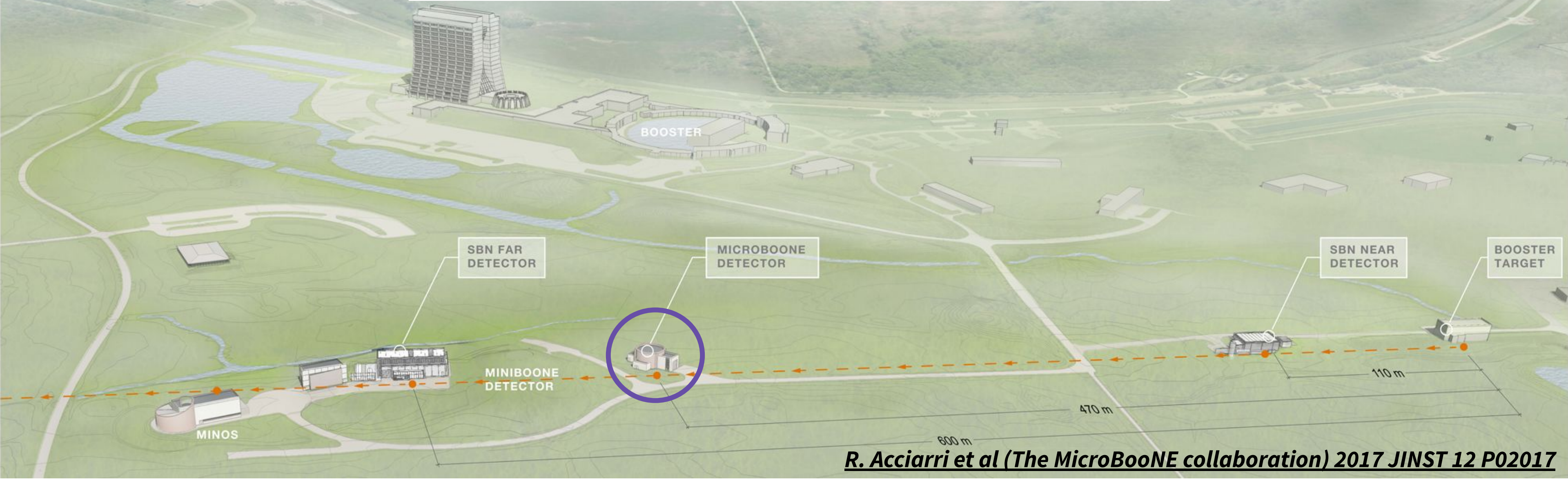
Searching for BSM physics with the MicroBooNE detector

Luis Mora Lepin, on behalf of the MicroBooNE collaboration
Pyhf workshop
CERN
05/12/2023

Outline

- The MicroBooNE detector
- Recap of LArTPCs
- Heavy neutral leptons and light dark matter
- A closer look on how we use pyhf

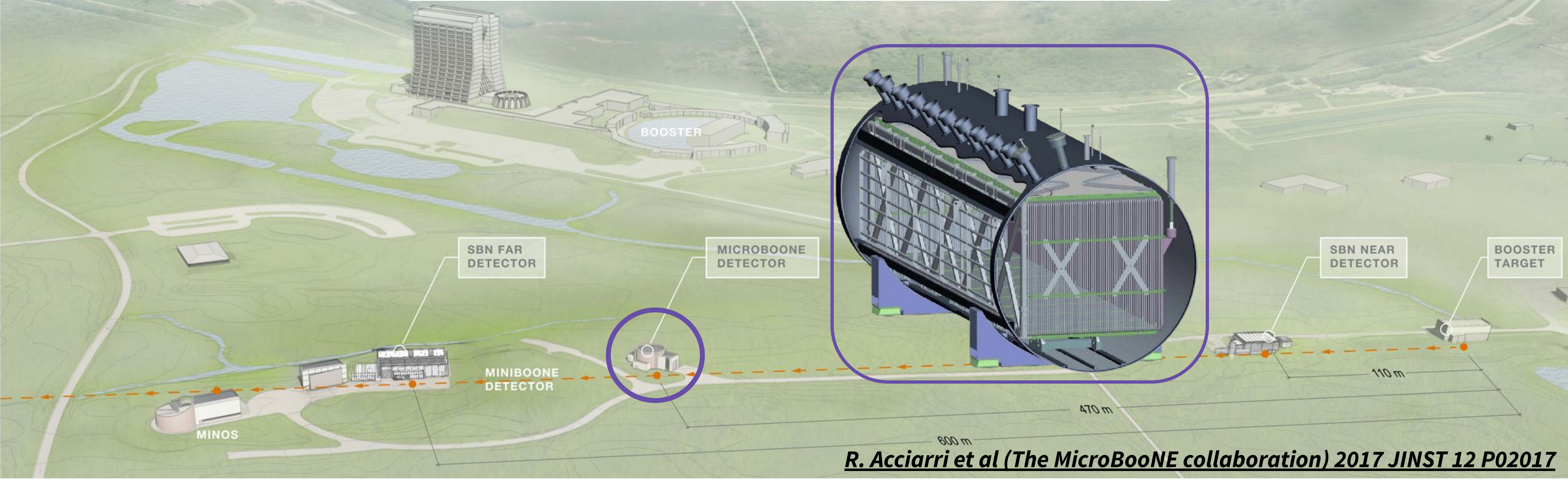
MicroBooNE at Fermilab



R. Acciarri et al (The MicroBooNE collaboration) 2017 JINST 12 P02017

MicroBooNE:
- Liquid argon time projection chamber (LArTPC)
- Active mass 85 tonnes
- Dimensions: 10.36 x 2.56 x 2.32 m^3
- At surface level

MicroBooNE at Fermilab



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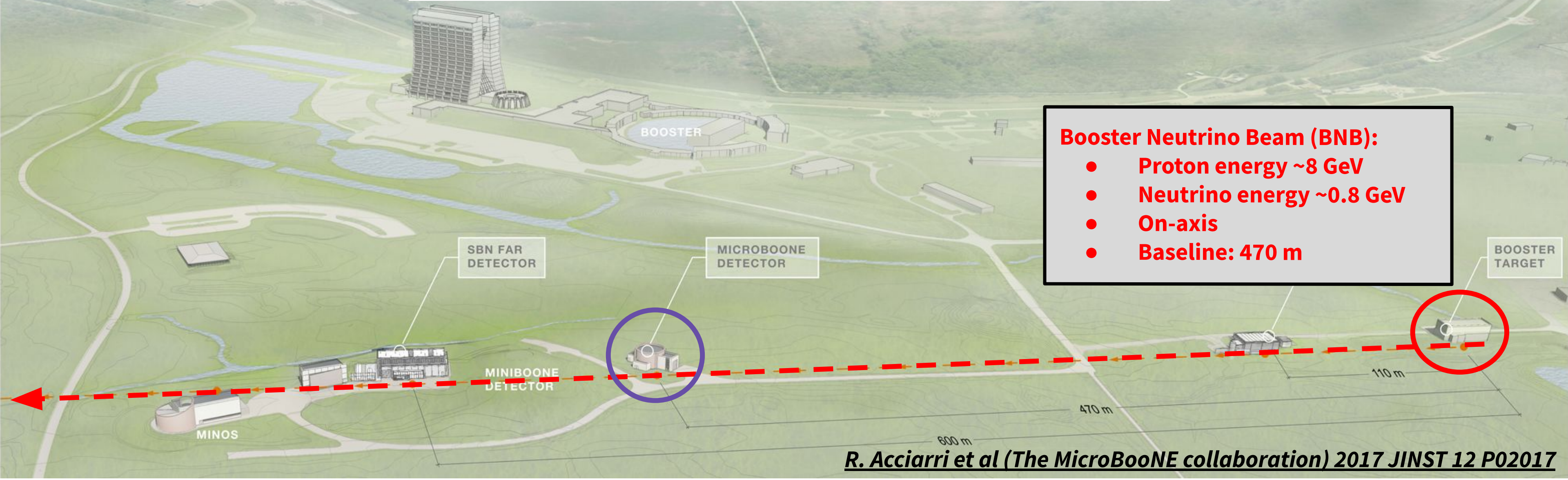

Booster Neutrino Beam (BNB):
- **Proton energy ~8 GeV**
- **Neutrino energy ~0.8 GeV**
- **On-axis**
- **Baseline: 470 m**

R. Acciarri et al (The MicroBooNE collaboration) 2017 JINST 12 P02017

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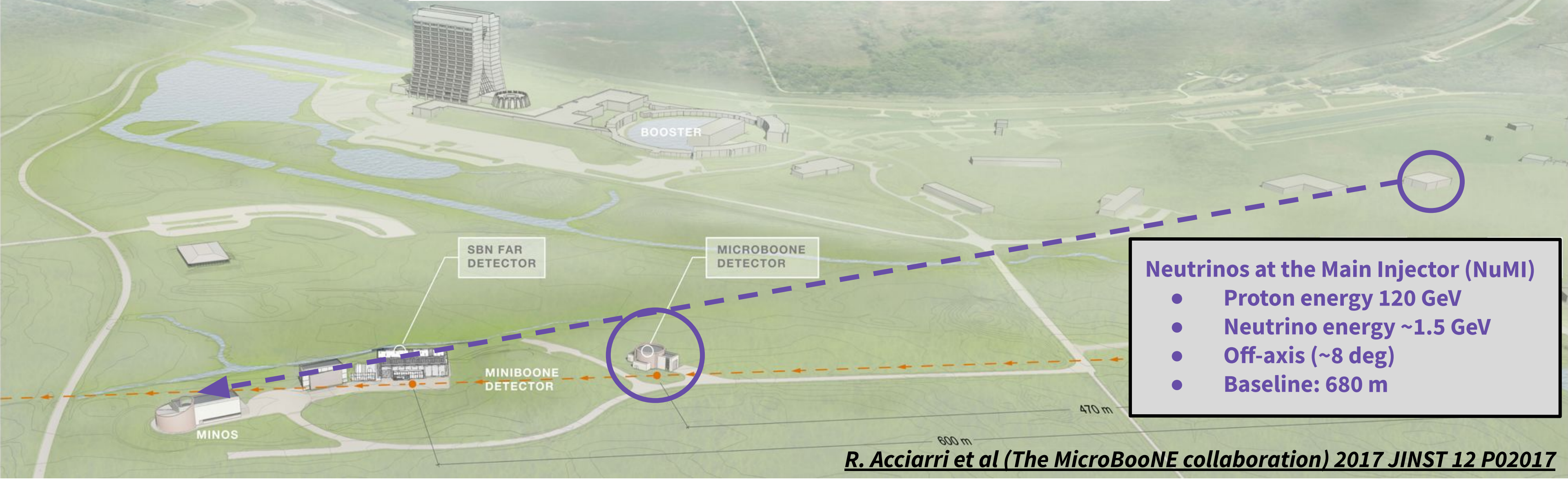

