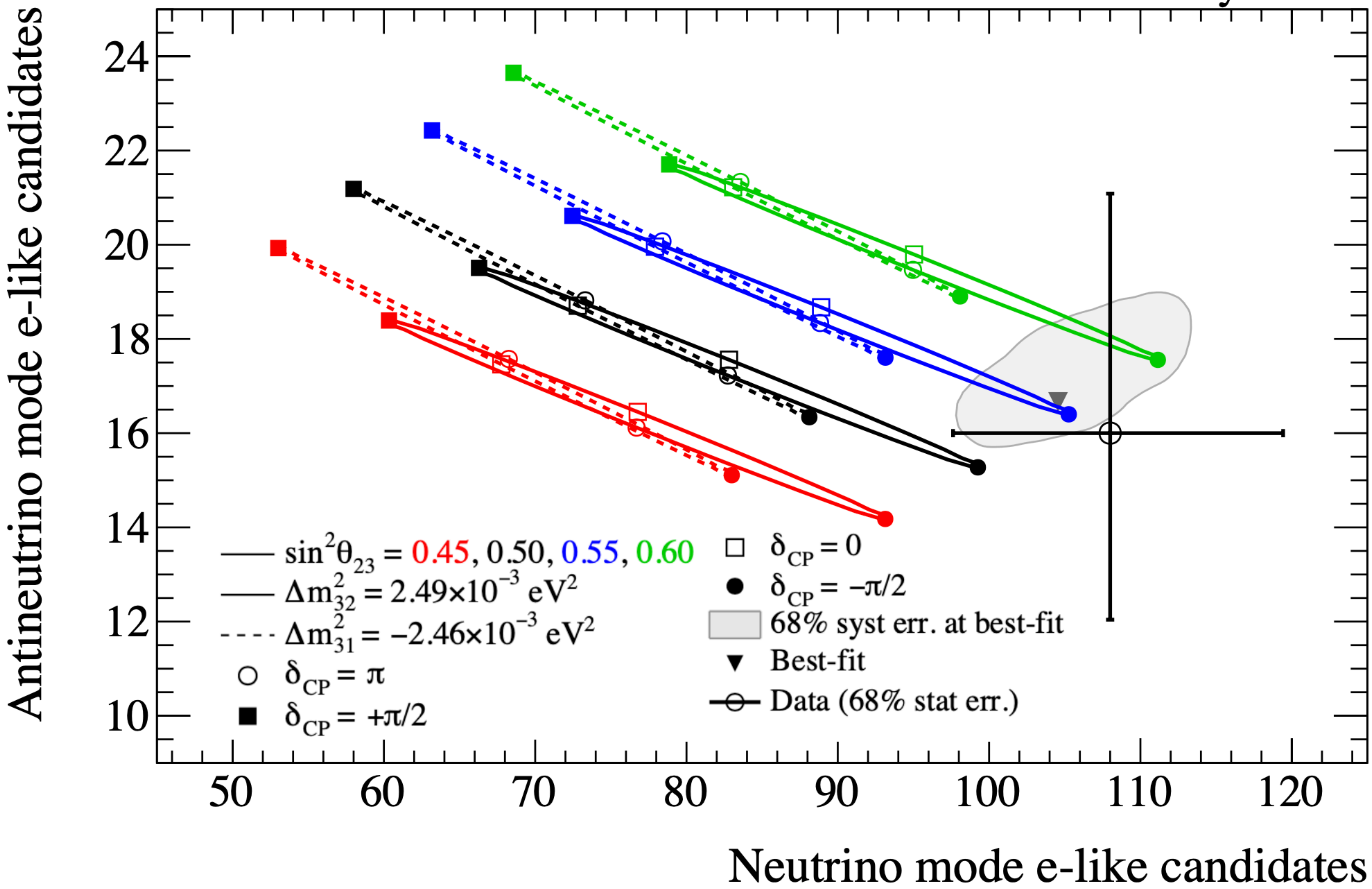

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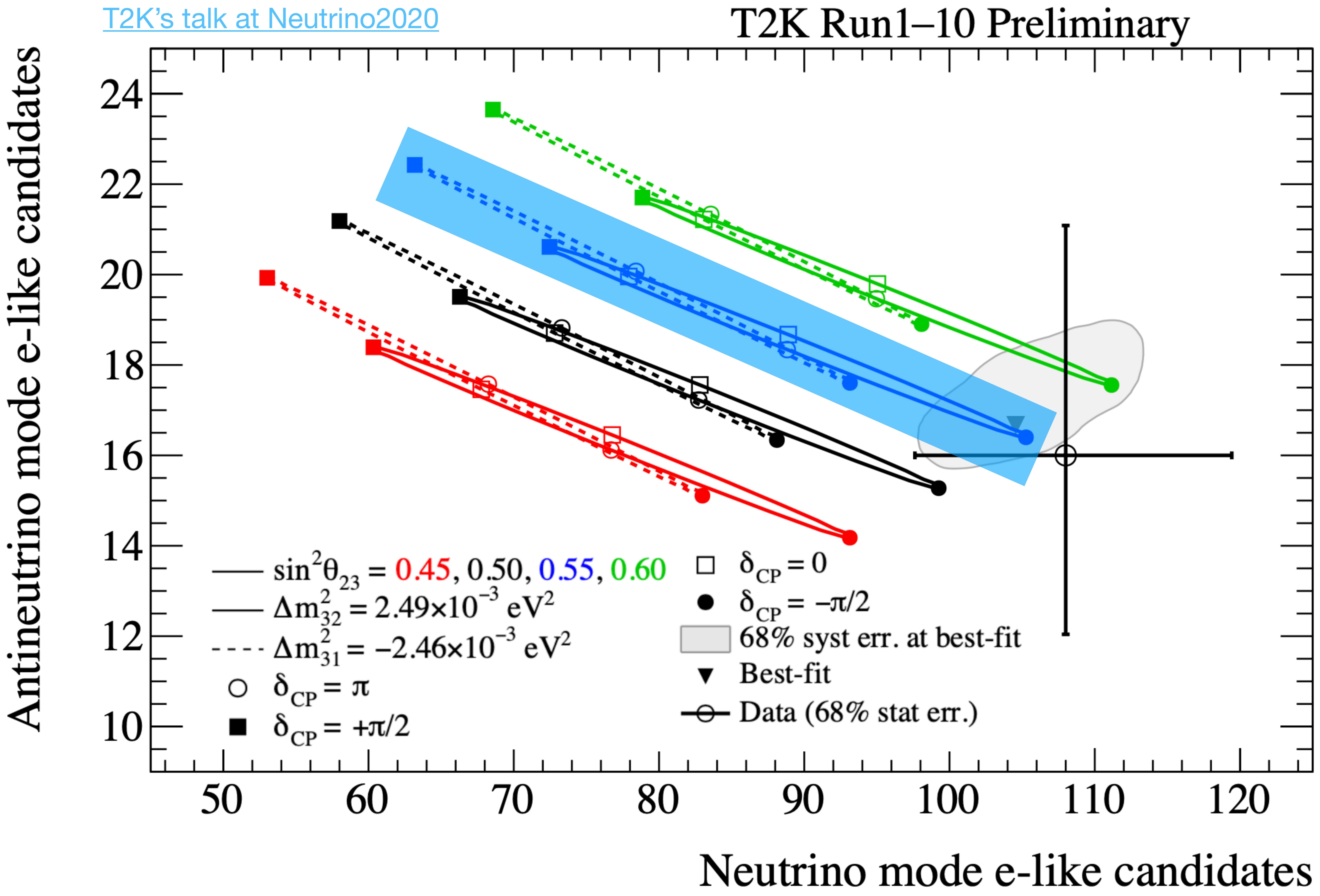

T2KNOvA.ipynb

OscProbs_Python.py

(Poorly annotated) python code to calculate oscillation probabilities in a constant matter density.

`OscProbs_Python.py`

Determining $x,\ y,\ z$

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T2K and NOvA Data vs. Expectations

