Point-source search in IceCube, integration with GraphNeT

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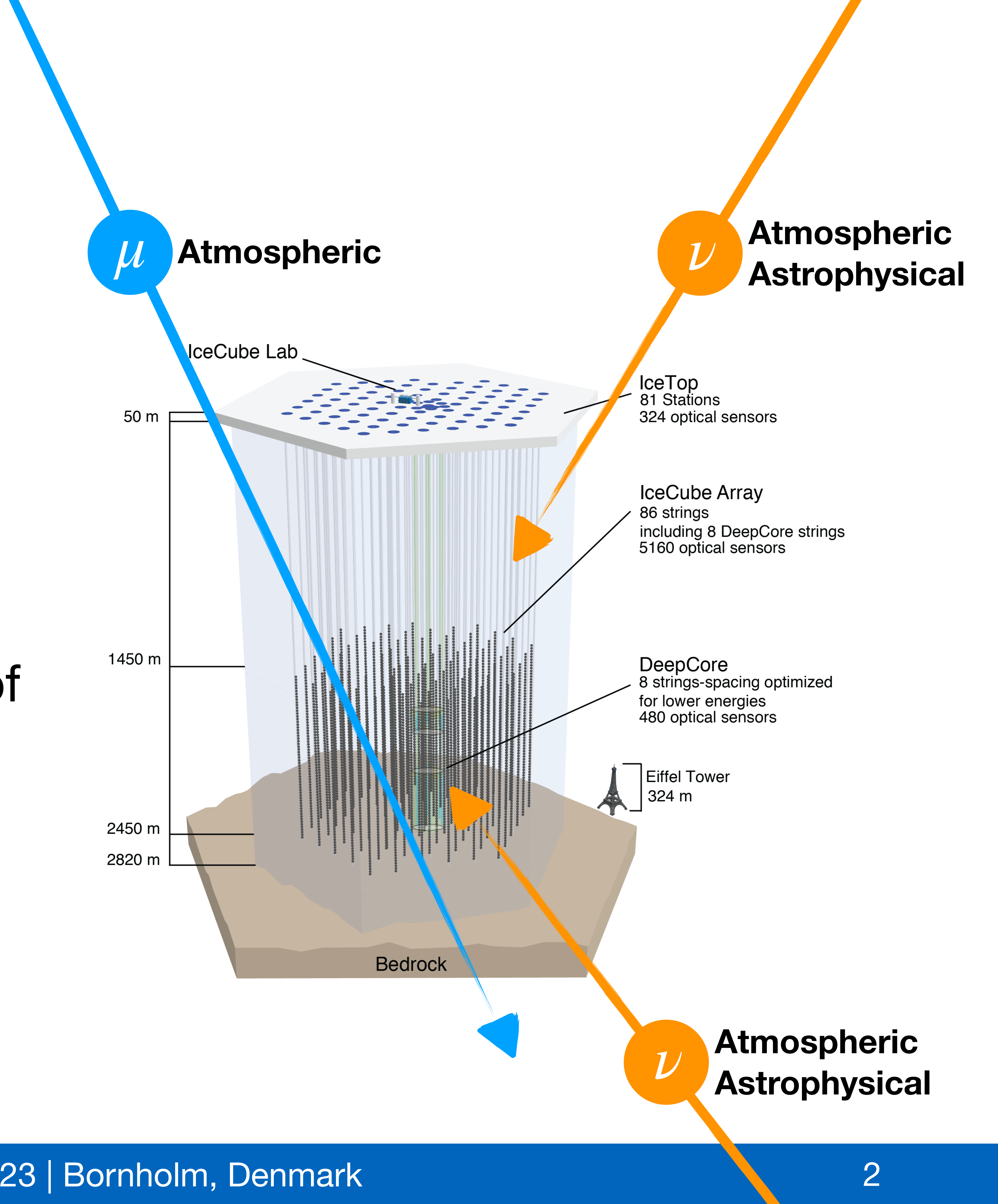
IceCube

- Cubic-kilometer Cherenkov telescope located at the geographic South Pole
- 5160 optical modules attached to 86 strings
- The ice is the target for CC interactions of atmospheric and astrophysical neutrinos

$$\nu_l + N \rightarrow l + N$$

- Cherenkov photons are measured by PMTs in the optical modules

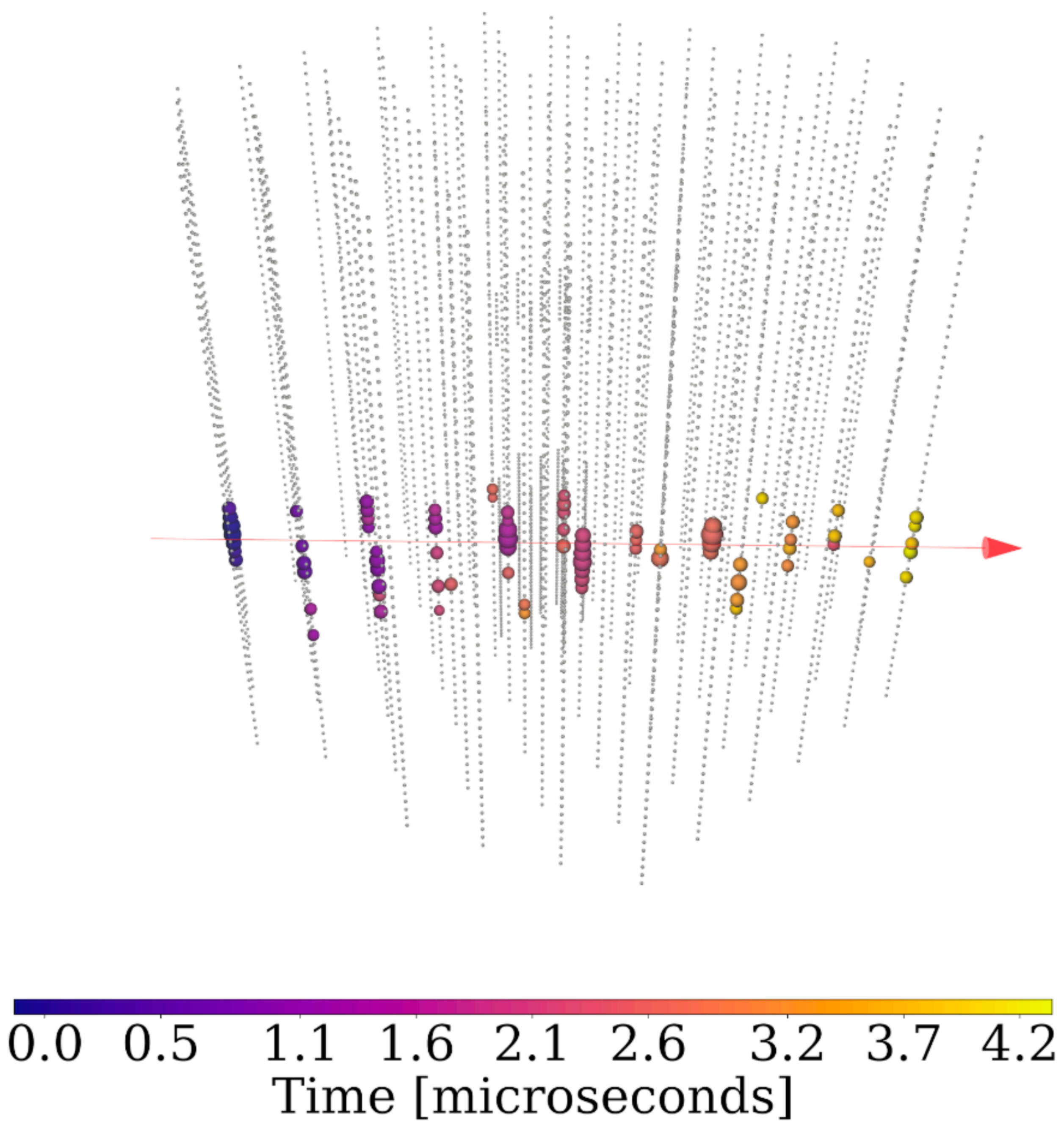


Main neutrino event signatures

- **Tracks**
  - ν_μ charged current interactions produce a muon, which loses its energy while travelling through the detector
  - Distribution of photon hits along a long path results in a **good angular resolution**
  - Difficult to estimate neutrino energy

- **Cascades**
  - ν_e charged current interactions produce an electron, which causes a forward electromagnetic cascade
  - The neutrino energy is fully deposited within the detector, good energy resolution

TRACKS (muons):
Good angular resolution
Excellent for pointing!



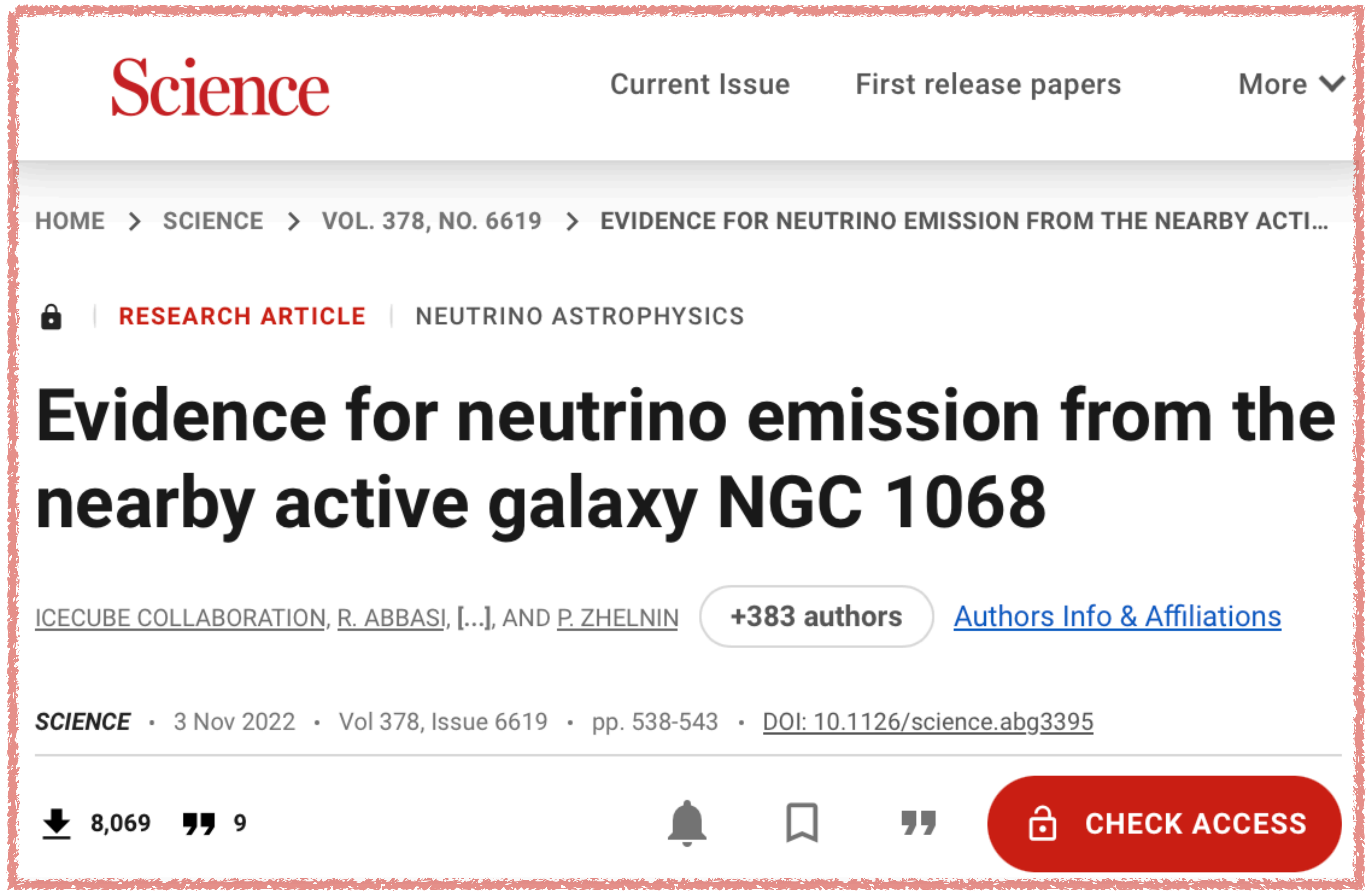
CASCADES:
Good energy resolution

Improved point-source analysis

- **NGC 1068 4.2σ** result using new methods:
  - KDE PDFs
  - BDT sigma estimation
  - DNN energy reconstruction