Neutrinos at the Main Injector (NuMI)
- **Proton energy 120 GeV**
- **Neutrino energy ~1.5 GeV**
- **Off-axis (~8 deg)**
- **Baseline: 680 m**

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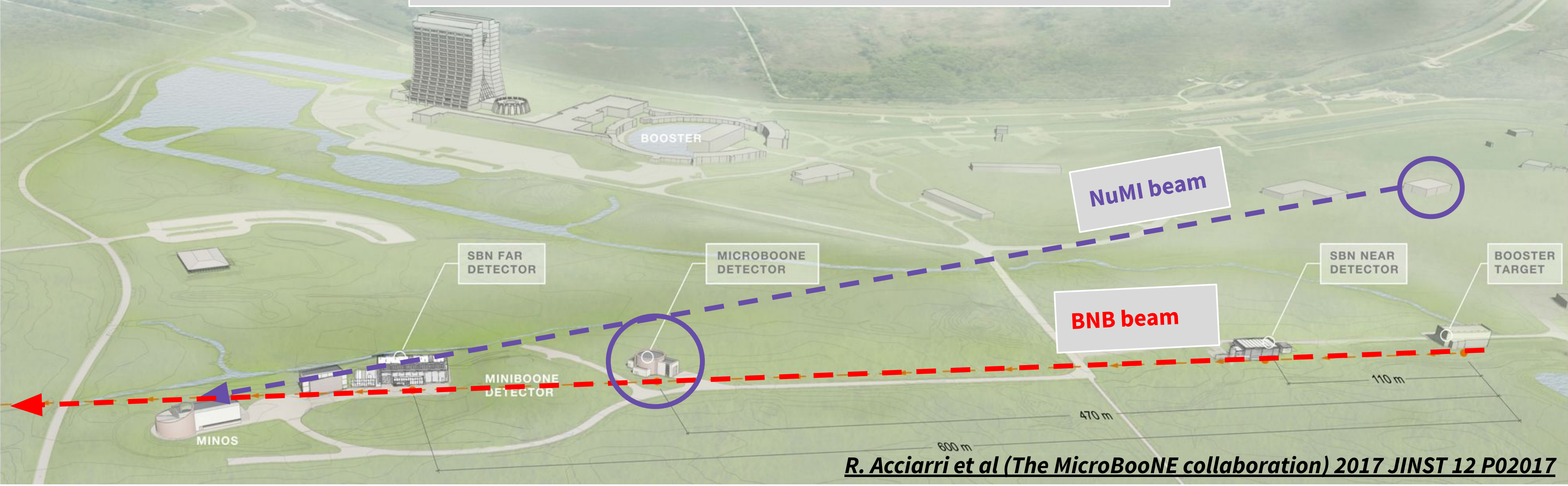

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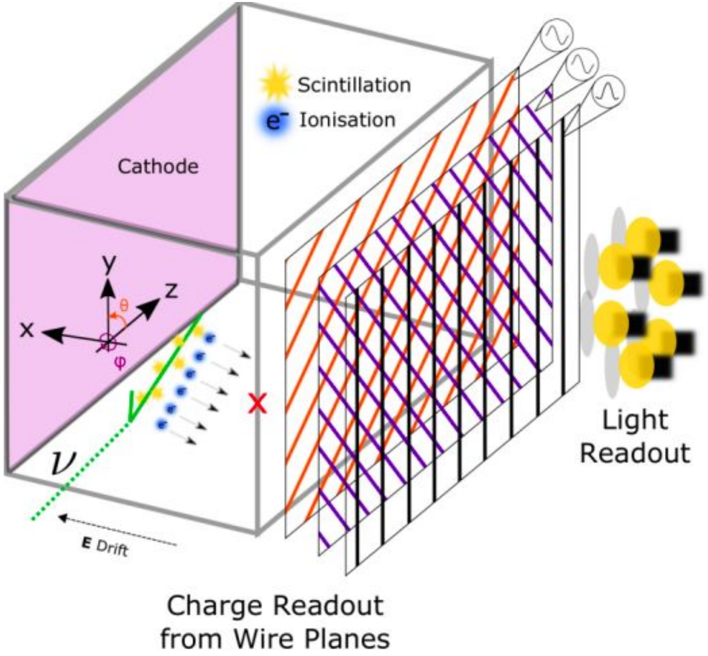
Rich physics program:

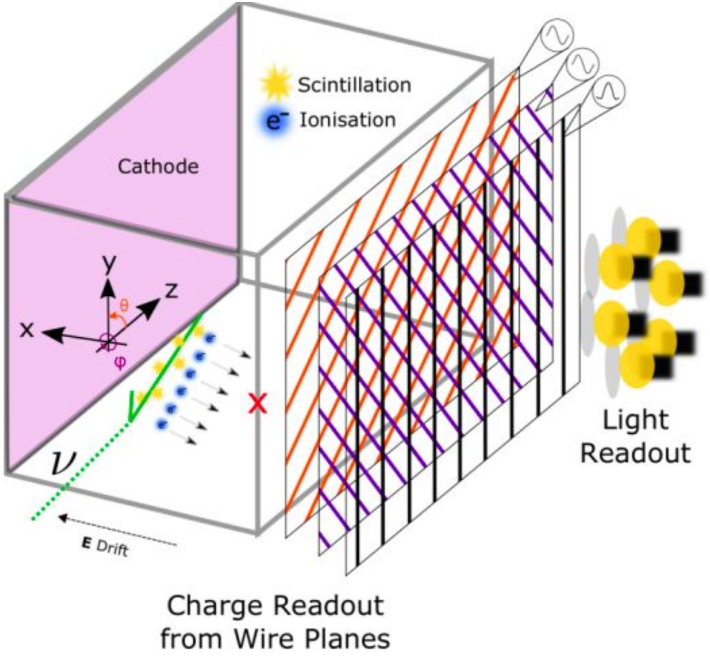
- Neutrino physics (Oscillations, cross section)
- BSM physics (This talk)
- LArTPC R&D

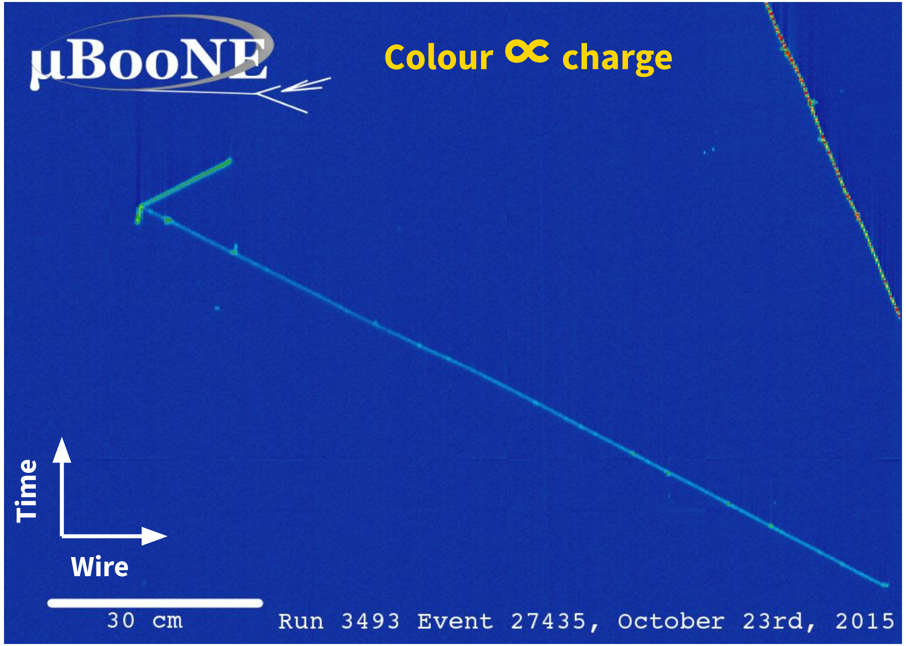
LArTPCs in a nutshell



- Light is collected by an array of PMTs
- Charge depositions are collected by three different ***wire planes*** with different orientations
- 3D reconstruction of the interactions
- 3 mm spatial resolution

LArTPCs in a nutshell





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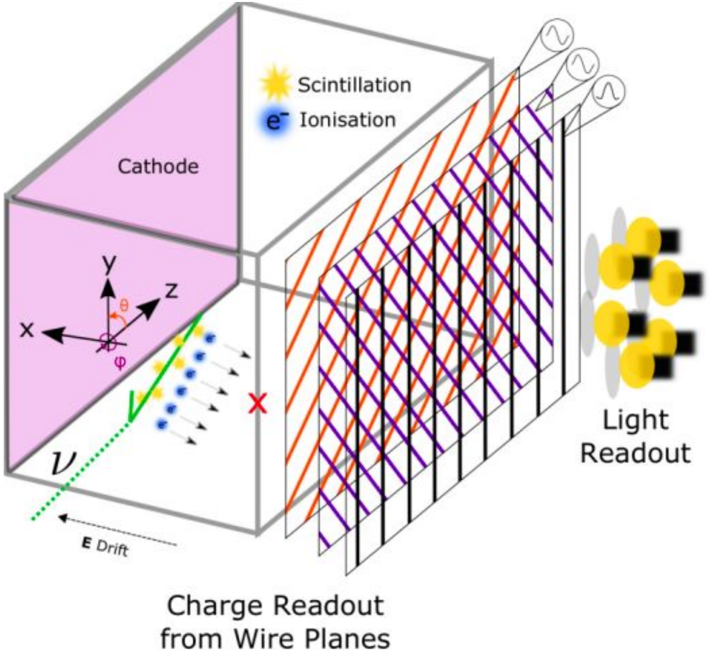

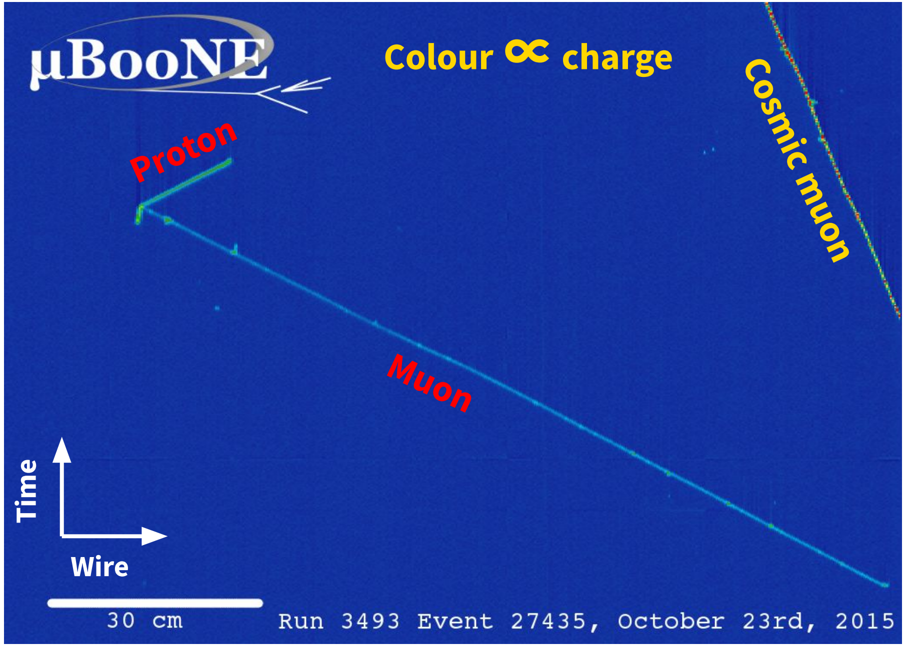

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What makes MicroBooNE a good place to search for BSM physics?