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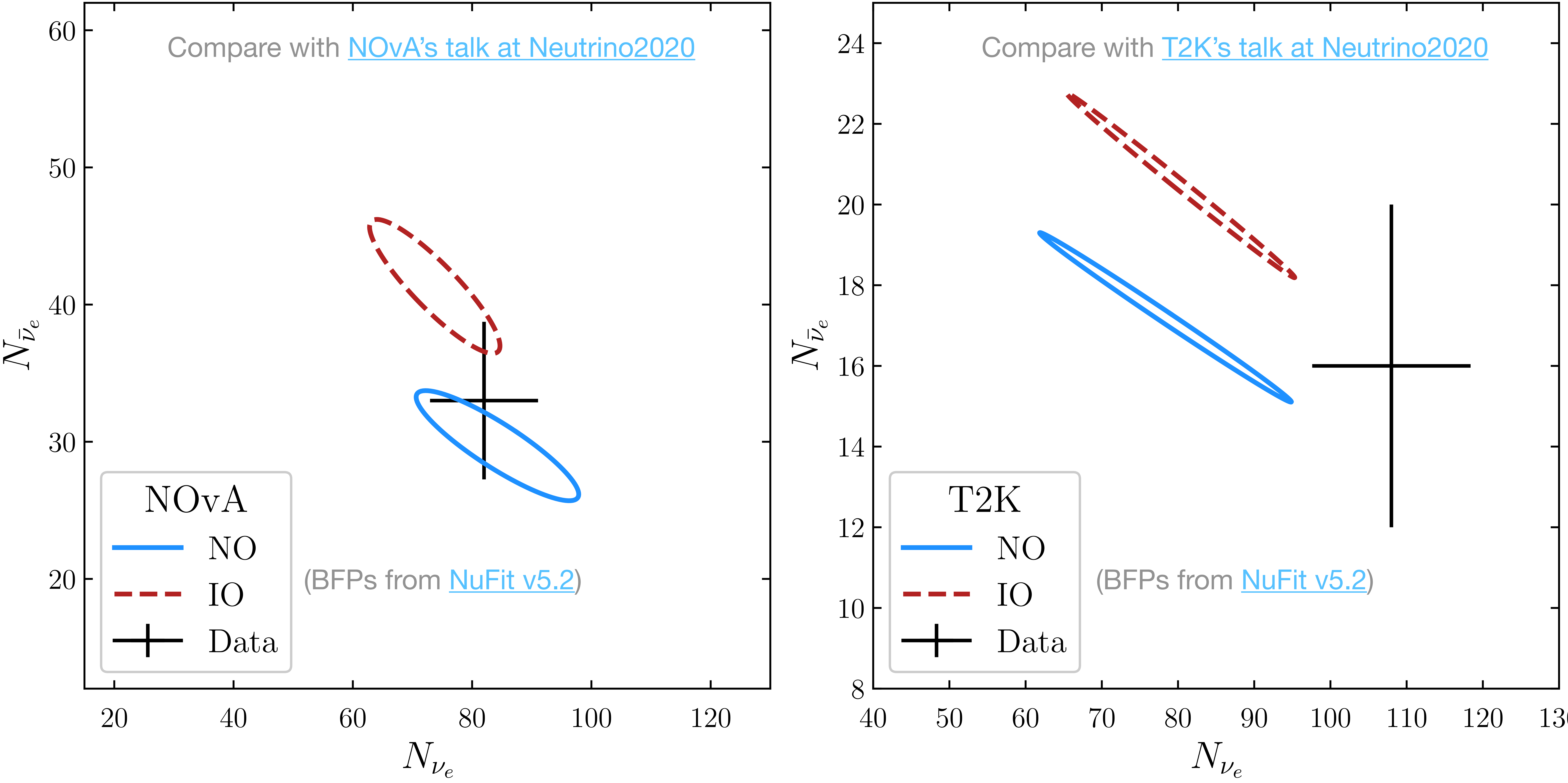
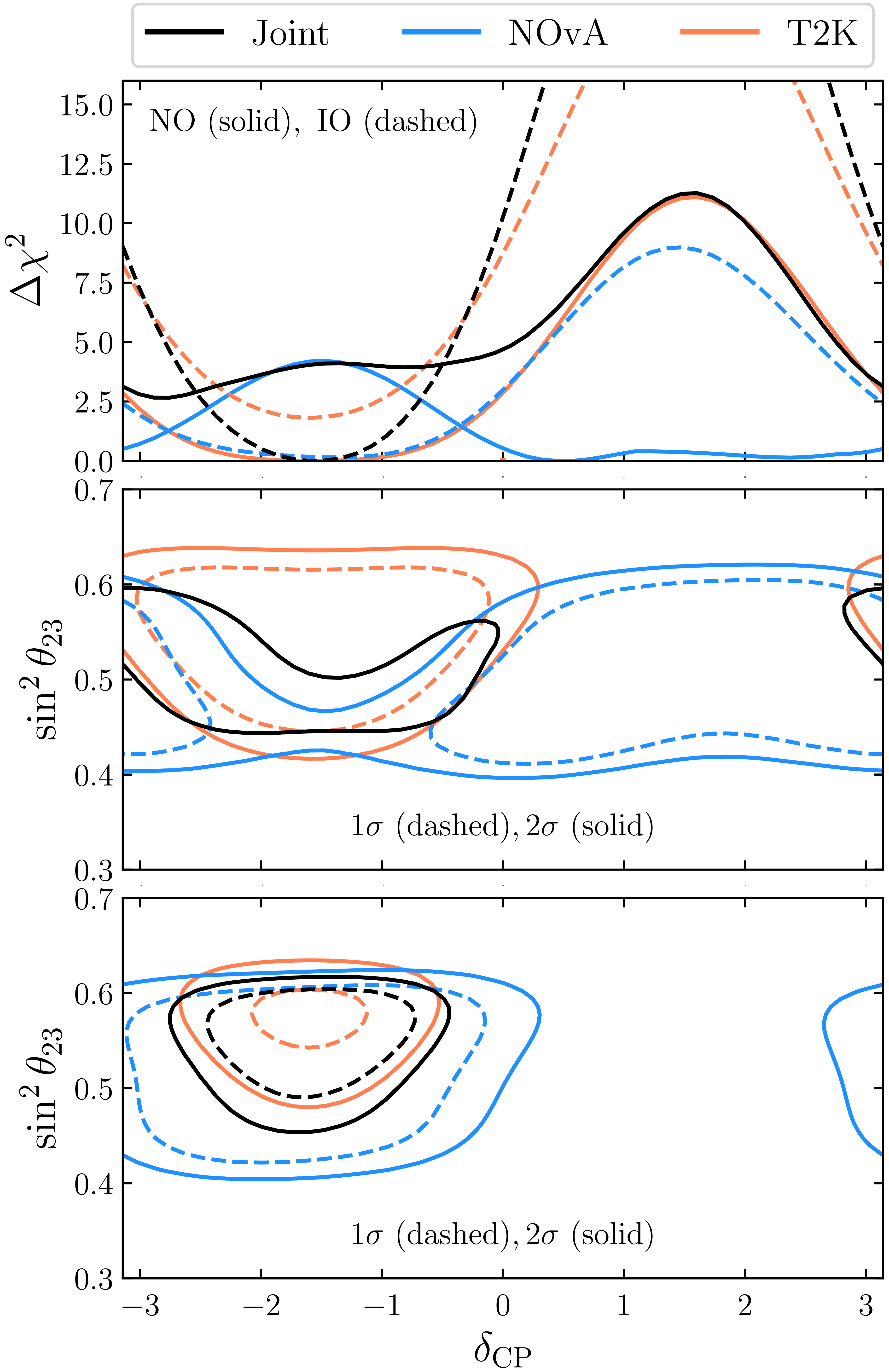