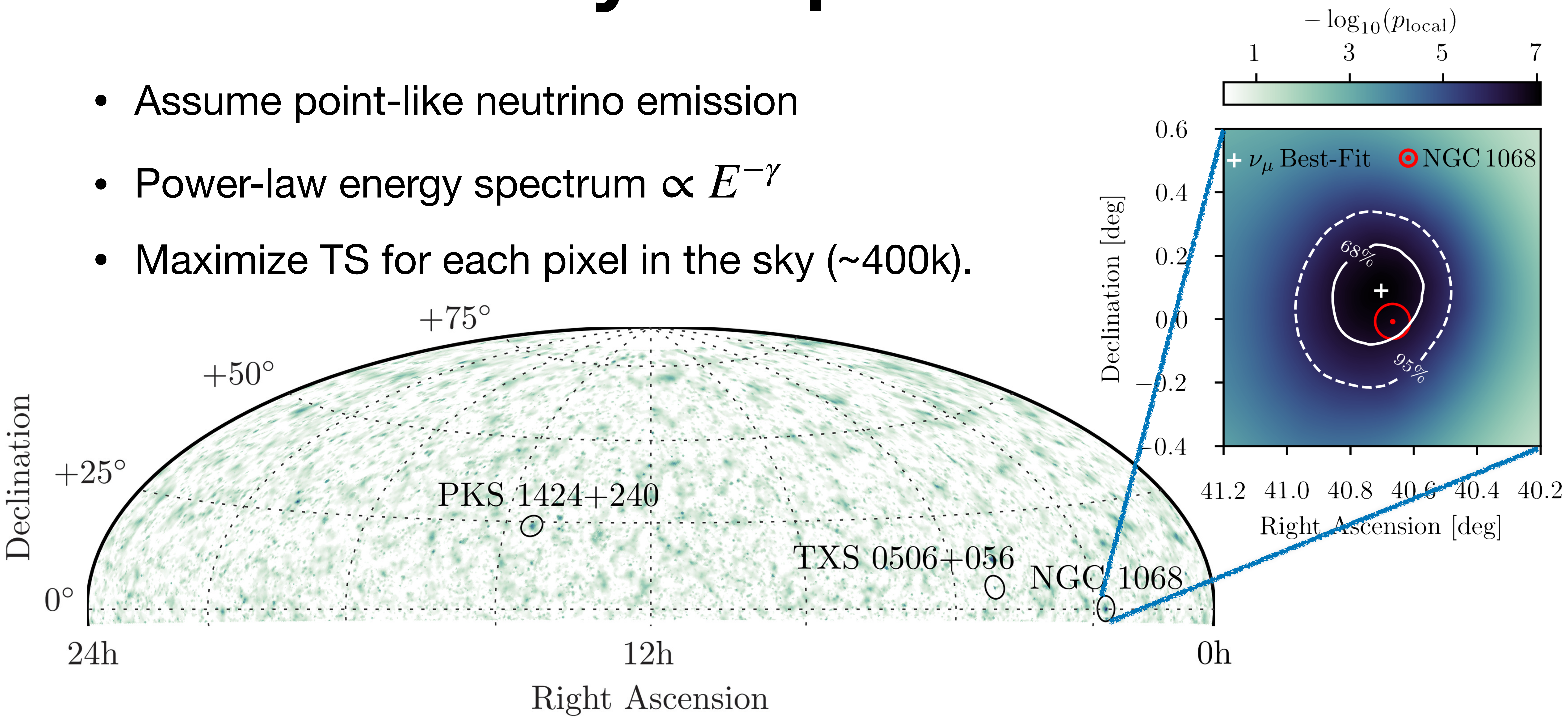
- 9 years of uniformly processed data, taken between 2011 and 2020

- Currently working on extending the analysis by 4 additional years!

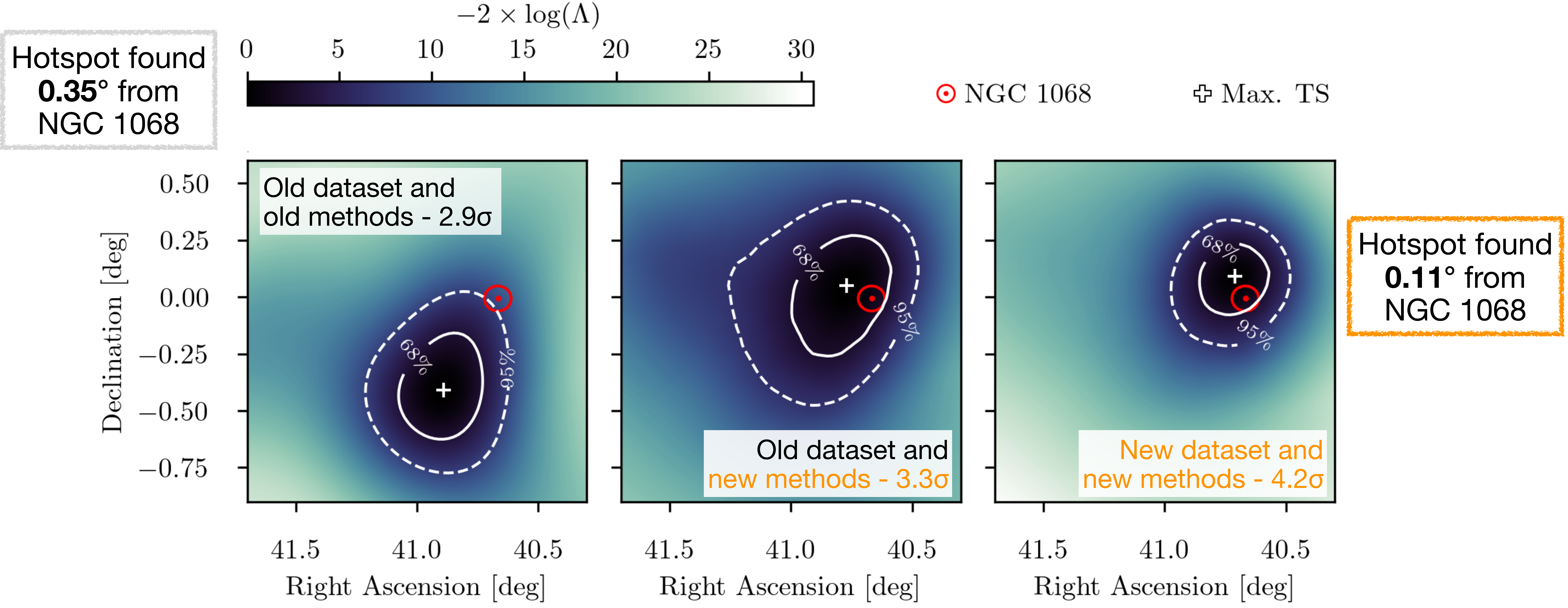


Neutrino sky map

- Assume point-like neutrino emission
- Power-law energy spectrum $\propto E^{-\gamma}$
- Maximize TS for each pixel in the sky (~400k).



Evolution of the brightest neutrino spot



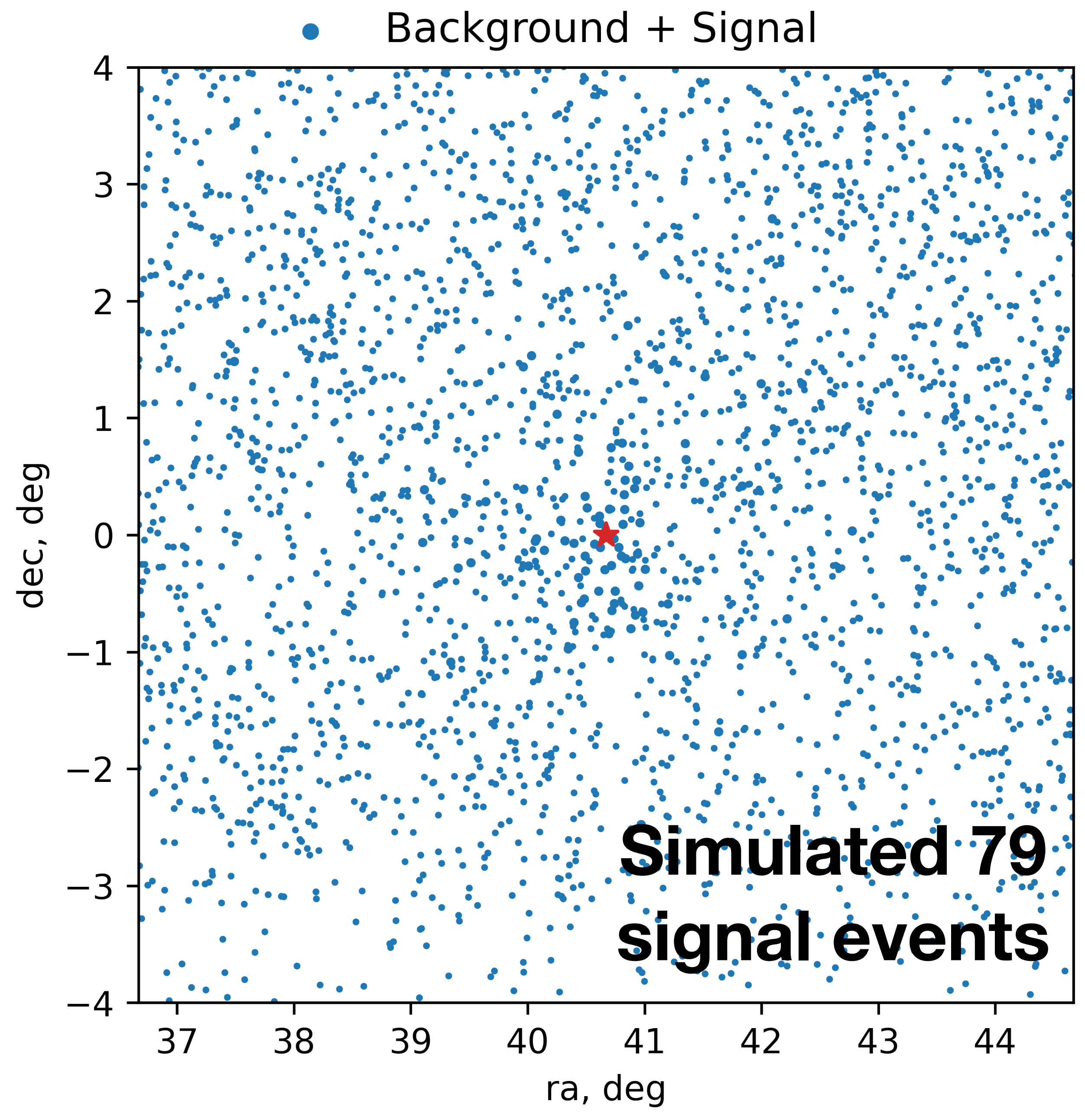
Analysis dataset

Northern tracks:

- Event selection is optimised for upgoing muons ($-5^\circ < \delta < 90^\circ$)
  - Mainly through-going, some starting and stopping tracks
- Uses Earth as a shield from the atmospheric muon background
- Has good agreement between data and Monte-Carlo simulations, which is crucial for improved methods
- Energy range of muons in experimental data — from 100 GeV to ~6 PeV
- ~200 GeV energy muon travels ~1 km in ice
  (https://arxiv.org/pdf/0807.0034.pdf)