- Access to high intensity proton beams (on-axis and off-axis)

- Good spatial and calorimetric resolutions, which translates in good particle identification

- Low detection threshold

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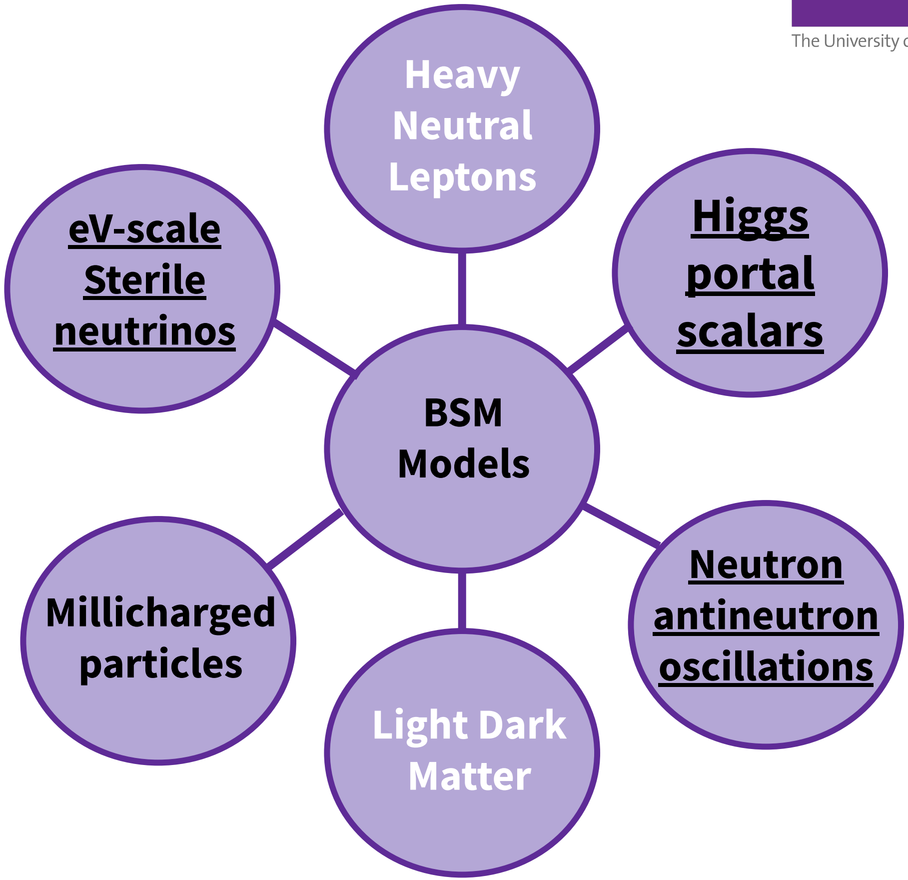


Where does pyhf fit in this story?

- We want to probe BSM models. This typically involves performing a hypothesis test and using many HEP-dedicated statistical tools, such as asymptotic approximations and the CLs method

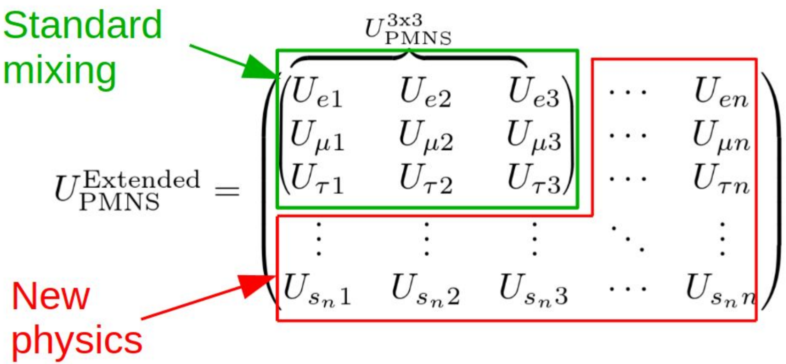
- Historically, in MicroBooNE this has been done with *RooStats* or with *COLLIE* (both C++ packages)

- Pyhf offers all the needed tools all of them embedded in Python, which is one of the most used languages nowadays

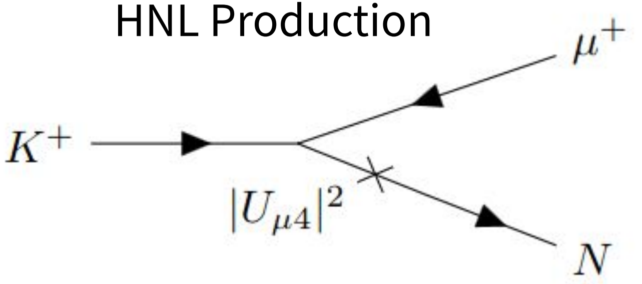
Heavy Neutral Leptons (HNLs)

- Right-handed fermion singlets (N)
- Masses from keV to GeV
- Mixing with SM neutrinos through the extended PMNS matrix
- Production and decay rate scale with $|U_{l4}|^2$
- MicroBooNE has performed several HNL searches, today I’ll focus on the most recent result (recently accepted by PRL)