Parameter Scan – NO vs IO

T2K/NOvA Results



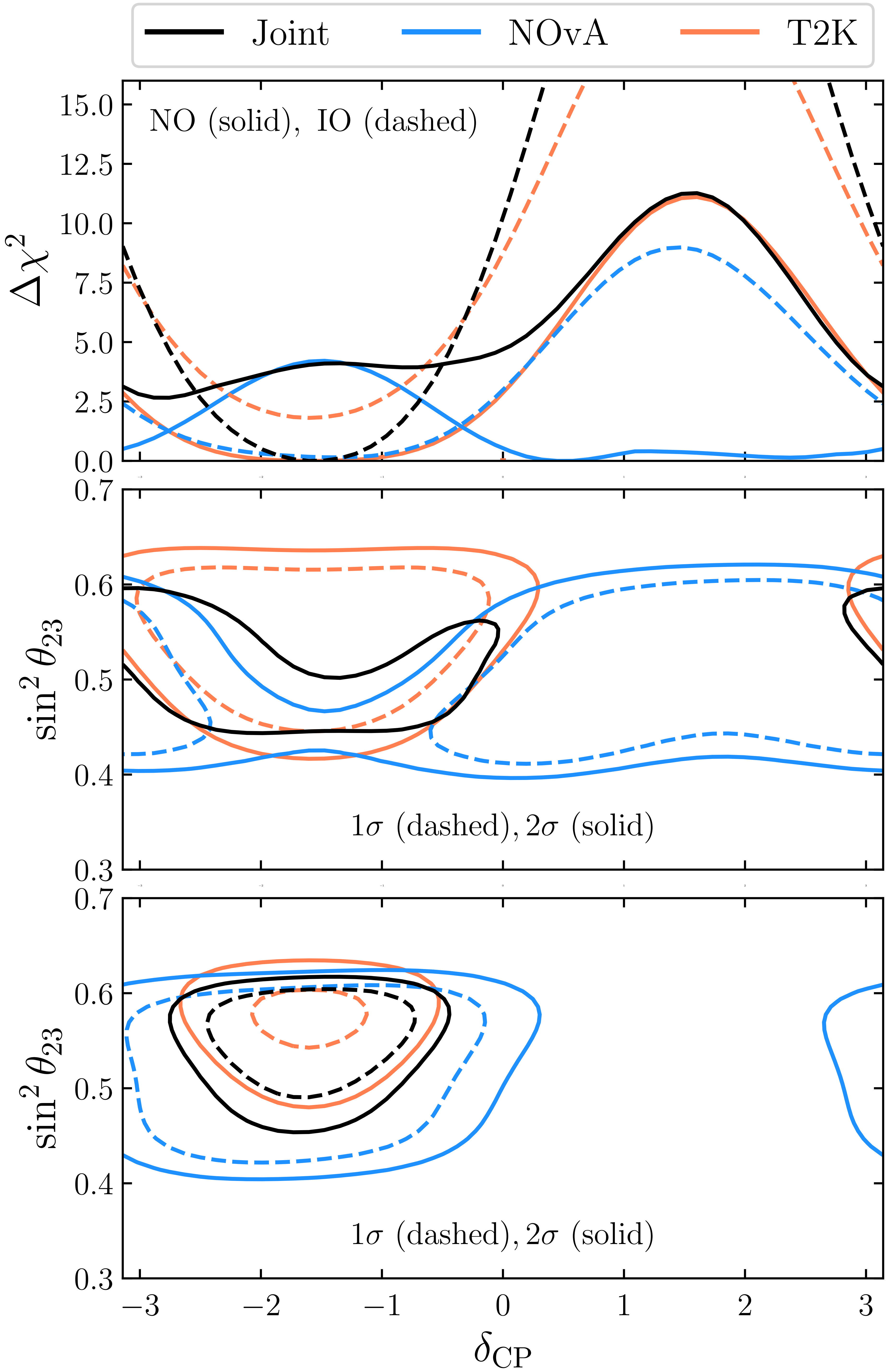
T2K/NOvA Results

Simplified approach relative to [2007.08526], but comparable results!