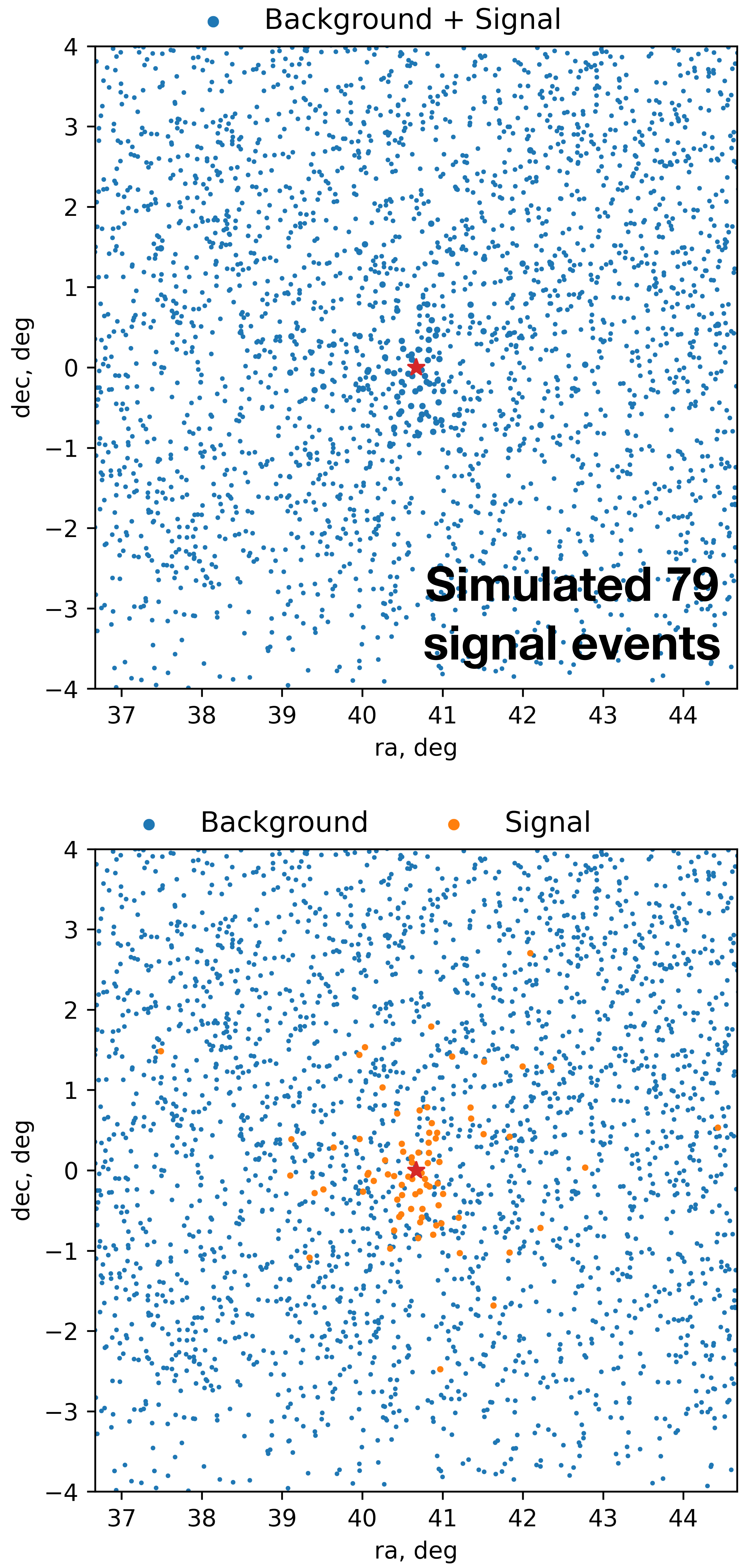
How data looks like

- We drown in background!
- The atmospheric and diffuse astrophysical neutrino fluxes are isotropic



How data looks like

- We drown in background!
- The atmospheric and diffuse astrophysical neutrino fluxes are isotropic
  - Point-source — search for signal clustering
- The atmospheric flux is orders of magnitude higher than the astrophysical one
  - Astrophysical diffuse flux of high-energy neutrinos measured by IceCube has a different spectral shape than the atmospheric flux



Likelihood construction

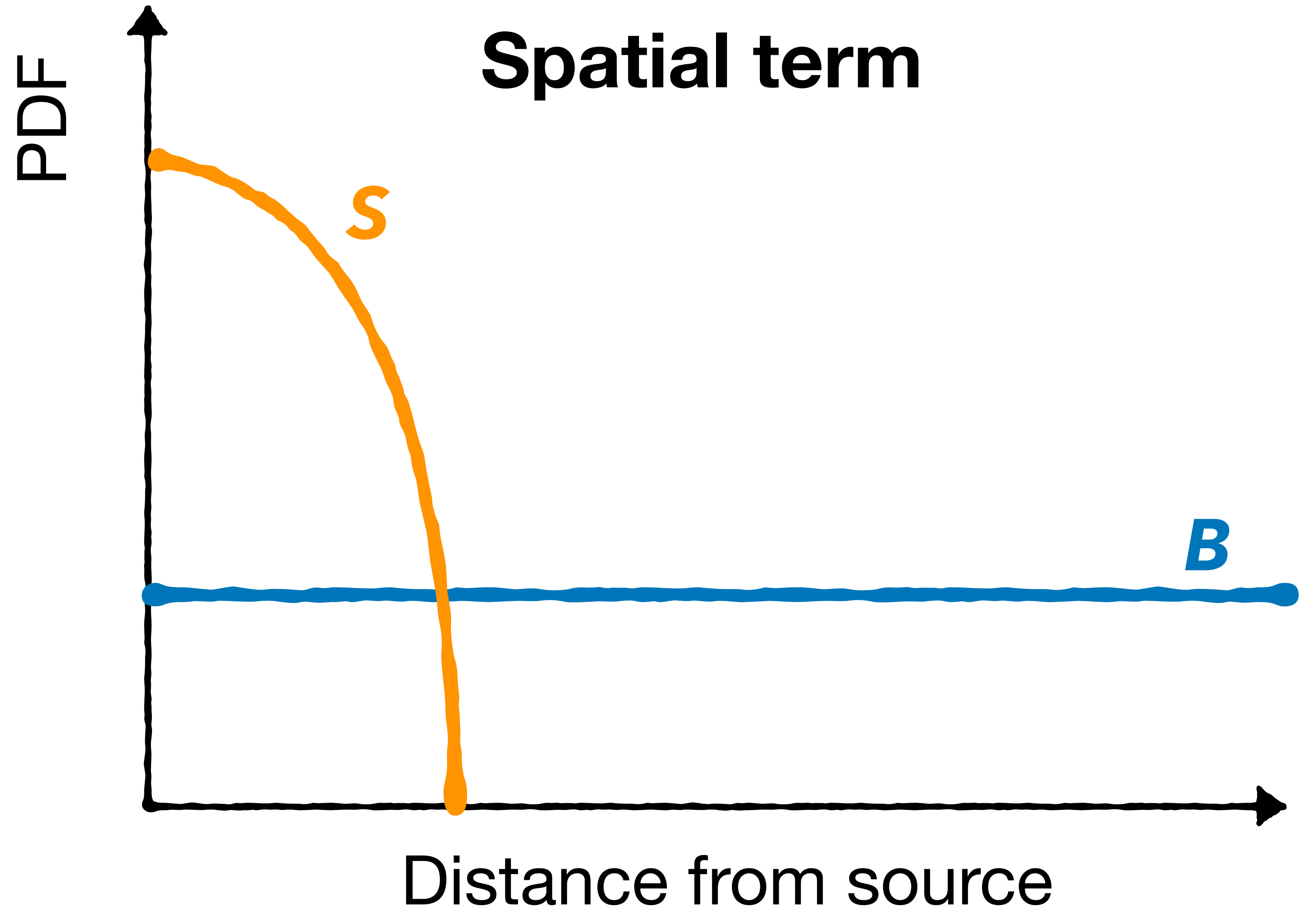
- The unbinned likelihood approach:

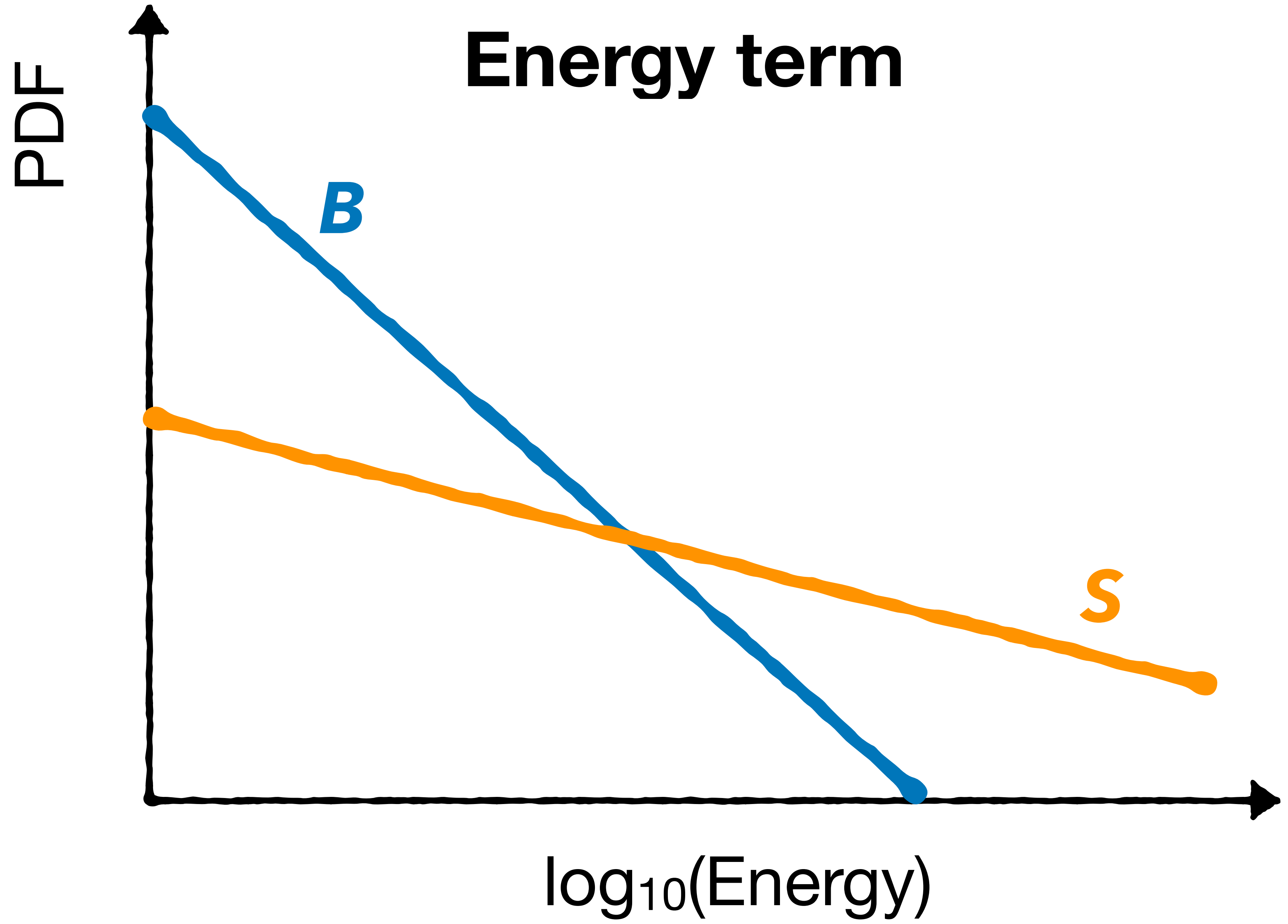
Signal — Background

$$\mathscr{L} = \prod_i^N \left[\frac{n_s}{N} \boxed{S_i} + \left(1 - \frac{n_s}{N}\right) \cdot \boxed{B_i} \right]$$

- Test-statistic — likelihood-ratio:

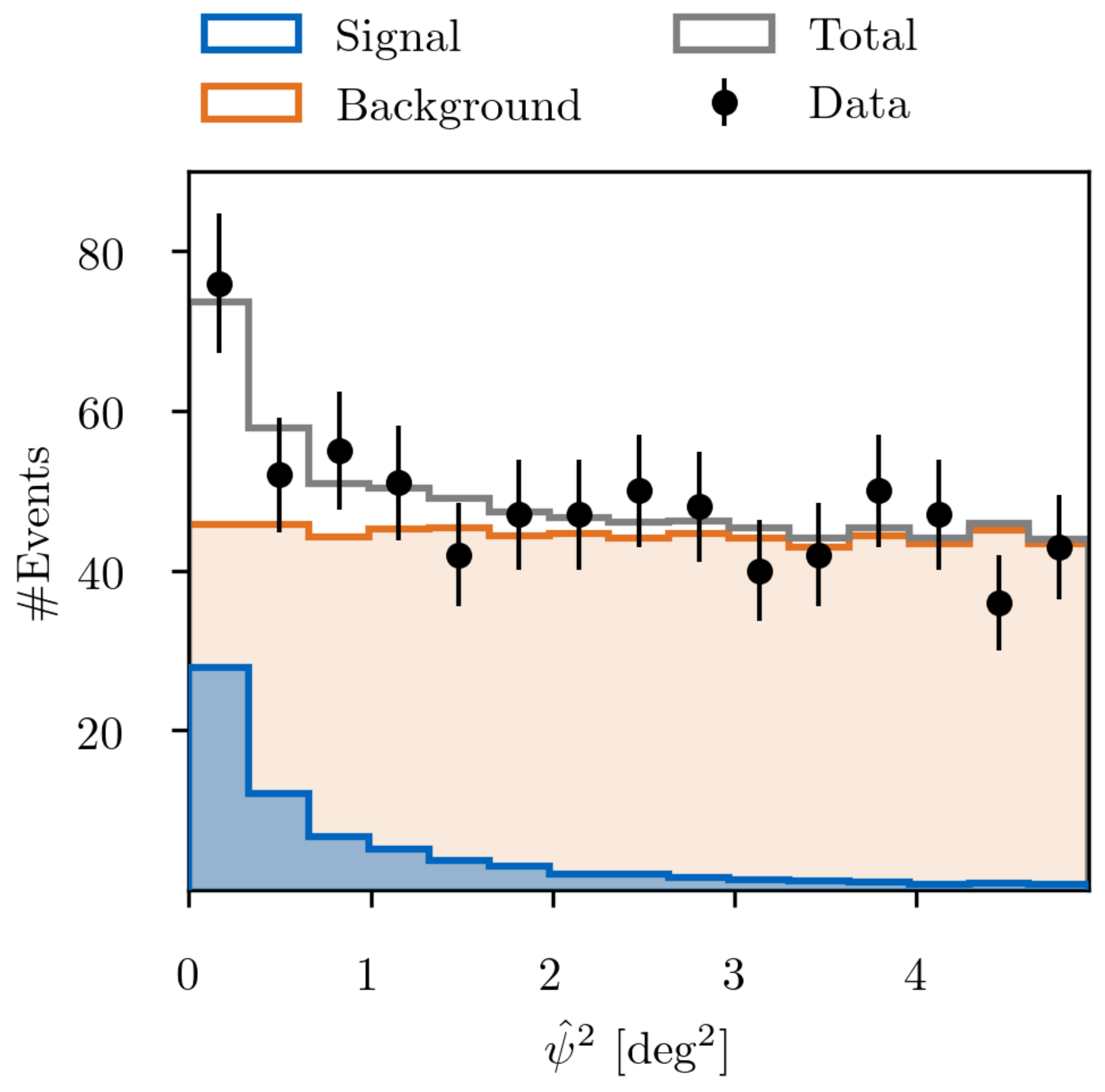
$$TS = -2 \log \left[\frac{\mathscr{L}(n_s = 0 \,|\, \mathrm{Data})}{\mathscr{L}(\hat{n}_s, \hat{\gamma} \,|\, \mathrm{Data})} \right]$$

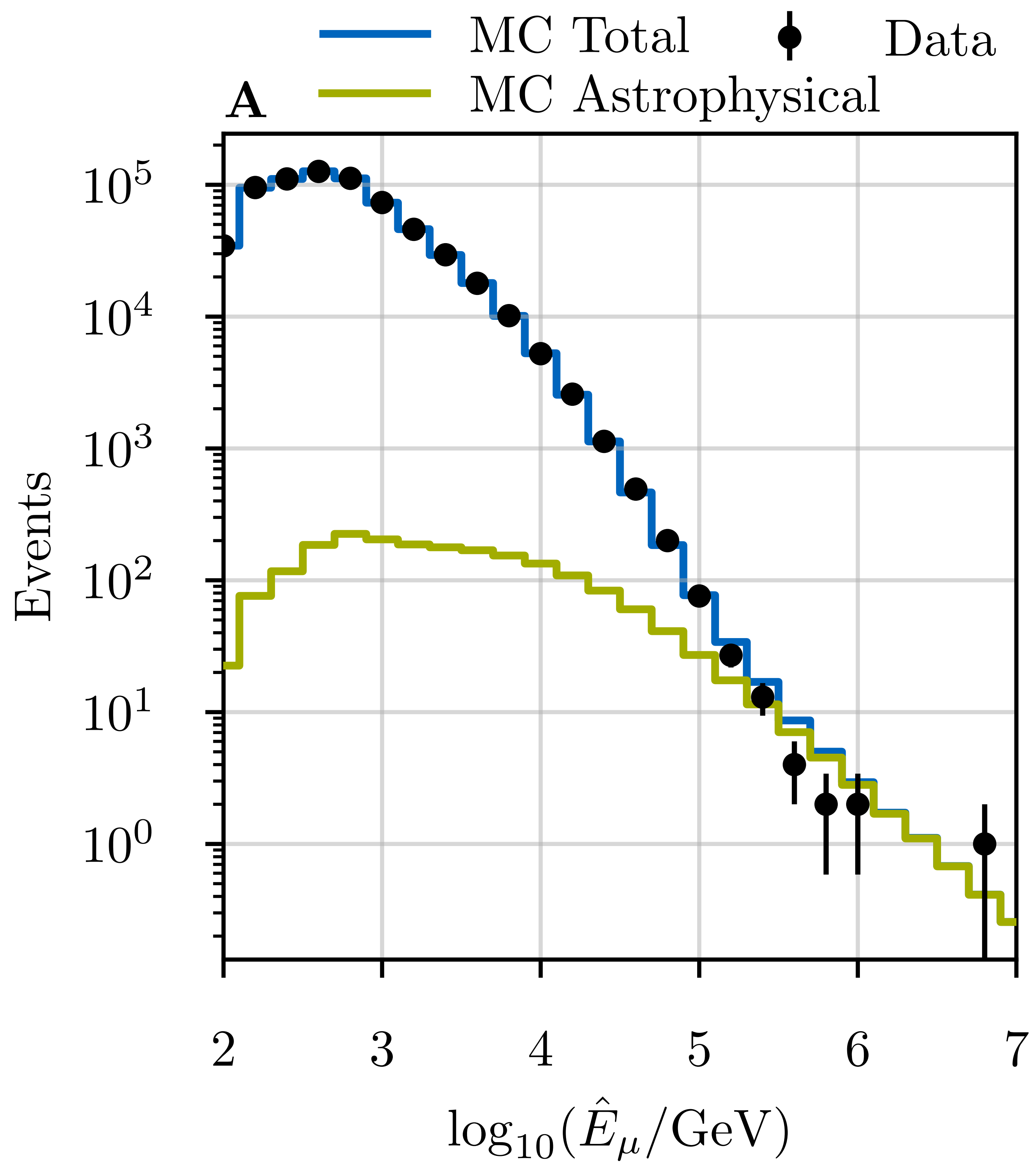




Signal spatial and energy terms

- Example of signal and background events distribution around the source position and difference in shape of energy distribution





Likelihood construction | Signal

Signal PDF

$$f(\{x\}, N|\theta) = \prod_{i=1}^{N} \left[\frac{n_s}{N} \cdot \boxed{f_s(x_i|\theta_s)} + \left(1 - \frac{n_s}{N}\right) \cdot f_b(x_i|\theta_b) \right]$$

Observables: $x_i = \{E_\mu, \vec{d}_\mu, \sigma\}$

Source param.: $\theta_s = \{\delta_s, \Phi_0 (\propto n_s), \gamma\}$

Signal Likelihood:

- 2 free parameters (the source declination δ_s is fixed):
  - spectral index γ
  - mean # signal events n_s

$$\left.\begin{matrix} \gamma \\ n_s \end{matrix}\right\} \quad \Phi_{\nu_\mu + \bar{\nu}_\mu} = \Phi_0 \left(\frac{E_\nu}{1\,\mathrm{TeV}} \right)^{-\gamma}$$

$$f_s(E_\mu, \vec{d}_\mu, \sigma | \theta_s) \sim \mathcal{S}(\boxed{\psi}^{*} | E_\mu, \sigma, \gamma) \cdot \mathcal{E}(E_\mu | \sin\delta_{src}, \gamma)$$

*Distance between the reconstructed event and the source positions

Likelihood construction | Background

Background PDF

$$f(\{x\}, N|\theta) = \prod_{i=1}^{N} \left[\frac{n_s}{N} \cdot f_s(x_i|\theta_s) + \left(1 - \frac{n_s}{N}\right) \cdot \boxed{f_b(x_i|\theta_b)} \right]$$

Observables: $x_i = \{E_\mu, \vec{d}_\mu, \sigma\}$

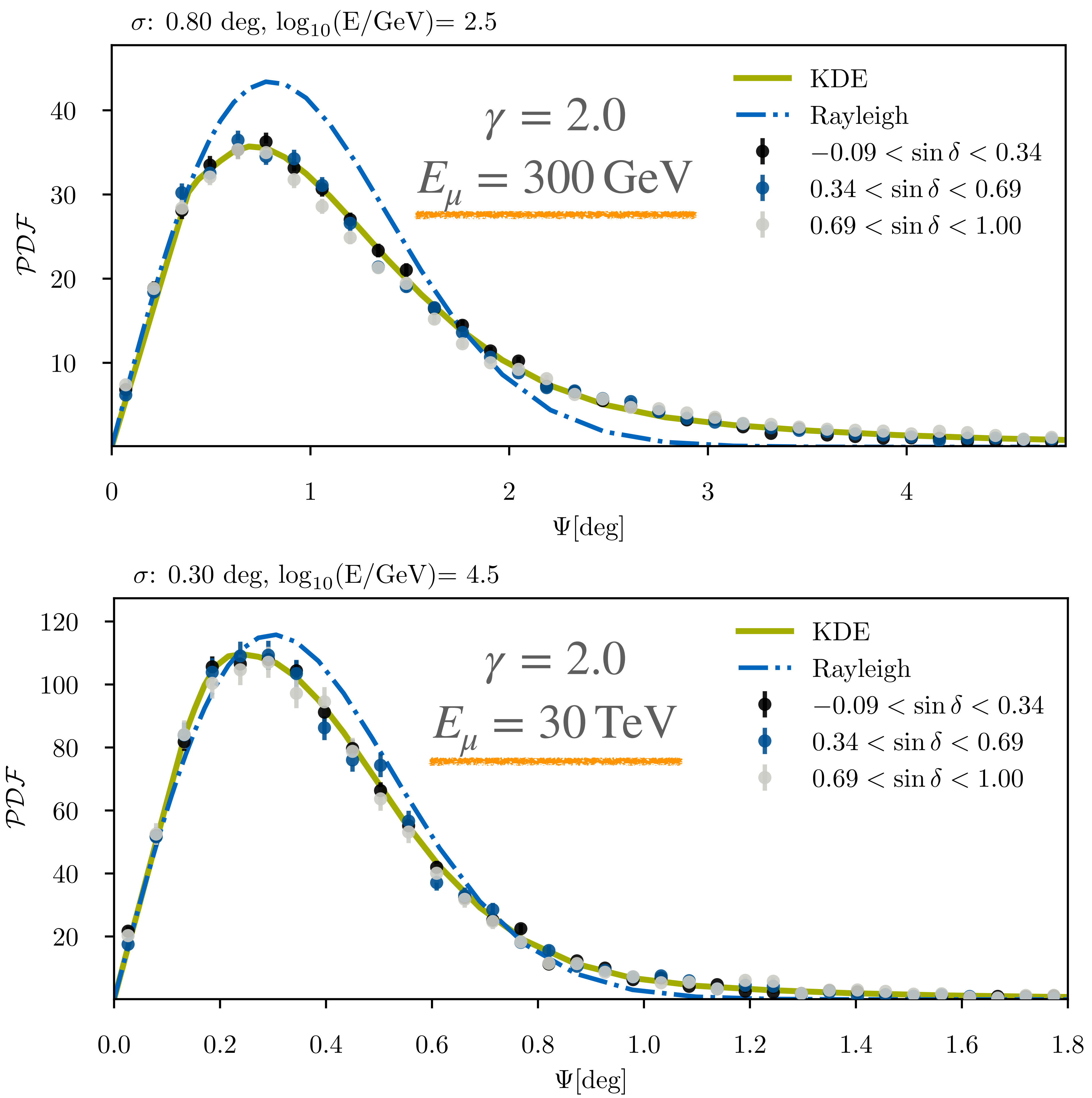
Source param.: $\theta_s = \{\delta_s, \Phi_0 (\propto n_s), \gamma\}$