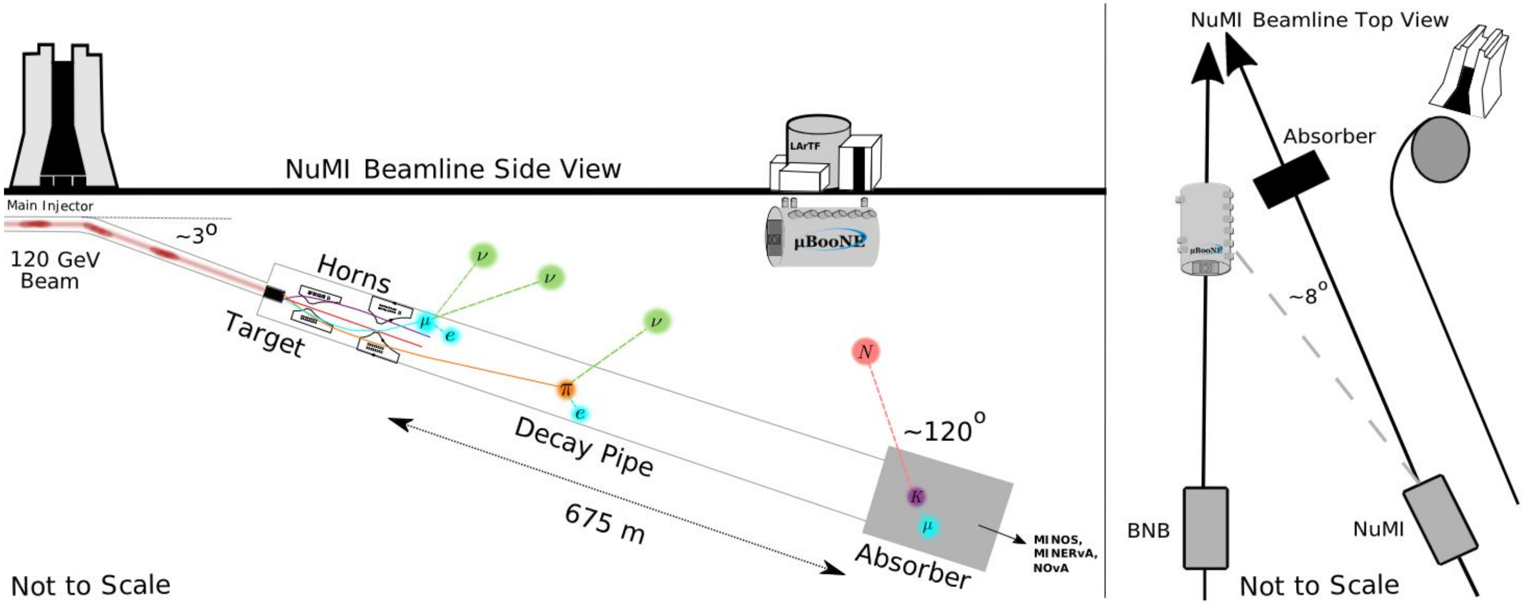
arXiv:2310.07660v1



HNL Production



HNL search strategy



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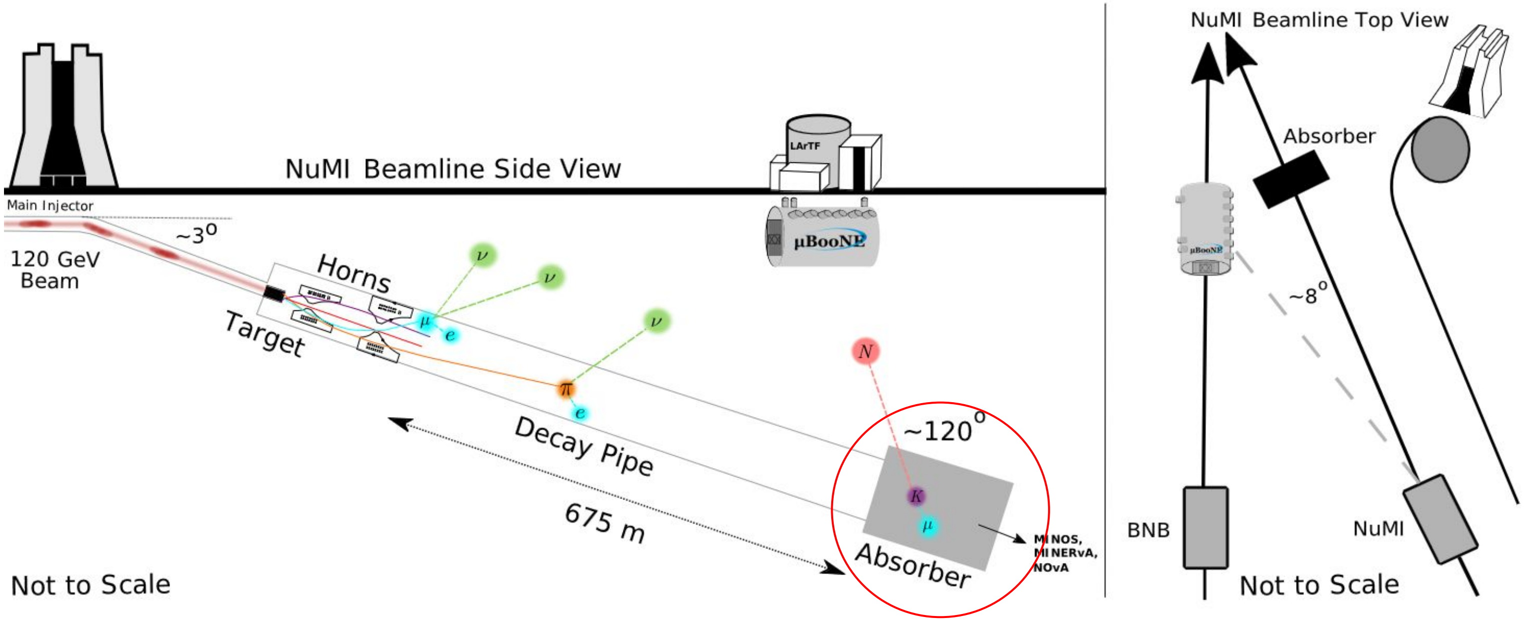
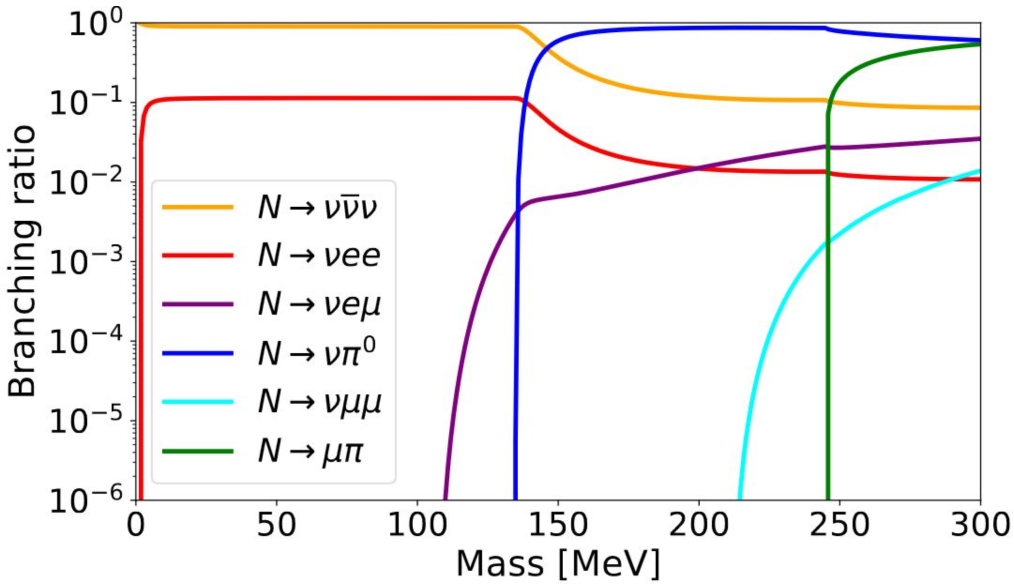
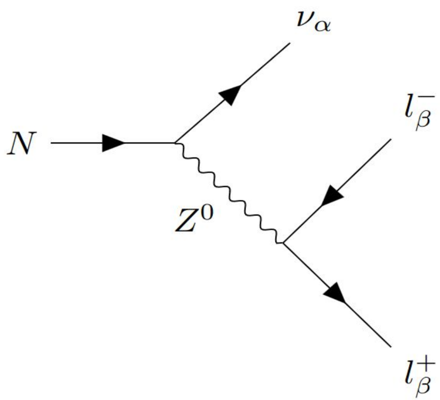


HNL decay channels



Decay mode into charged leptons (e^+e^-)



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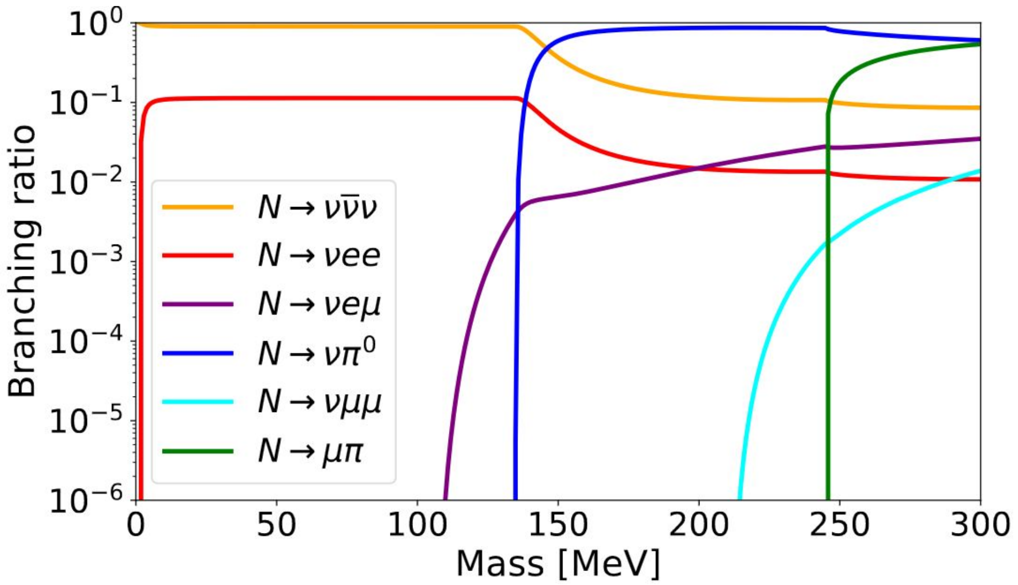

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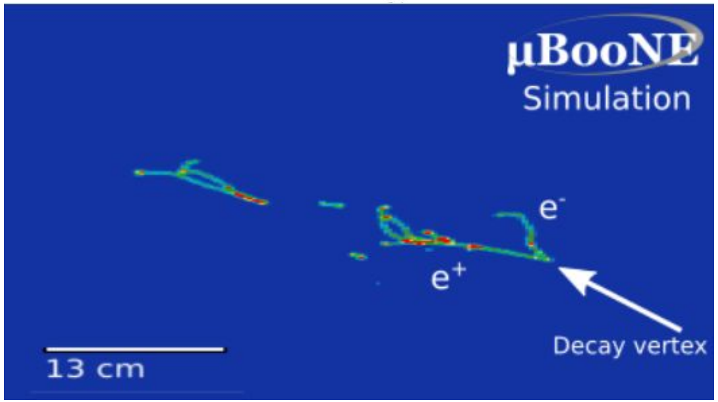

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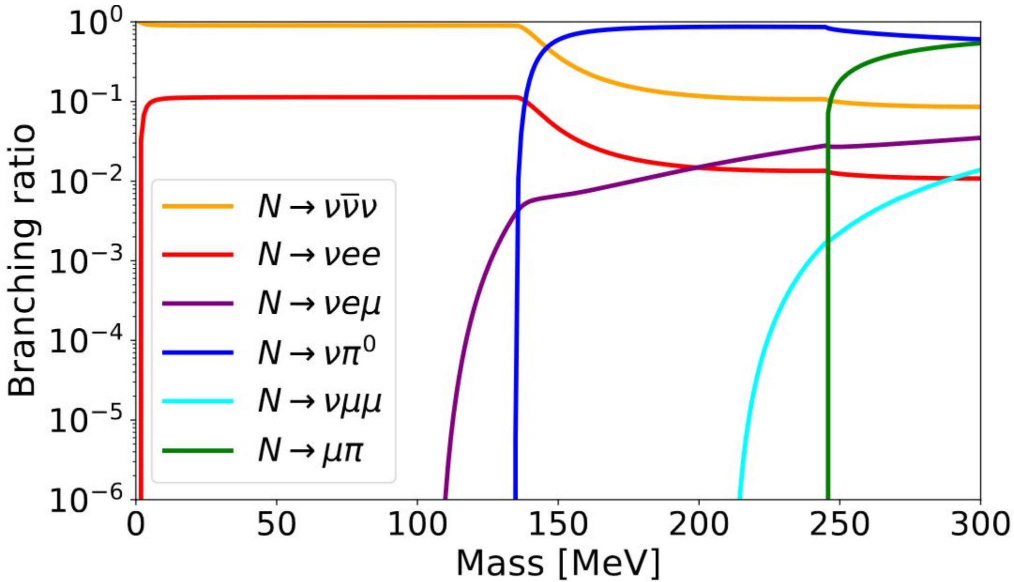
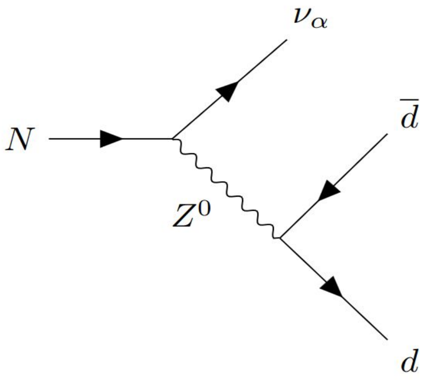


Decay mode into neutrino and a neutral pion



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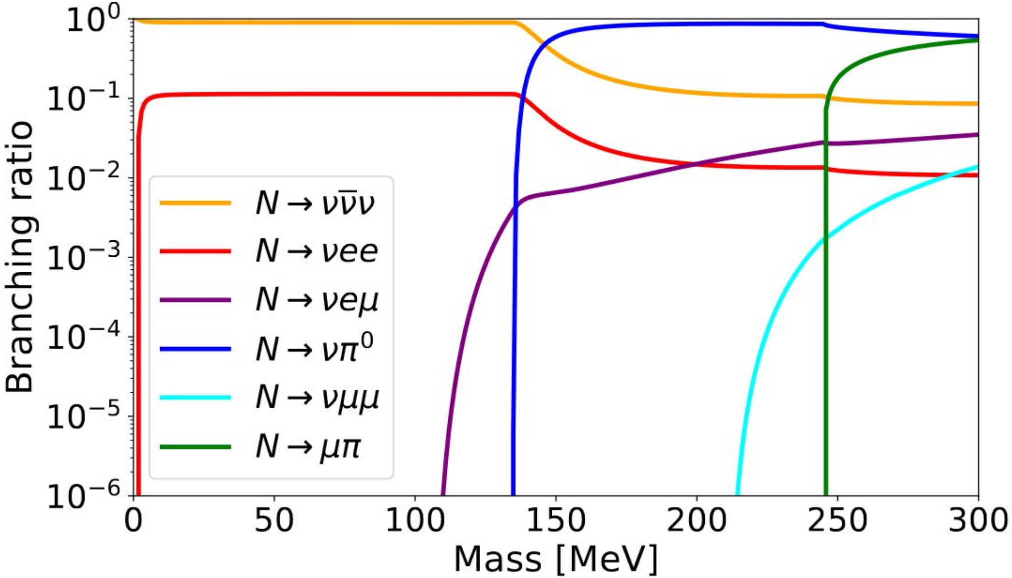