NOvA: $\Delta\chi^2 = 0.15$ (NO)

T2K: $\Delta\chi^2 = 1.81$ (NO)

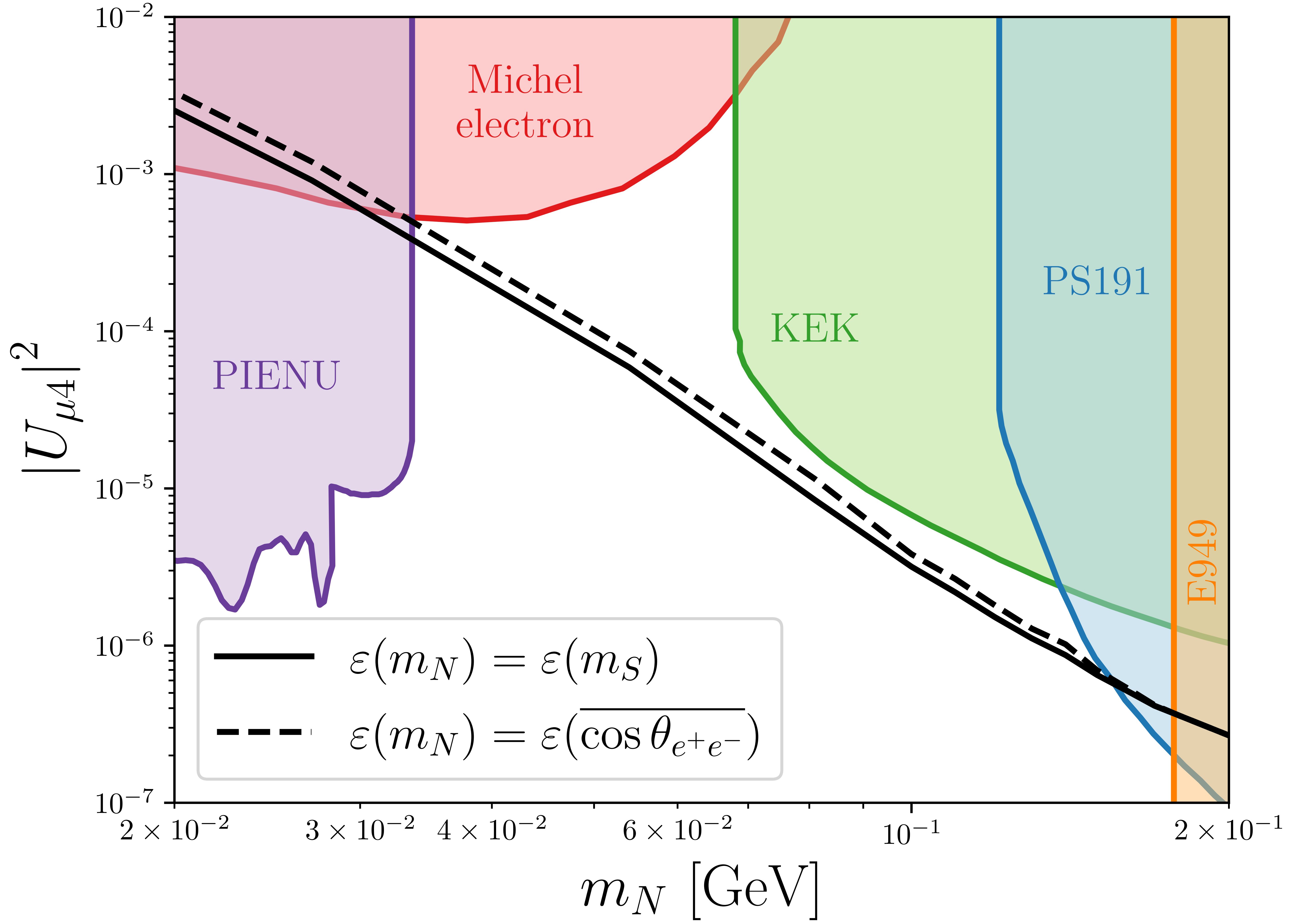
Joint: $\Delta\chi^2 = -2.66$ (IO)