Background Likelihood:

- No free parameters
- Background flux expectations is fixed through atmospheric models (MCEq)

$$f_b(E_\mu, \vec{d}_\mu, \sigma) = \frac{1}{2\pi} f_b(E_\mu, \sin\delta_\mu)$$

Better modelling of the spatial PDF



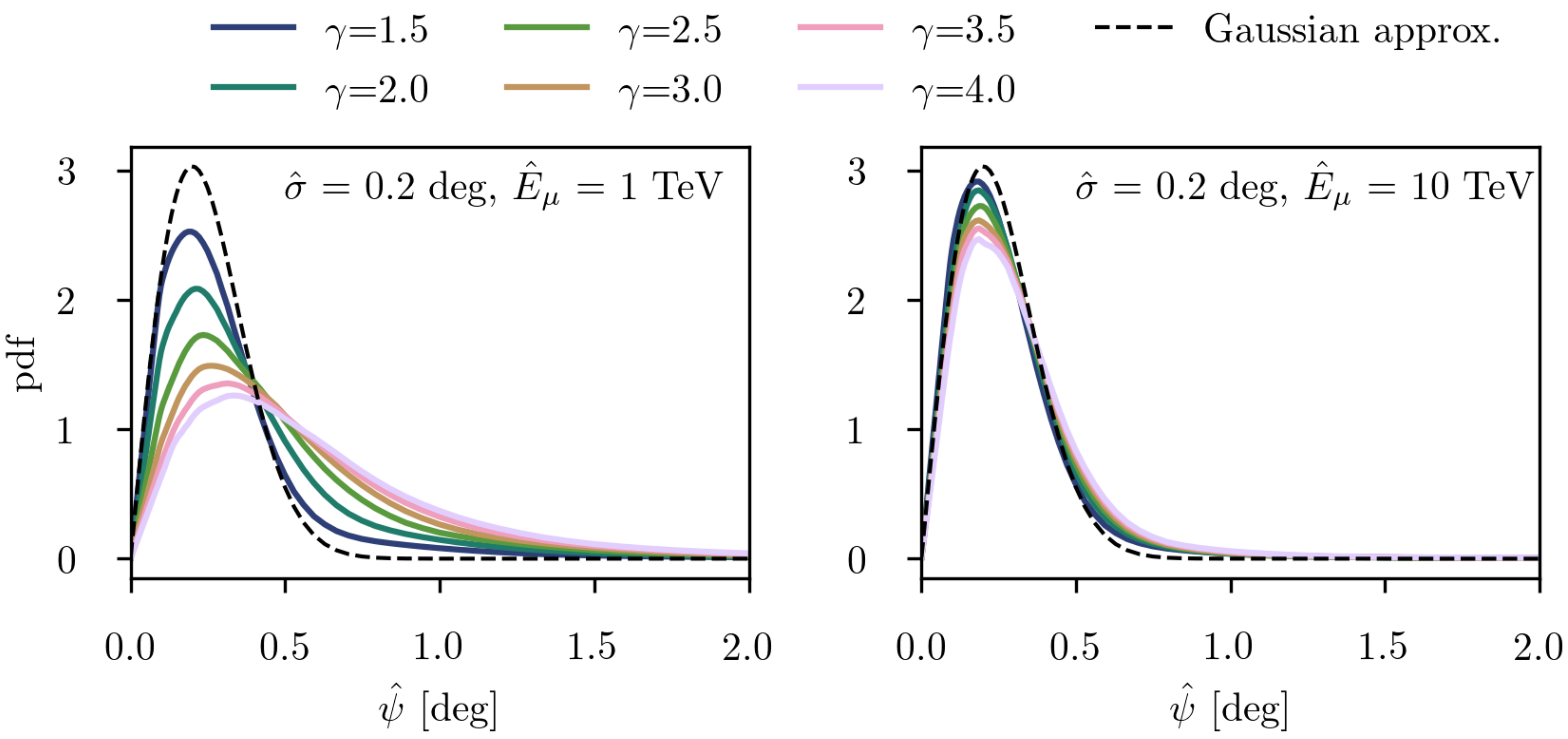
Analytic approximation: $f^{spatial}_{Gaussian} = \frac{1}{2\pi\sigma} e^{-\frac{\Psi^2}{2\sigma^2}}$

- Rayleigh (1D-projection of 2D Gauss) doesn't describe our simulations properly, especially for low energy events!

New MC-based construction: $f^{spatial}_{KDE} = \frac{1}{2\pi \sin\psi} f_s(\psi | E_\mu, \sigma, \gamma)$

- Numerical non-parametric construction of the PDFs based on MC using Kernel Density Estimation (KDE)

Better modelling of the spatial PDF



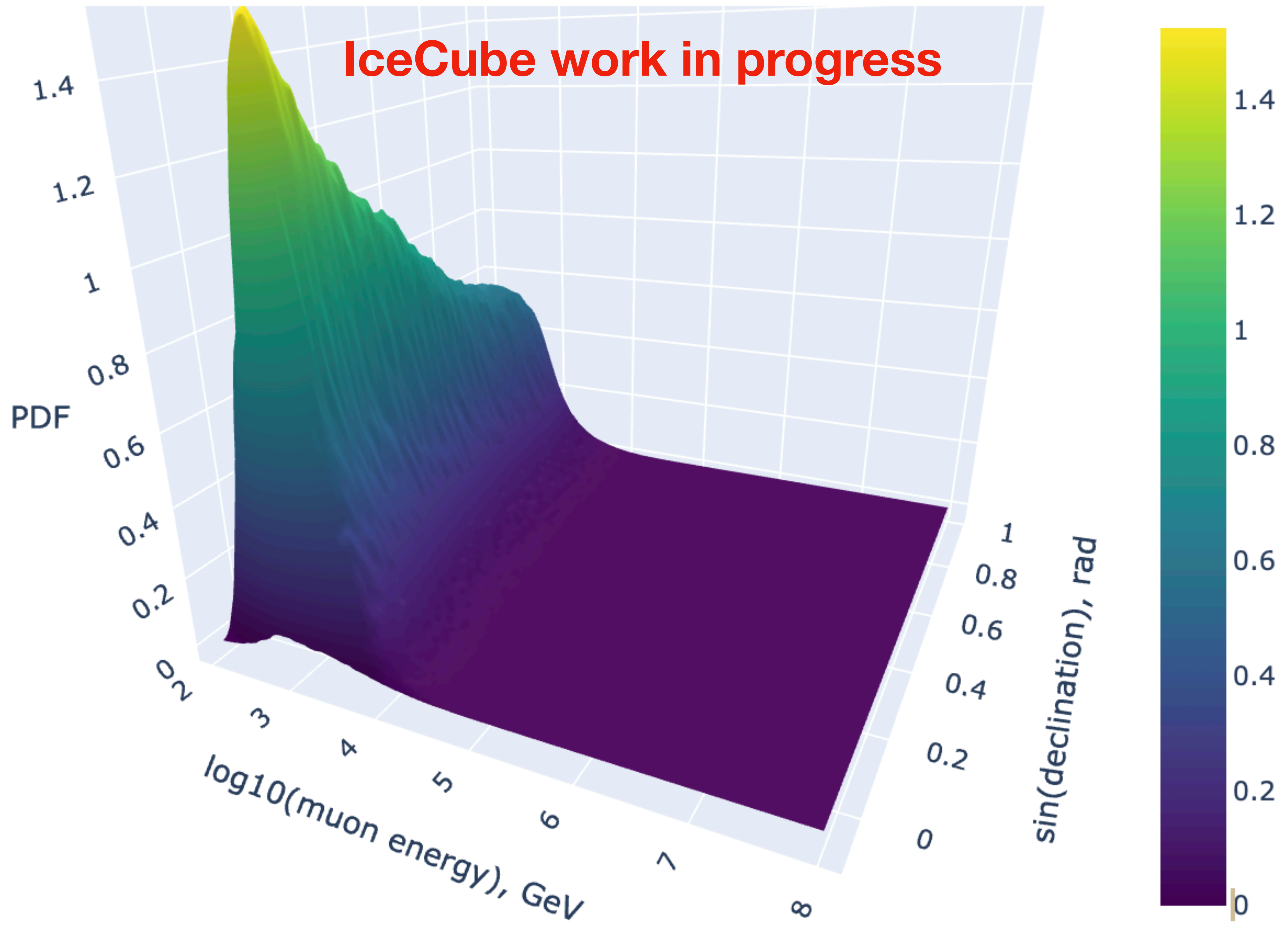
- The KDE approach reproduces the spectral index-dependent, non-gaussian tails seen in simulations

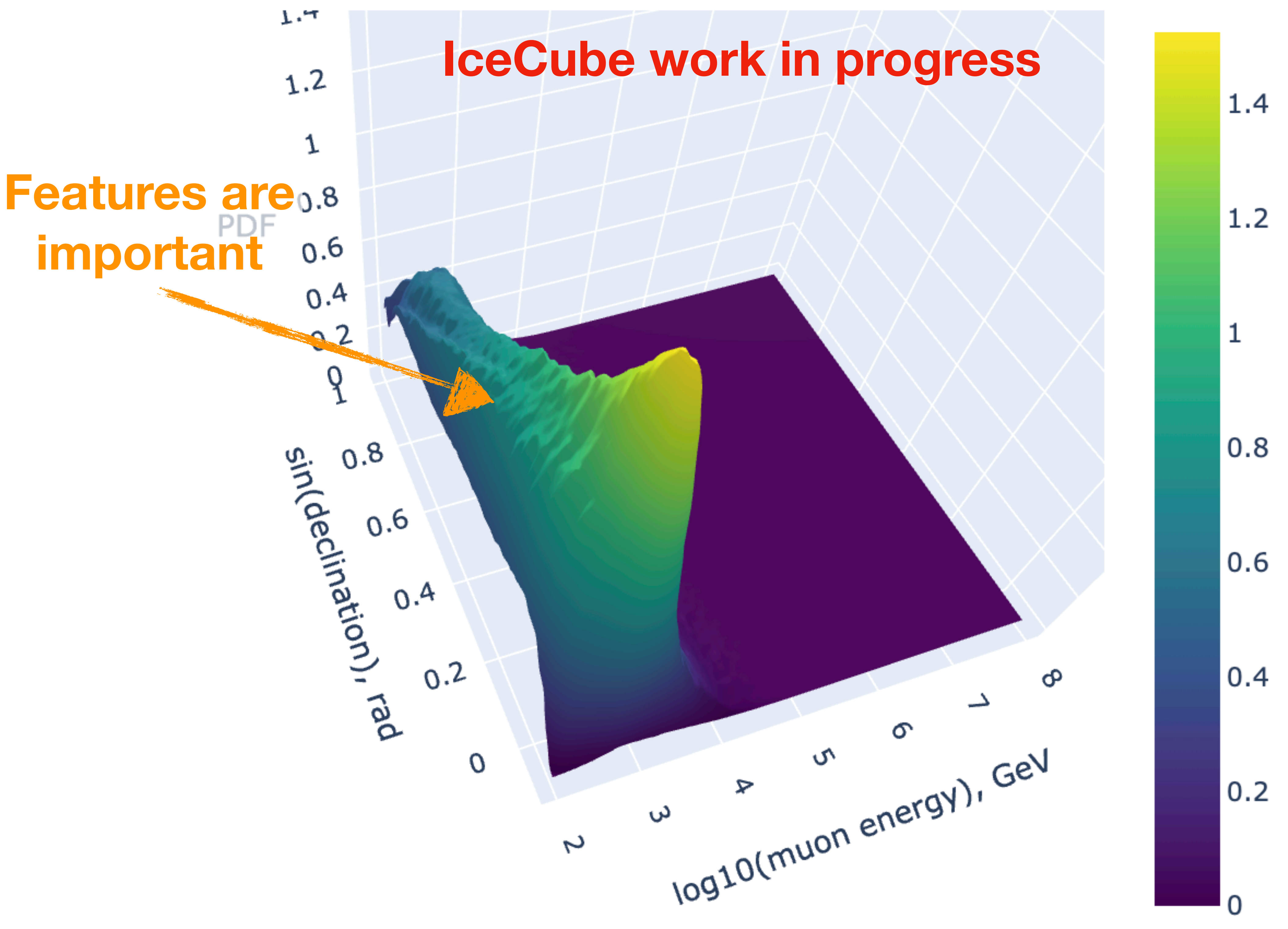
$$f^{spatial}_{KDE} = \frac{1}{2\pi \sin\psi} f_s(\psi | E_\mu, \sigma, \gamma)$$

- Especially important for softer spectral indices!