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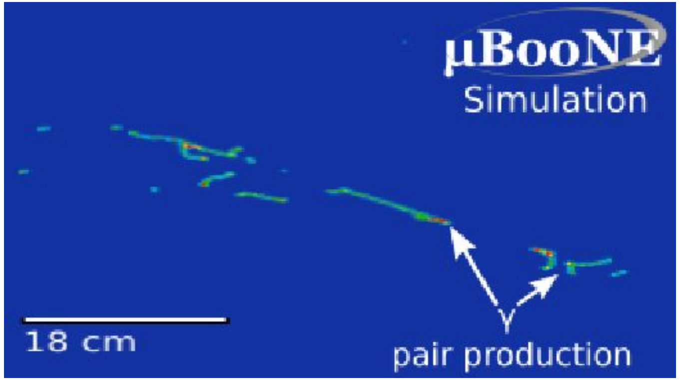
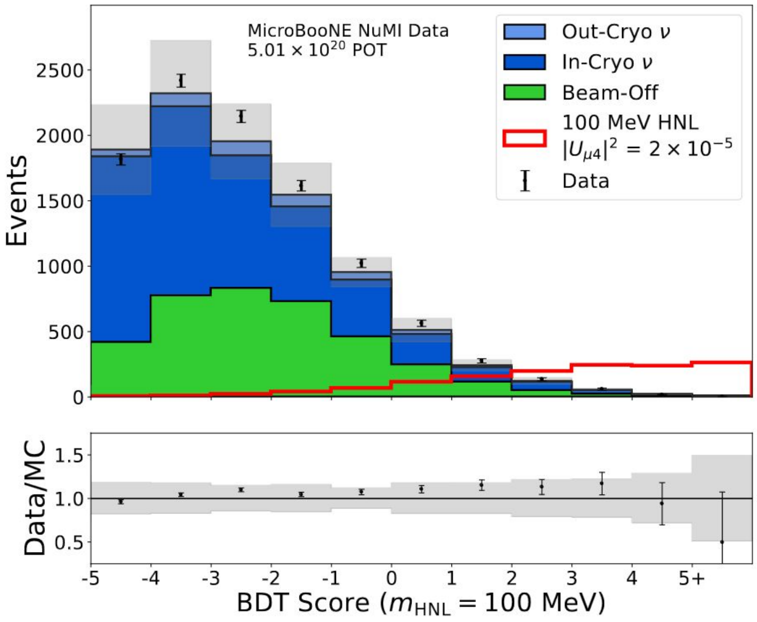


HNL analysis

- The BDT (**XGBoost**) distributions are passed to pyhf to set limits
- Background samples: Cosmic ray interactions and neutrino interactions
- Two different channels: MicroBooNE Run 1 and **Run 3 (shown here)**



Light Dark Matter (LDM)

- DM models with masses below the WIMP mass range are becoming attractive due to their rich phenomenology
- They might also explain the observed DM abundance
- Typically, these models include a new force carrier and one or more DM species

$$\mathcal{L} = \mathcal{L}_{\mathrm{SM}} + \mathcal{L}_\chi - \frac{1}{4}F'_{\mu\nu}F'^{\mu\nu} + \frac{1}{2}M^2_{A'}A'_\mu A'^\mu - \frac{\varepsilon}{2}F'_{\mu\nu}F^{\mu\nu}$$

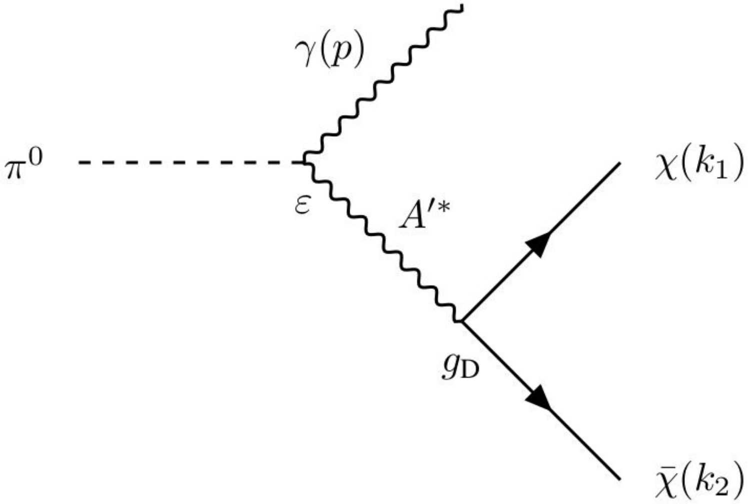
$$\mathcal{L}_\chi = \begin{cases} i\bar{\chi}\not{D}\chi - M_\chi\bar{\chi}\chi, & \text{(Dirac fermion DM)} \\ |D_\mu\chi|^2 - M_\chi^2|\chi|^2, & \text{(Complex scalar DM)} \end{cases}$$

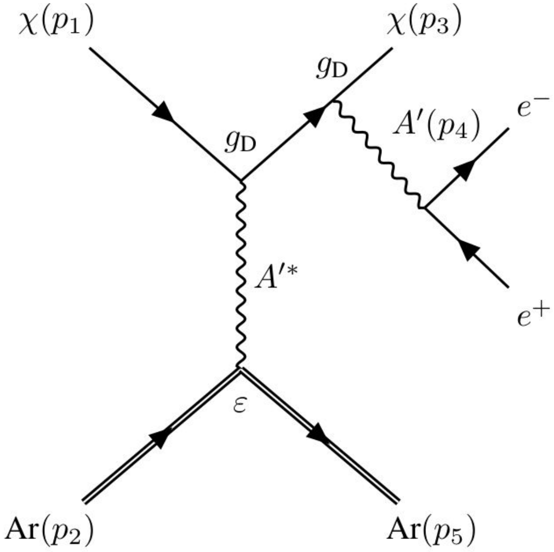
Mass regime:

$$M_{A'} < 2M_\chi$$

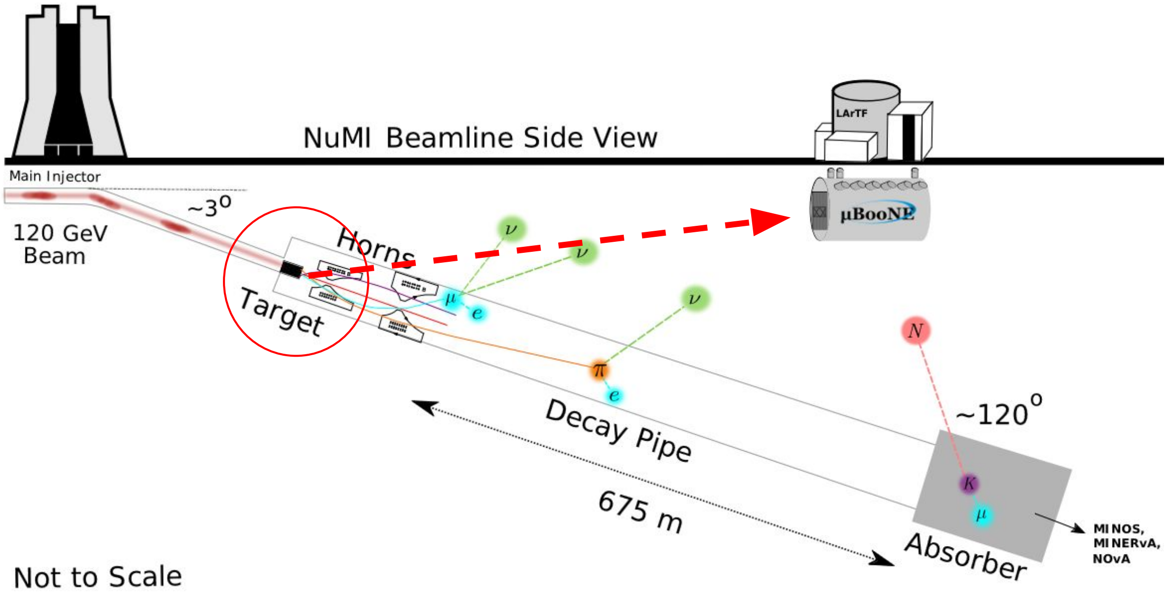
The dark trident interaction

- DM candidate can be produced at fixed-target facilities through neutral meson decays
- Off-axis search of DM scattering has been proposed in: **arXiv:1809.06388**
- Interaction channel: DM scattering with the emission of an on-shell dark photon