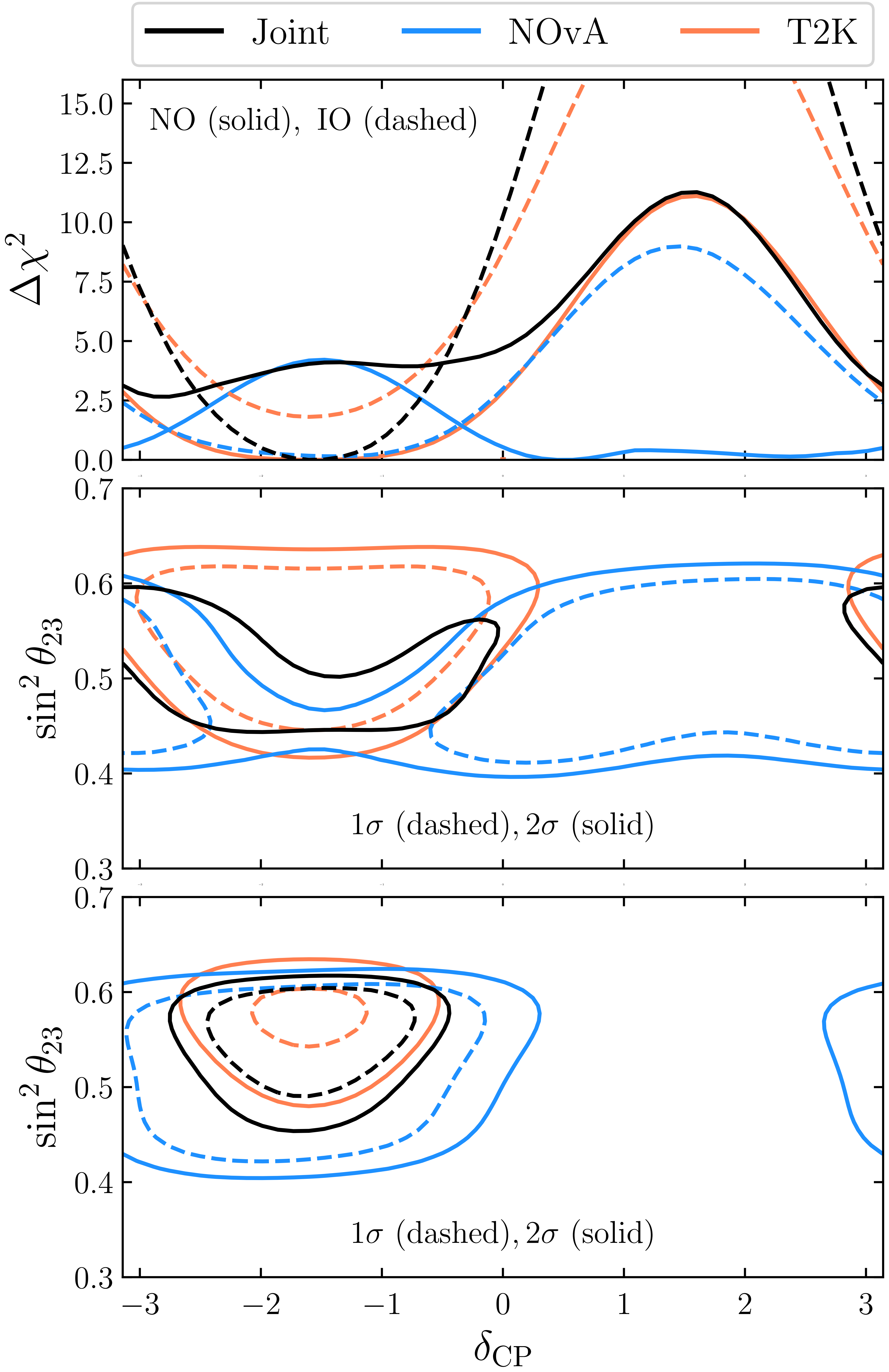


Takeaways

Neutrino data can often be interpreted in novel ways — the more information afforded to outside phenomenologists, the more reliable the results will be.