Background KDE PDF example

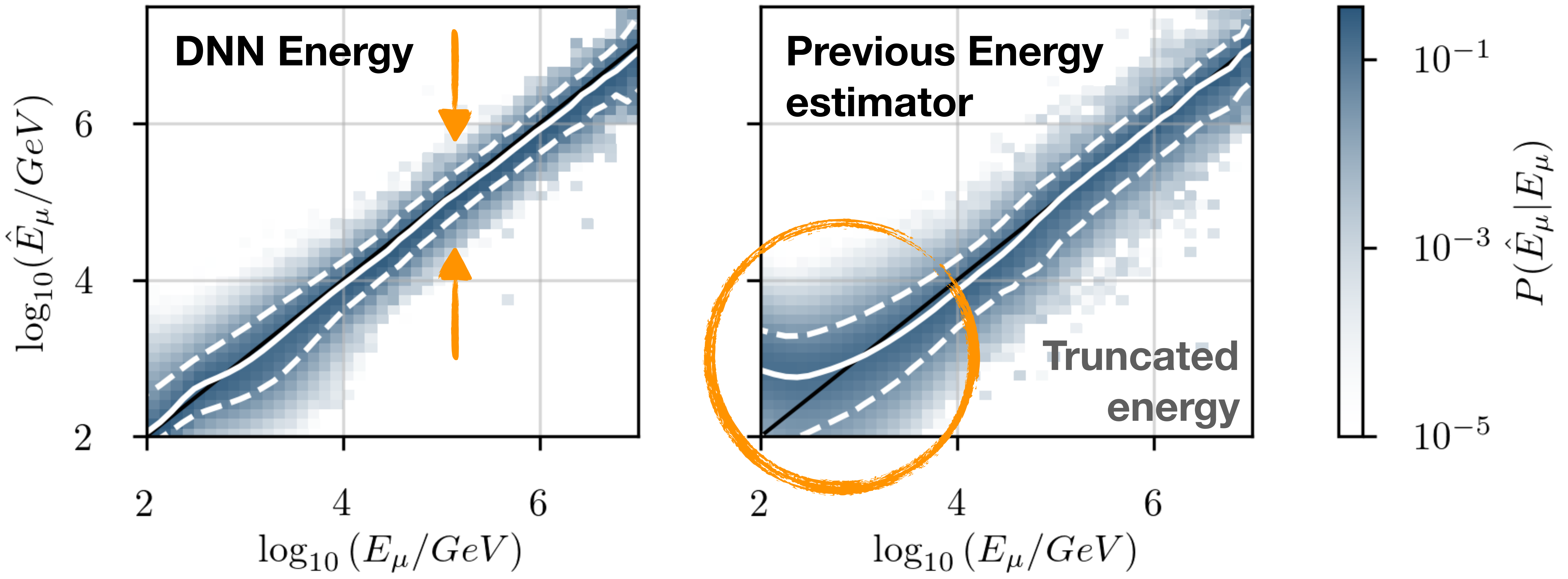
- We use B-Splines (photospline package) to approximate the KDE output
- Evaluation is quite slow, could be a good exercise for NN?
  (signal spatial PDF is 4D!)



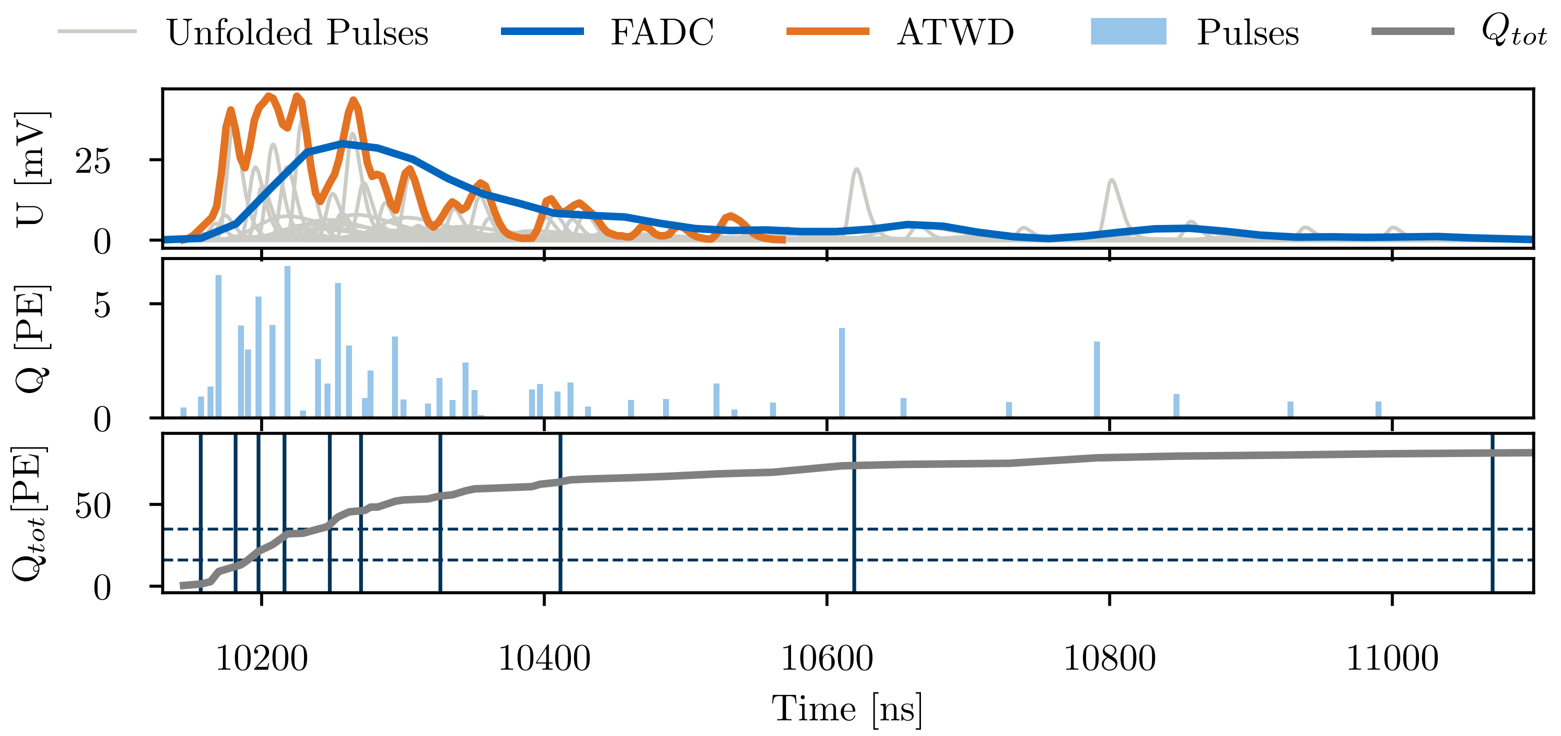


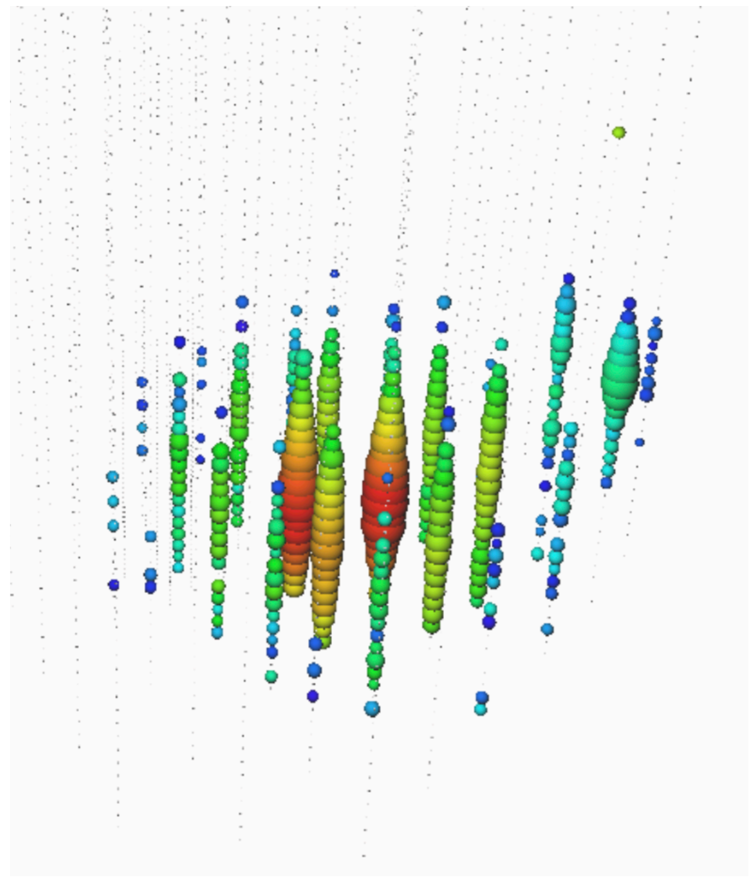
DNN-based energy estimator

- Deep Neural Network energy estimator:
  - Improves resolution by >30% above 10 TeV.
  - Resolves muon energy degeneracy below 1 TeV
  - Produces better background-signal separation, especially at low energies

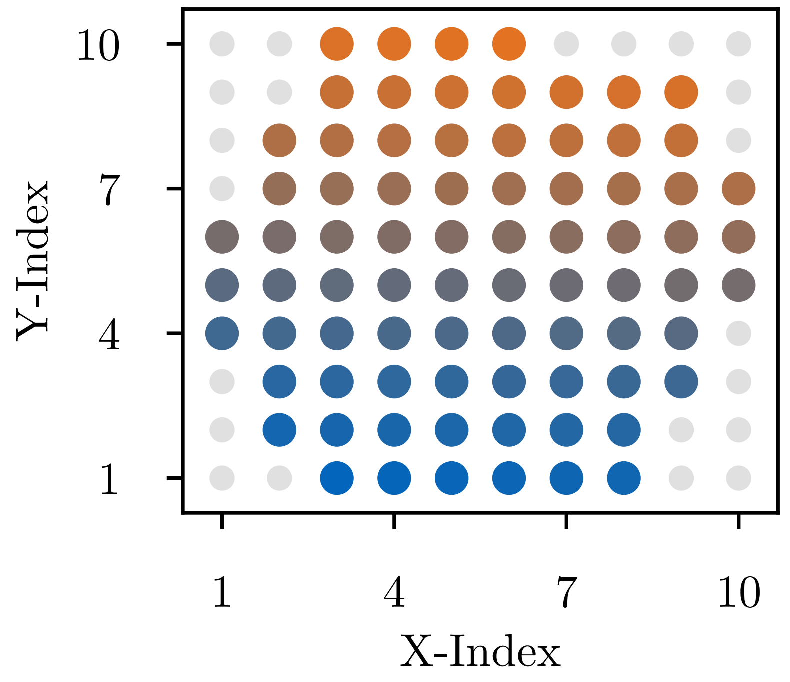


DNN overview





Input of Shape
10 x 10 x 60 x 15



DNN

Muon energy on entry

- Treating IceCube data as a 4D image and training a DNN with large-scale Monte Carlo simulations

Features (charge and time):

- Total charge & charge after 10 ns, 50 ns, 100 ns [p.e.]
- Time of the first hit, time spread, standard deviation of the time [ns]
- Time after which 1%, 3%, 5%, 11%, 15%, 20%, 50%, 80% of the charge have been collected [ns]