Dark trident search strategy



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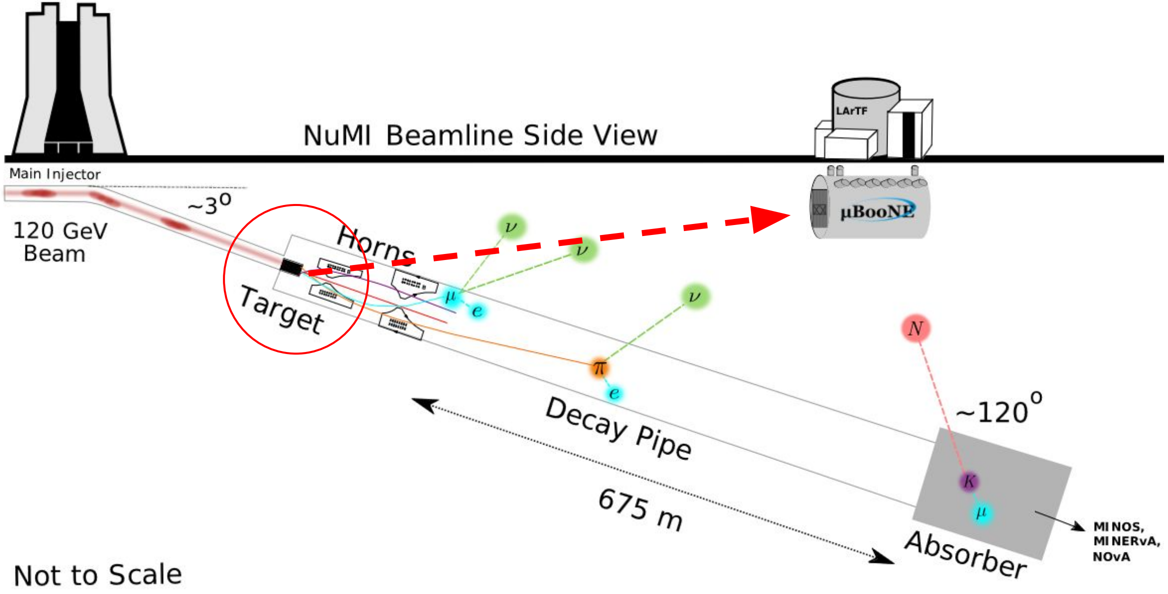
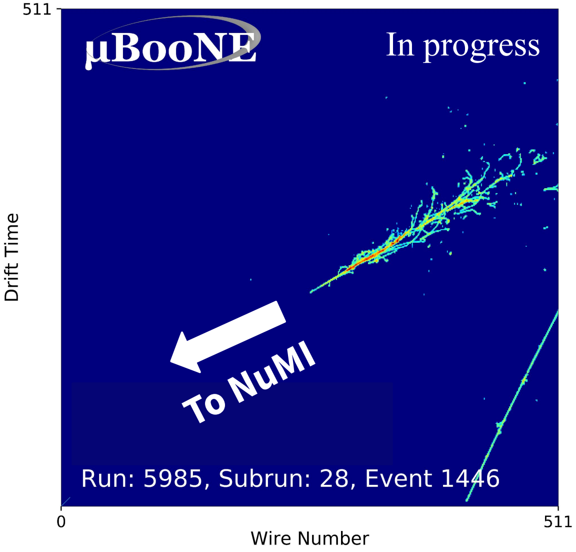
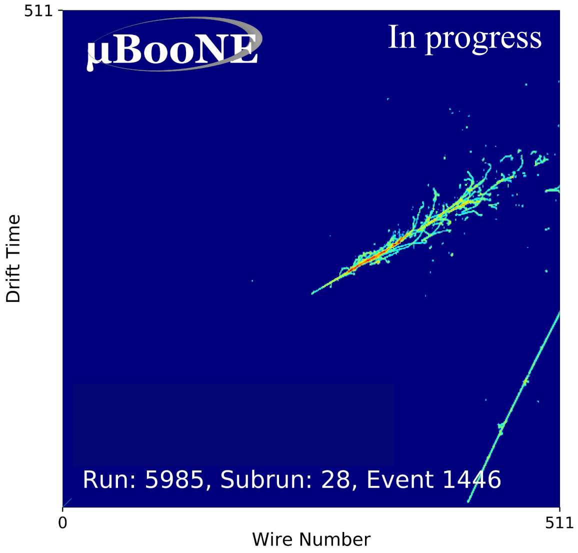




Dark trident analysis

- Backgrounds: neutrino interactions and cosmic muons crossing the detector
- We trained a convolutional neural network to discriminate signal from background
- Analysis relies on the 2D images produced by MicroBooNE



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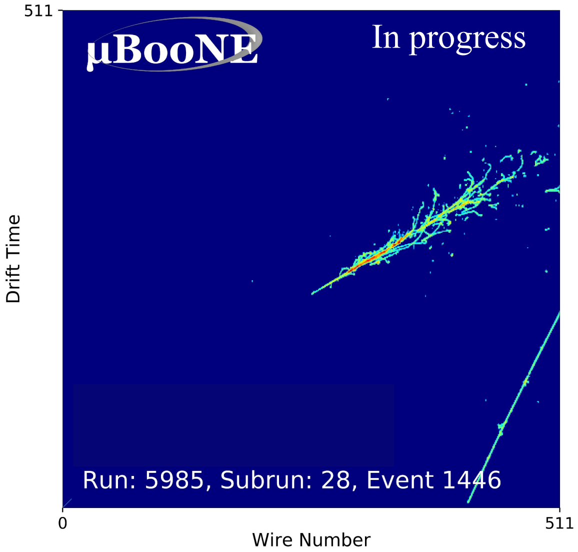
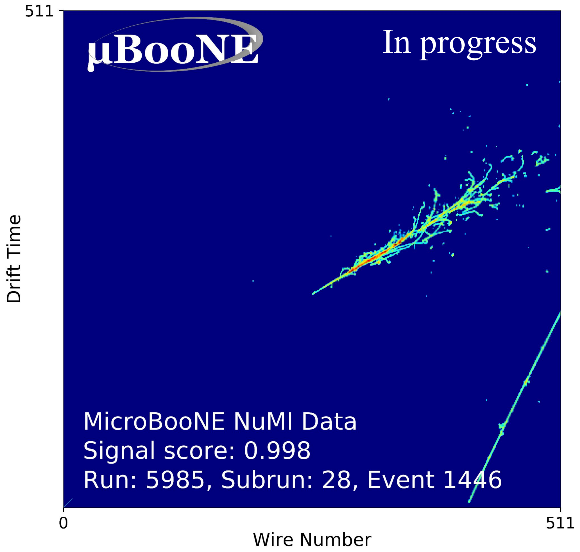
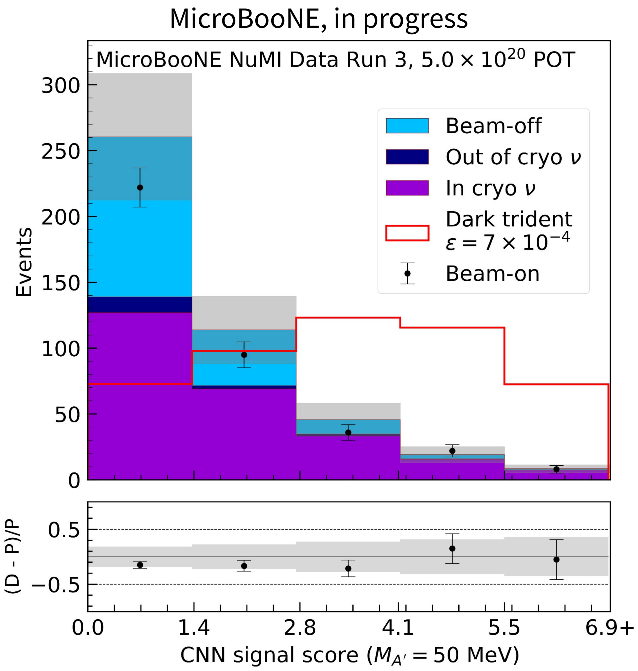


PyTorch



Dark trident analysis

- The CNN score distributions are passed to pyhf to set limits
- Uncertainties on the background and signal samples are included using modifiers
- Two different channels: MicroBooNE Run 1 and **Run 3 (shown here)**



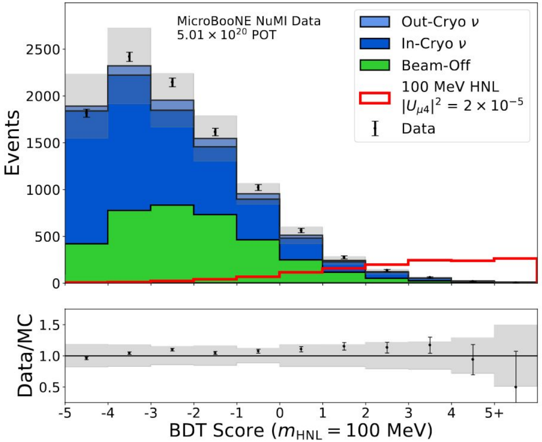
A closer look on how we use pyhf

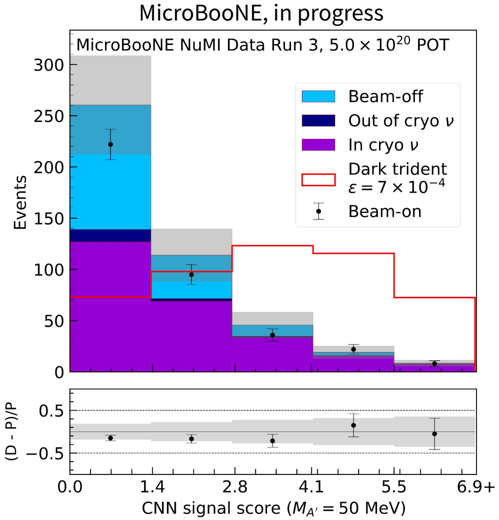
Starting point: distributions

Both analysis have a similar workflow. We used as a guide the tutorial presented in:

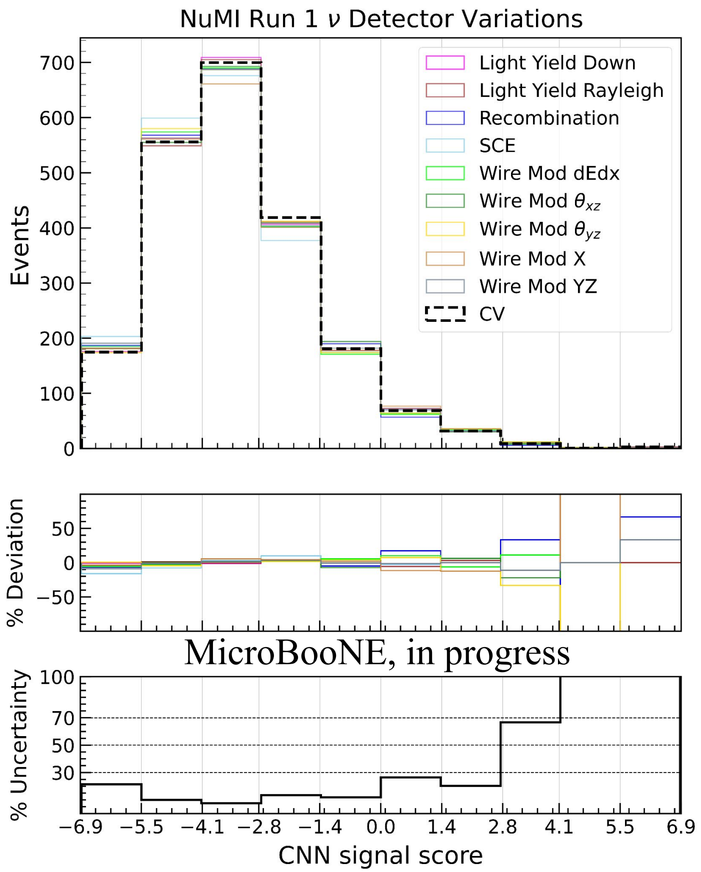
https://pyhf.github.io/pyhf-tutorial/HelloWorld.html