Reinterpretations allow us to perform as wide of a range of searches as possible, including those not yet imagined. Be curious!





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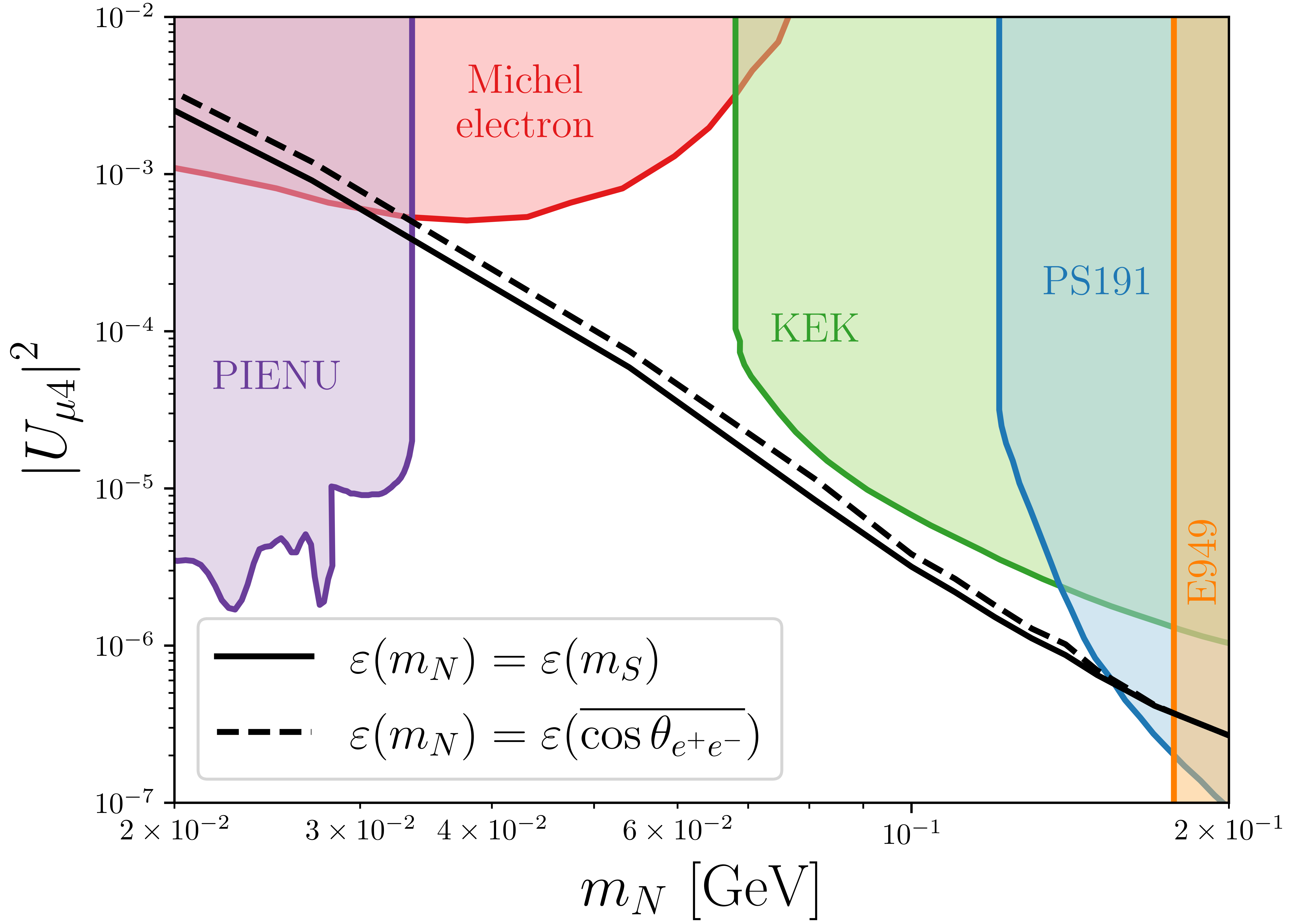