Replacing DNN with GraphNet

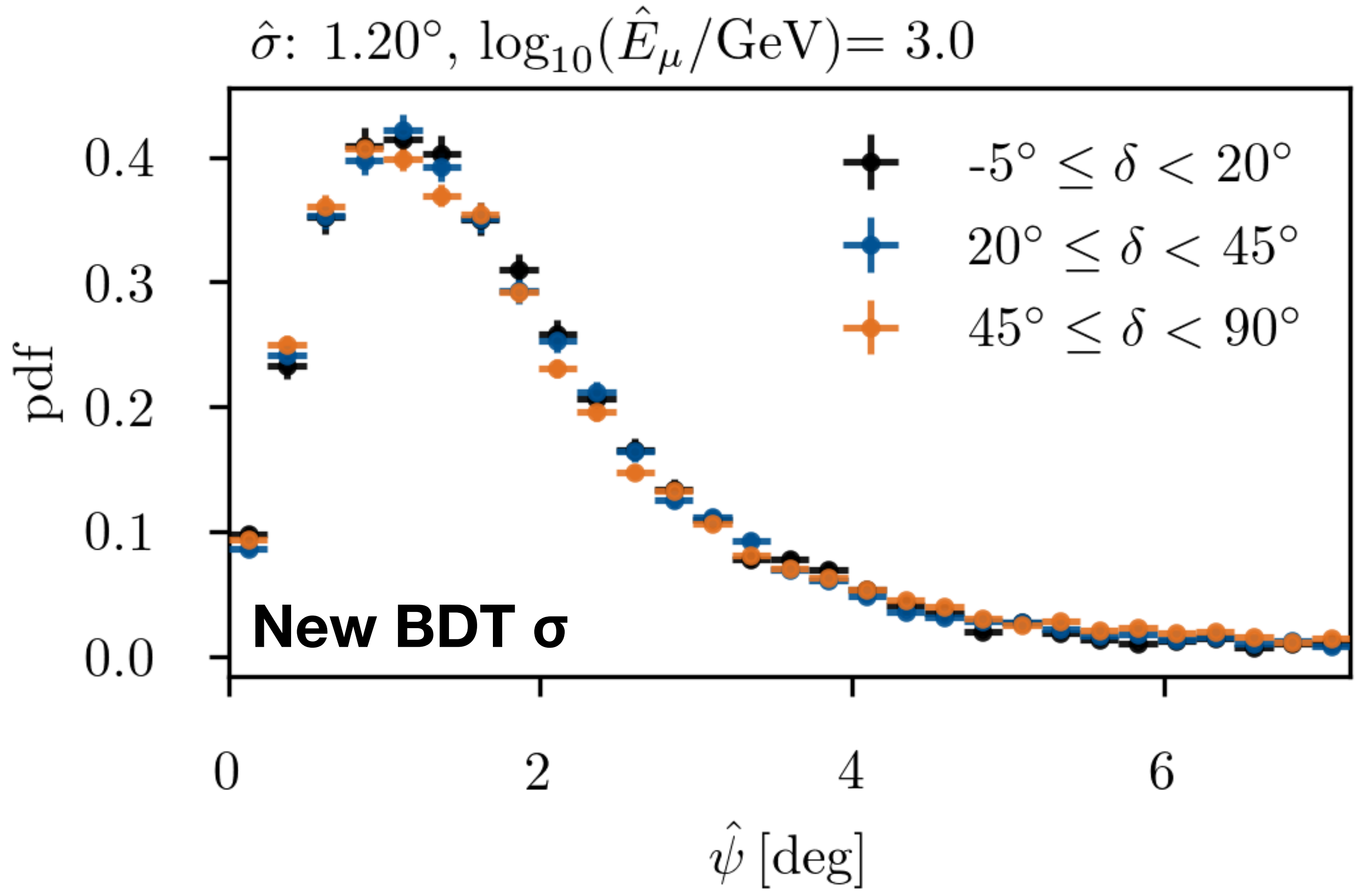
- Work in progress by Rasmus, initial impression of 20-40% improvement in energy resolution

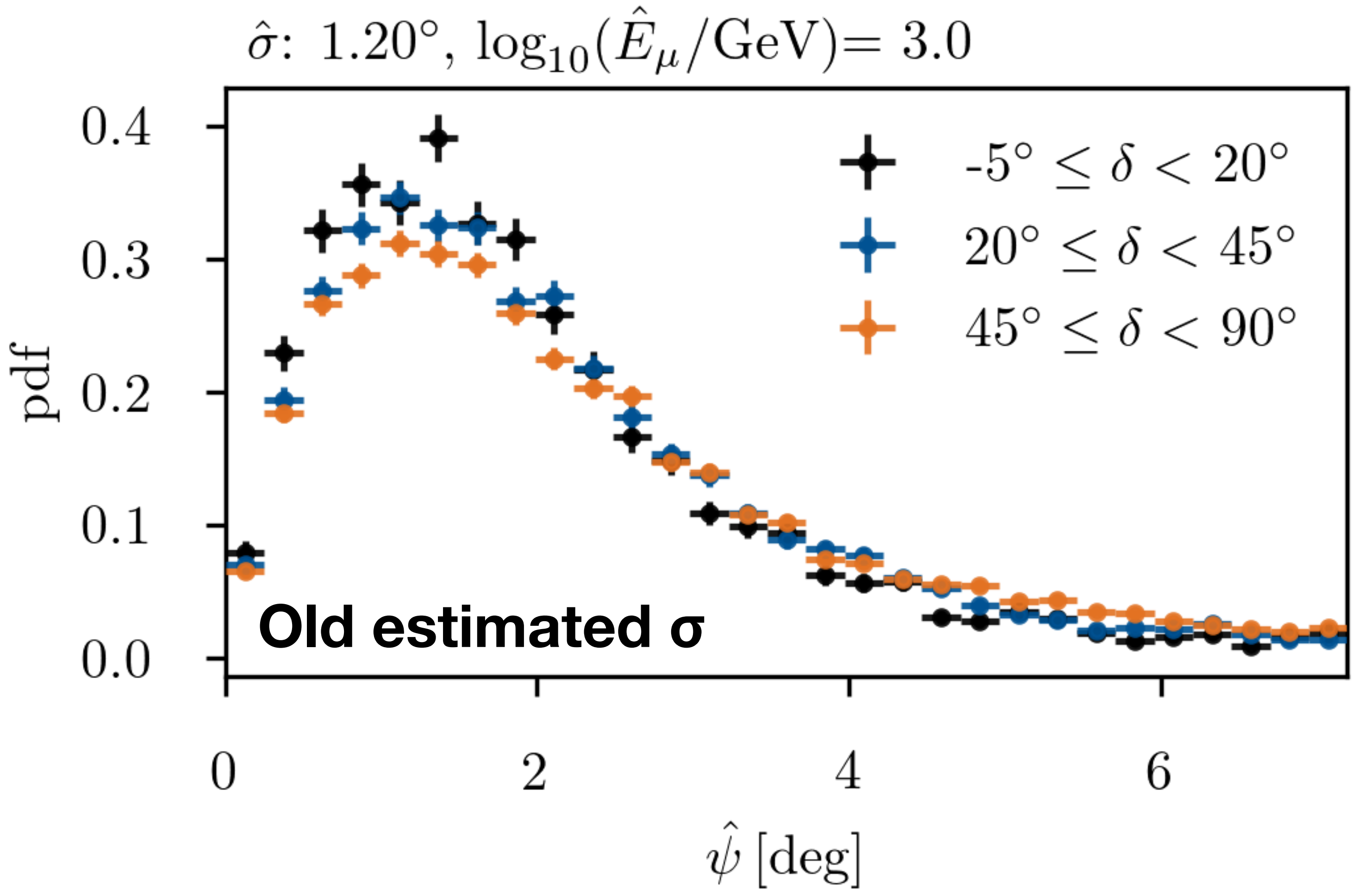
- DNN takes O(month) to train, while GNN — O(days)
  - Allows faster iterations of testing and optimisations

- We have two detector geometry configurations:
  - IC79 — data taken during 2010 season, 5 less strings on the detector edge
  - IC86 — data taken during 2011-2022 seasons
  - GraphNet does not have a problem using different geometries