Our first step was to setup the distributions using the **JSON** template, declaring the signal strength as the parameter of interest



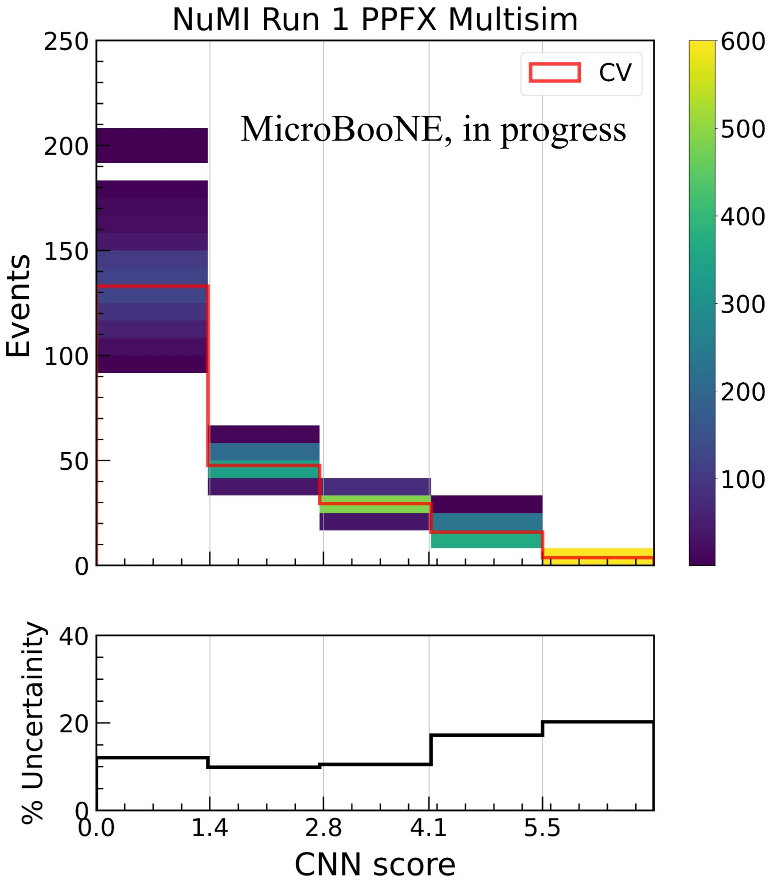


Uncertainties: resimulating method



- Method used for uncertainties where one effect is turned on/off, or one parameter value is changed by 1 standard deviation
- It involves creating alternative samples by resimulating the nominal sample
- This is typically the approach we take for detector modelling uncertainties
- We add all the detector-related uncertainties in quadrature
- We declare this as an **uncorrelated shape sys in pyhf**

Uncertainties: reweighting method



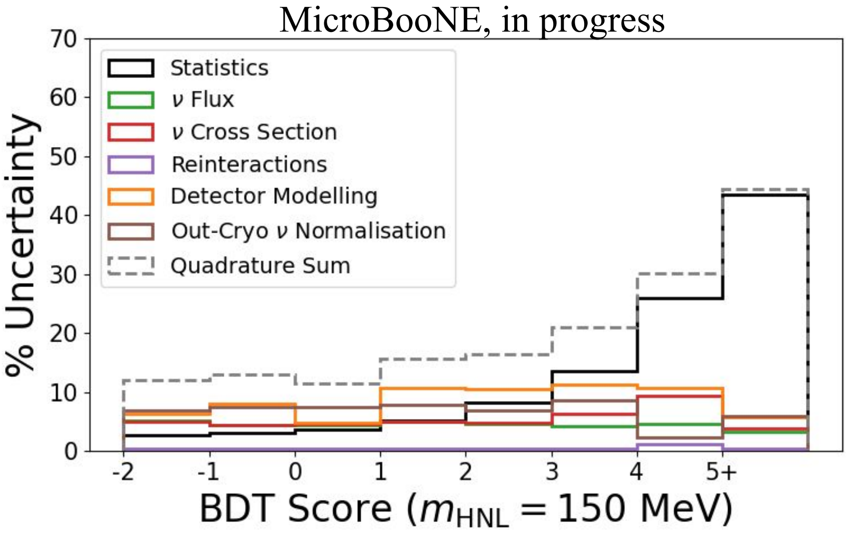
- Multiple parameters are simultaneously samples to create alternative models. We repeat many times to create an ensemble
- New distributions are obtained by reweighting the nominal sample
- In MicroBooNE we apply this to neutrino flux, cross section and reinteractions in Ar
- We declare this as an **uncorrelated shape sys in pyhf**

Summary of uncertainties

- The uncertainties are passed to the JSON template using different modifiers
- We also include bin-to-bin correlations and between runs
- We tried different correlations, but some of them are subdominant

HNL search uncertainties

Uncertainty source	Correlations			Form of modifier
	bins	sig. & bkg.	runs	
MC statistical	N	N	N	Gaussian
Detector variations	N	N	N	Poisson
Absorber KDAR Flux	Y	N/A	Y	Gaussian
Out-of-cryostat ν normalisation	Y	N/A	N	Gaussian
Genie, Flux and reinterations	N	N/A	N	Poisson



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μBooNE

MANCHESTER 1824
The University of Manchester

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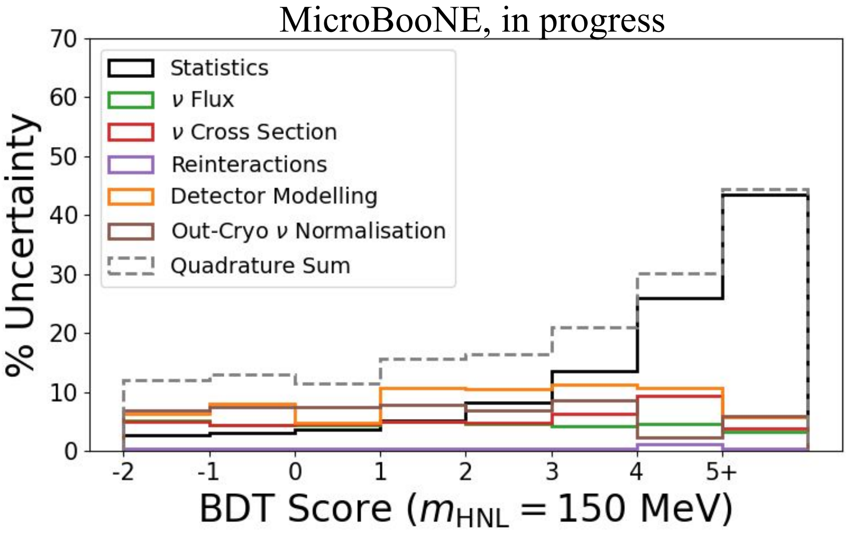

Is it possible correlate bin-by-bin shape uncertainties across signal and background?

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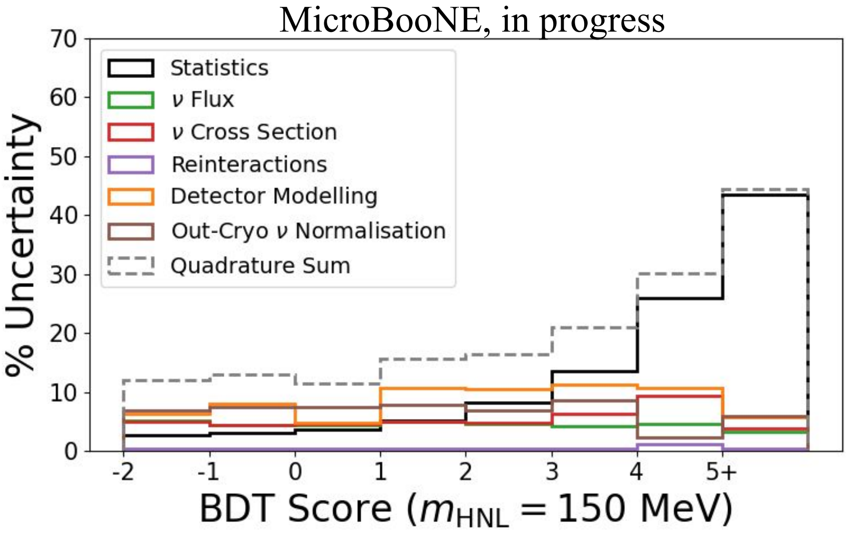

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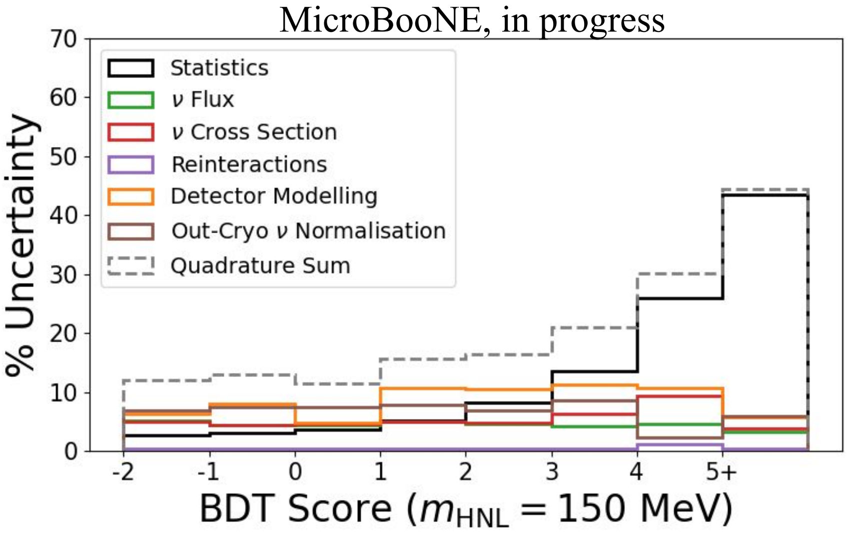
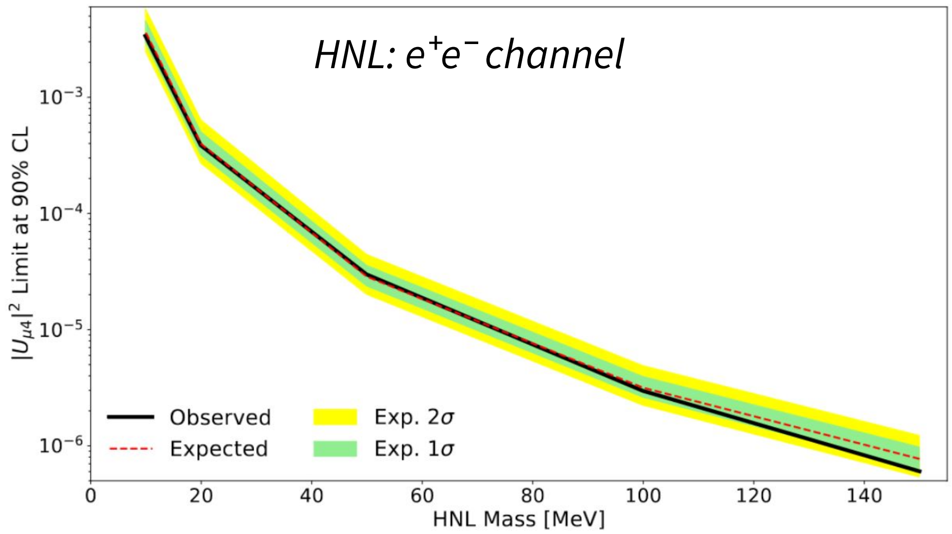
Genie, Flux and reinterations	N	N/A	$\boxed{\text{N}}$	Poisson