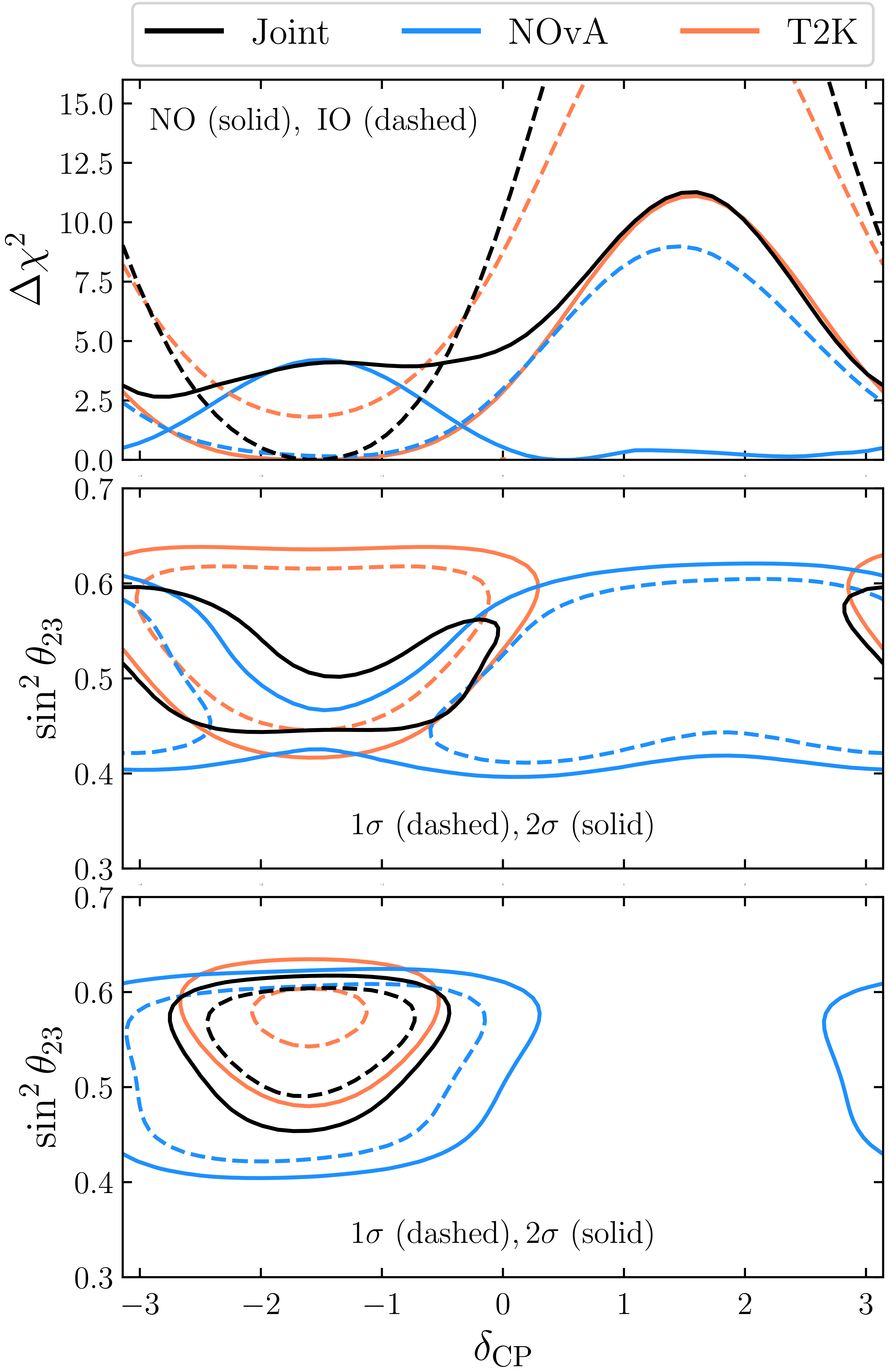

Neutrino data can often be interpreted in novel ways — the more information afforded to outside phenomenologists, the more reliable the results will be.

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