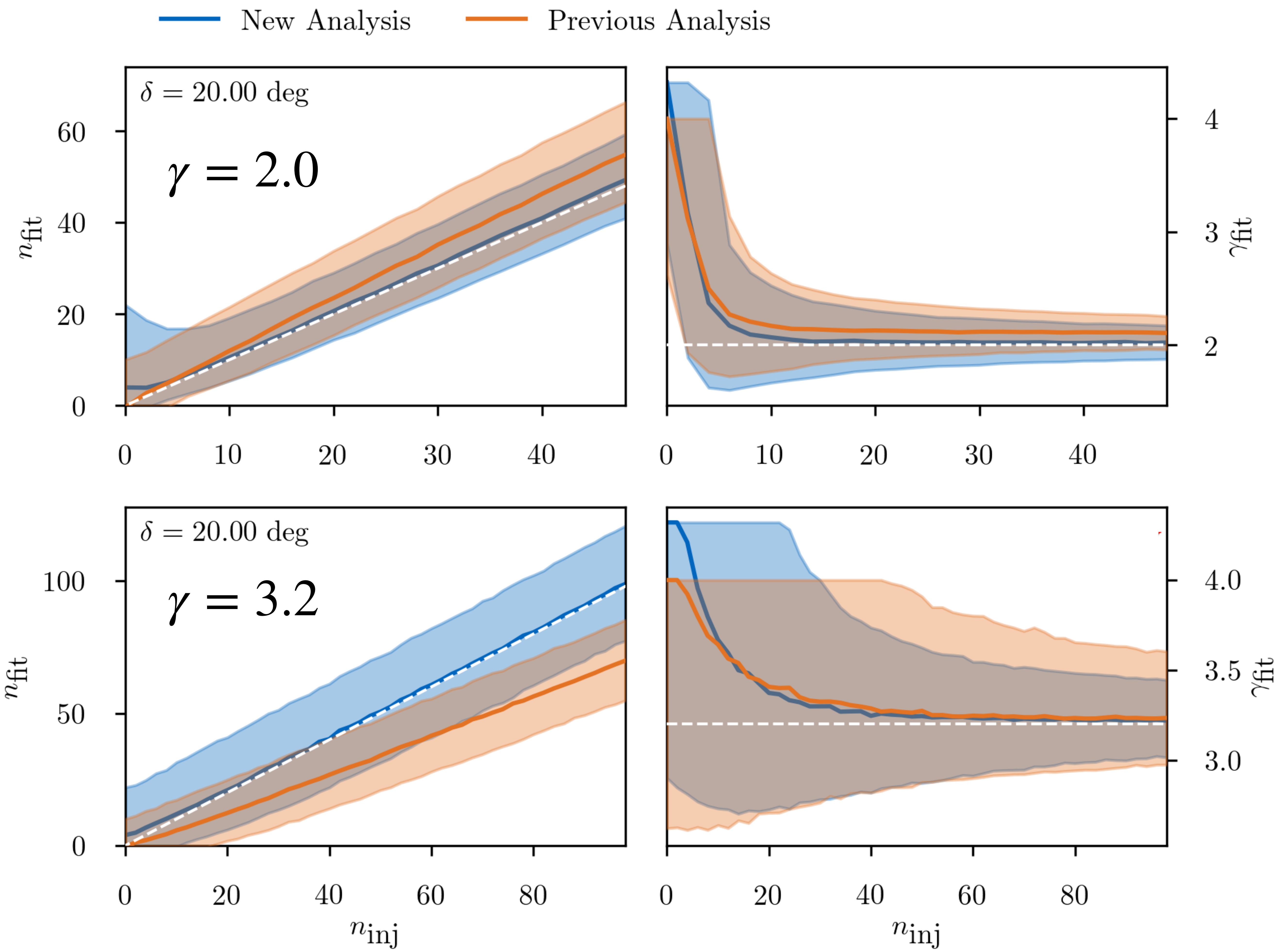
BDT uncertainty estimator

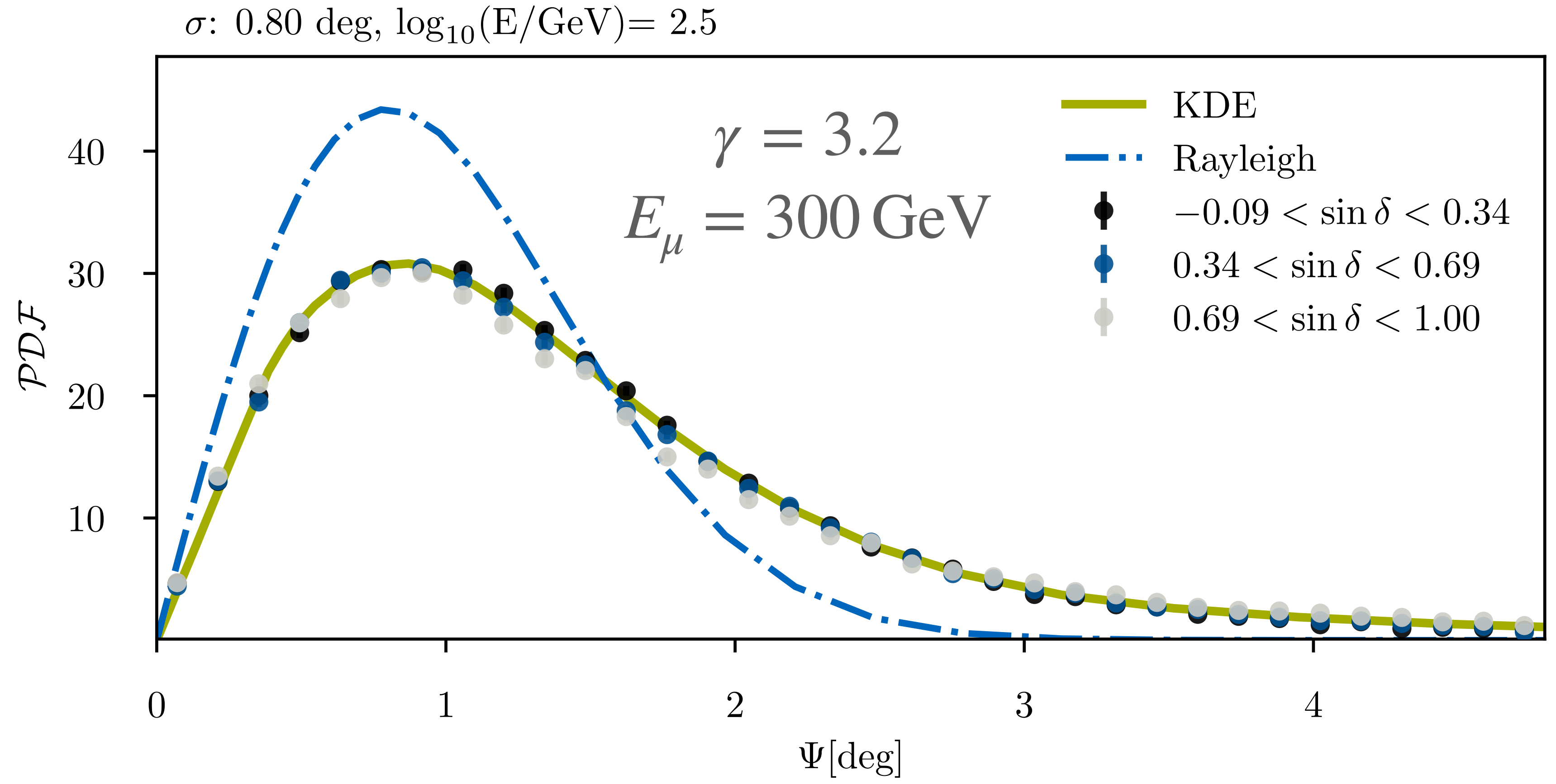
- Boosted Decision Tree angular uncertainty estimator:
  - The BDT angular uncertainty $\sigma(E_\mu, \gamma)$ **parameterises the median of the opening angle** between true and reconstructed muon direction (reconstruction error)
  - The kinematic angle between ν_μ and μ is accounted in spatial KDE PDF construction
  - Takes the track declination as input, thus providing the conditional independence of the spacial PDF from the source declination $\mathcal{S}(\psi \,|\, E_\mu, \sigma, \gamma)$





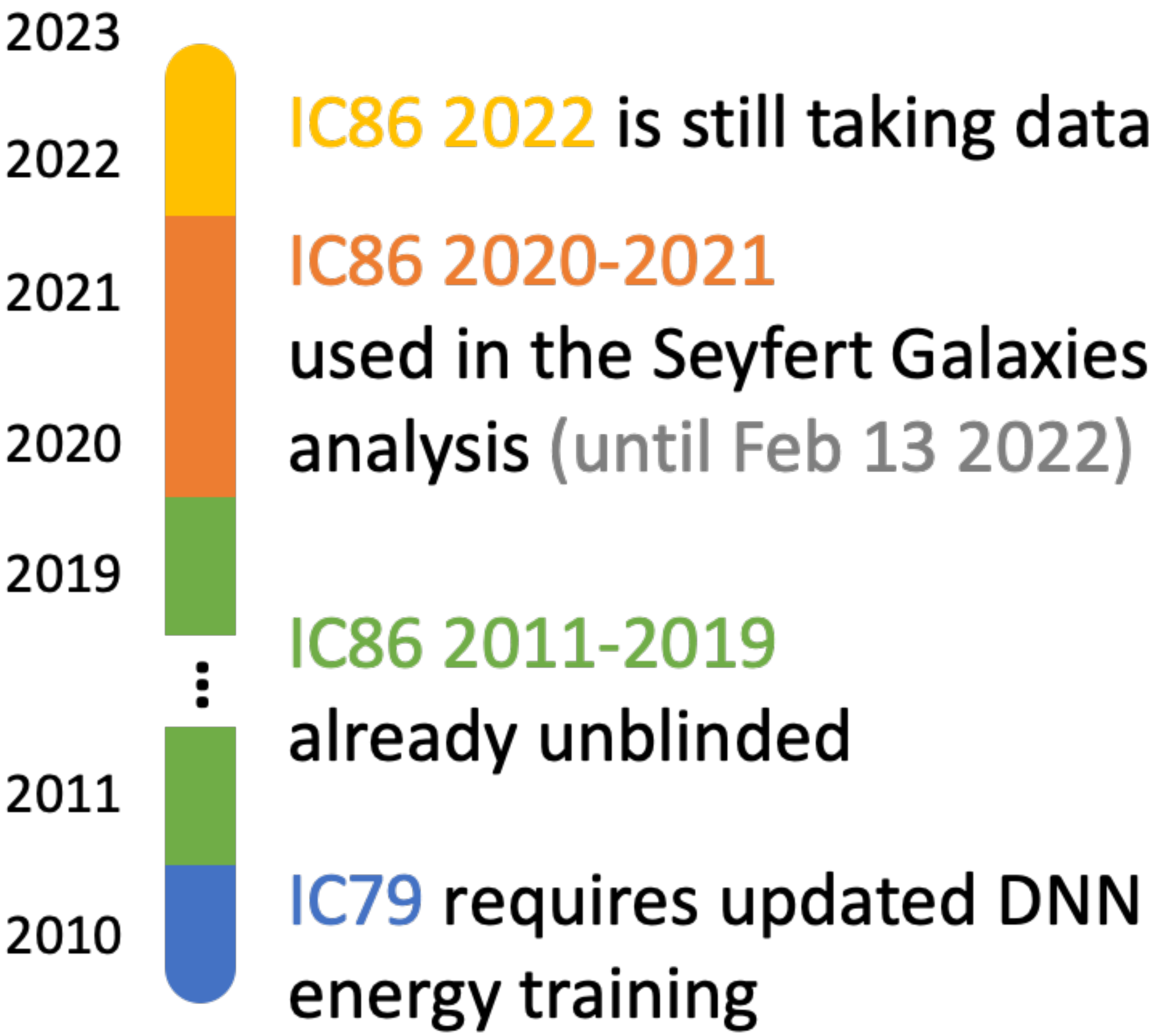
Analysis performance — unbiased Maximum Likelihood Estimators





- Unbiased estimates of the MLE, thanks to a better description of the signal pdf
- Soft spectra: the coverage of the long tail of the pdf recovers many low energy events
- The improved energy estimation contributes to better constrain soft spectral indices
- Overall, the new analysis proves to be better at characterizing the source spectral emission!

Extending improved PS analysis



- Assuming that NGC 1068 emits a constant neutrino flux, possibility of reaching 5σ with additional data
- Double MC simulations dataset
  - More accurate KDE PDFs description
- Replace DNN with GNN for energy reconstruction
  - Better constrain on best fit γ
  - More accurate spatial PDFs

Summary and future ideas

- Improved analysis methods and likelihood description give unbiased estimates of MLE

- Improvements in energy reconstruction
  - Initial tests by Rasmus look promising!
- Future: better directional reconstruction
  - GNN already performs better than SplineMPE at the lowest energies
  - Looking forward to do comparisons with methods from Kaggle!

- Working on adding more data and consolidating data processing pipeline
  - KDE PDFs are model flux dependant, have to regenerate in order to test different model hypotheses

Backup

Spline performance

- Likelihood minimizer takes 10-100 steps -> Total time O(1s)

Evaluation of 20000 random points

```
%%timeit
bg_spline(data_bg) # 2d spline
```

```
3.05 ms ± 83.1 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

```
%%timeit
sig_spline(data_sig) # 3d spline
```

```
4.91 ms ± 112 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

```
%%timeit
sig_spline_4d(data_sig_4d) # 4d spline
```

```
8.11 ms ± 164 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

KDEs in likelihood

In order to calculate the conditional probabilities in the point-source likelihood we make use of the law of total probability, i.e. $P(A \mid B) = P(A, B)/P(B)$. For the signal likelihood we therefore need to generate four KDEs:

- $f_s\left(\psi, E_{reco}, \sigma \mid \gamma\right)$ and $f_s\left(E_{reco}, \sigma \mid \gamma\right)$ to obtain $f_s\left(\Psi \mid E_{reco}, \sigma, \gamma\right)$

- $f_s\left(E_{reco}, \delta_{src} \mid \gamma\right)$ and $f_s\left(\delta_{src} \mid \gamma\right)$ to obtain $f_s\left(E_{reco} \mid \delta_{src}, \gamma\right)$

In addition one more KDE is needed for the background case:

- $f_s\left(E_{reco}, \delta_{src} \mid \text{conv atm + diffuse astrophysical}\right)$

Top 3 results from catalog search

Source Name	Source Type	α [°]	δ [°]	$\hat{n}_s$	$\hat{\gamma}$	$-\log_{10} p_{\mathrm{local}}$	$\Phi_{90\%}$
NGC 1068	SBG/AGN	40.67	-0.01	79	3.2	7.0 (5.2 σ)	9.6
PKS 1424+240	BLL	216.76	23.80	77	3.5	4.0 (3.7 σ)	11.4
TXS 0506+056	BLL/FSRQ	77.36	5.70	5	2.0	3.6 (3.5 σ)	7.5

BDT features

- In addition to energy and paraboloid σ, these include an estimate of the position of the largest energy deposition in the detector, a measure of the stochasticity of the event energy loss pattern, the track declination, and angular separations between different track reconstruction methods.

angular error estimators

- paraboloid sigma w.r.t muon direction (“sigma_pull_corrected_psi_mu_hybrid_energy_2.0”)
- angular error asymmetry (“pbf_ratio”)

angular distance between directional reconstructions

- mpe : splinempe (“psi_mpe_splinempe”)
- linefit : splinempe (“psi_linefit_splinempe”)
- splinempe (L3) : splinempe (final) (“psi_splinempe_l3_max”)

energy estimators

- truncated energy (“loge_trunc”)
- DNN energy (“loge_dnn”)
- maximum millipede energy loss (“loge_millipede_max_loss”)
- maximum relative millipede energy loss (“millipede_rel_highest_loss”)
- nchannel (“n_hit_doms”)

stochasticity estimators

- truncated energy peak loss / median loss (“log_e_loss_summary_truncated_PoM”)
- reduced chi2 of linear energy loss pattern (“e_loss_summary_truncated_chi2_red”)

location in the detector

- z-component of center of gravity (“cog_z”)
- radial distance to center of gravity (“cog_rho”)

other

- zenith angle from splinempe (“spline_mpe_zenith”)
- cascade score from diffuse BDT (“casc_score”)
- (“avg_dist_q”)