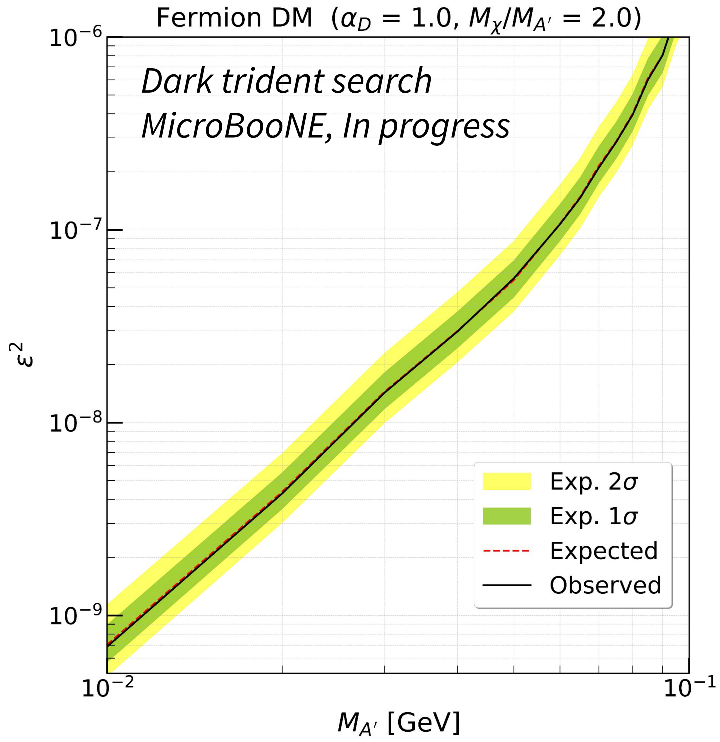
- We also tried these as histosys and correlate them



Upper limits: asymptotic

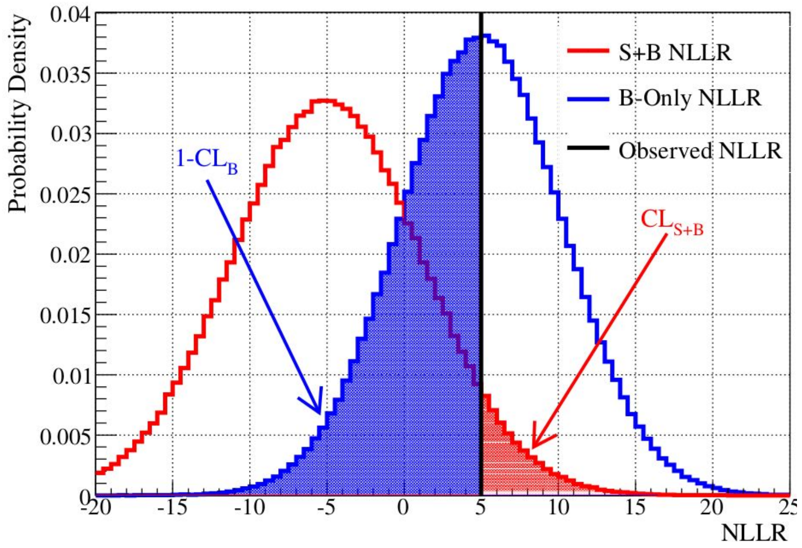
- We calculate 90% CLs upper limits with the method: **pyhf.infer.intervals.upper_limits.upper_limit()**
- The process is repeated for different parameter combinations depending on the model





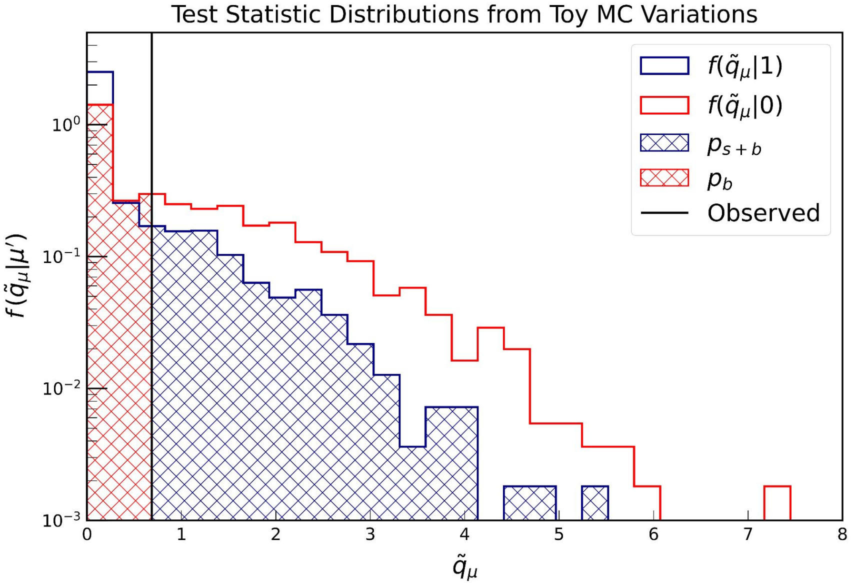
Comparison: COLLIE

- COLLIE is a C++/ROOT package built within the D0 collaboration (no longer maintained)
- Goal is similar to pyhf: Provide a framework for statistical modelling and inference
- **Only NLLR (t_mu)**
- Only toy-based calculations
- Results obtained are comparable to the ones we obtained with pyhf (~10%)



Upper limits: Toy-based

- In both analysis we also cross checked the limits obtained from the asymptotic approach with the limites obtained using toys. This was done only for one mass point
- We used 2000 toys and then we calculated the limits “by hand”
- The results agree with those from the asymptotic method within 5%



Is there a quick pyhf-way to plot the respective asymptotic functions for qtilde?

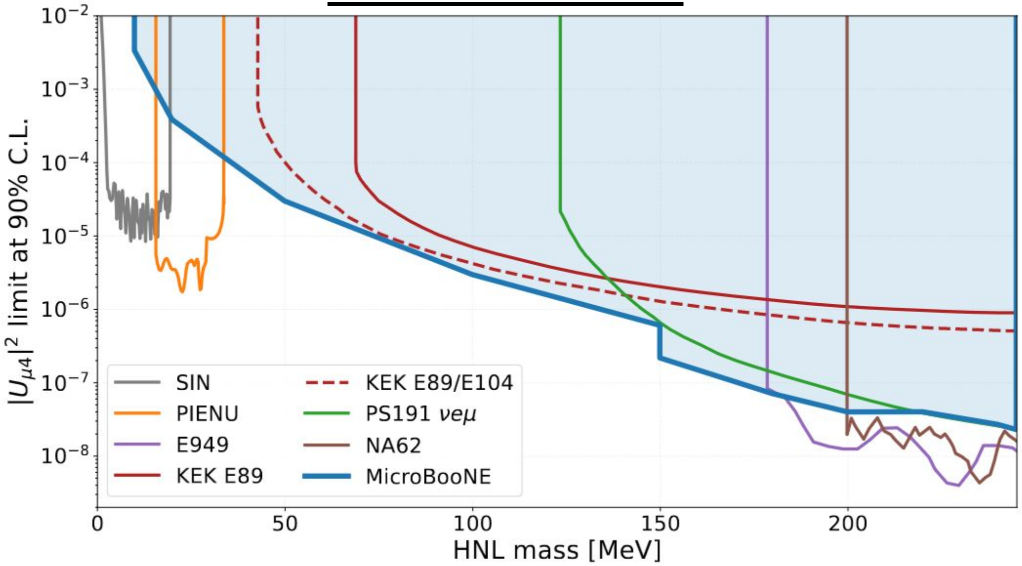
Conclusions

- Pyhf has been used in recent BSM searches in MicroBooNE
- We recently published a new HNL search (accepted by PRL), which is the first MicroBooNE analysis using pyhf
- Our dark trident search also uses pyhf, and will be public soon (stay tuned!)

Things we like:

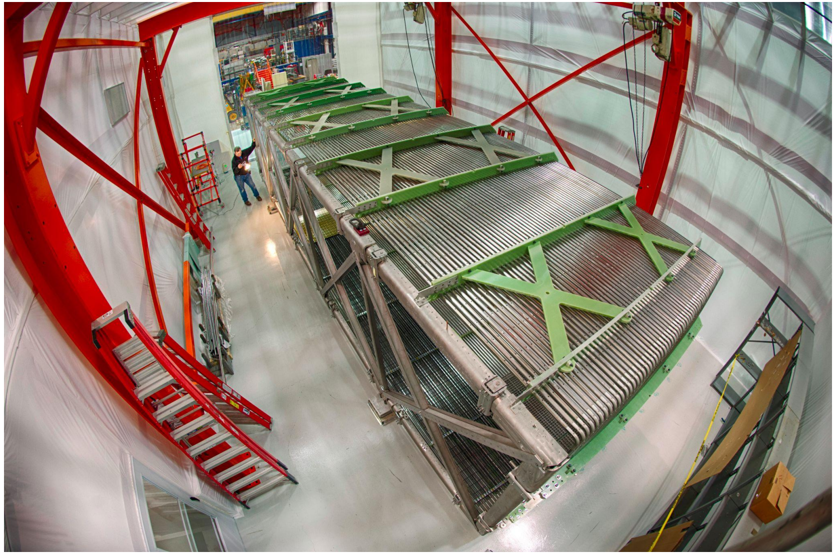
- Good synergy with other python packages: XGBoost, Pytorch
- Flexibility to construct models and store them
- Allows different uncert correlations and test statistics

arXiv:2310.07660v1



Thanks for your attention!

Appendix: The MicroBooNE detector



Appendix: MicroBooNE data