Convolutional Neural Networks for Pulse Shape Discrimination in Liquid Argon

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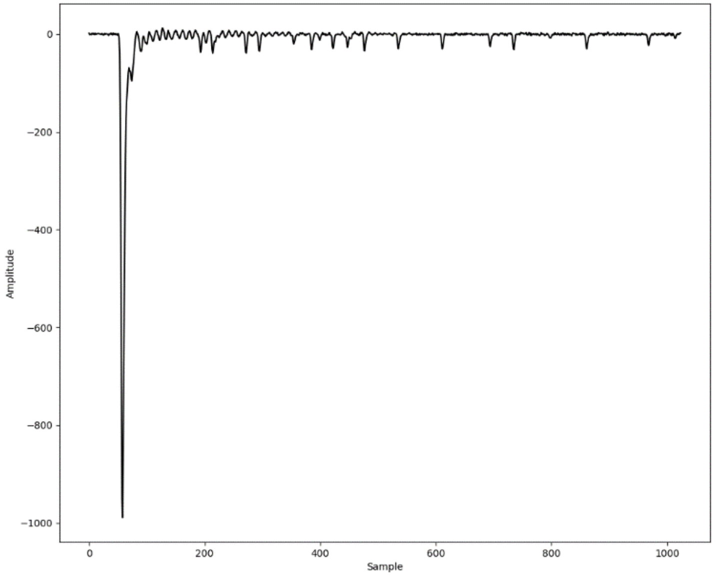
NPML Lightning Talks
June 17th, 2020

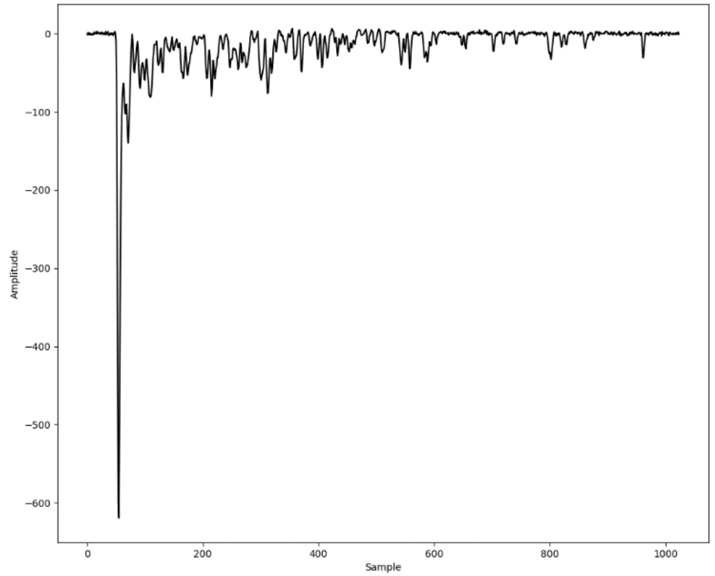
Liquid Ar Scintillators

- Bright scintillator (40 photons/keVee)
- Well-known nuclear quenching factor
- Emission timescales:
  - 6 ns (singlet)
  - 1.6 μs (triplet)
- Electron recoils (ER) and nuclear recoils (NR) yield different ratio in exited state populations -> **Pulse Shape Discrimination** (PSD)
- Scintillation light wavelength: **128 nm** (requires wavelength shifting)
- Benefit of using liquid noble gas – **Scalability**
- LAr detectors used for neutrino beams, dark matter, **coherent elastic neutrino-nucleus scattering (CEvNS).**

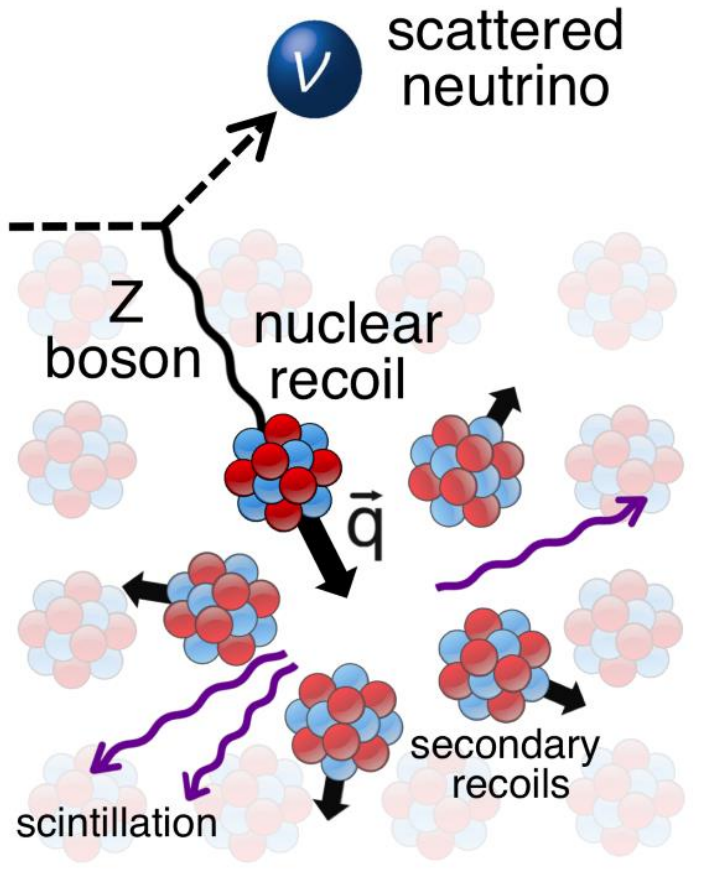
Nuclear Recoil



e^- / γ



Coherent Elastic Neutrino-Nucleus Scattering

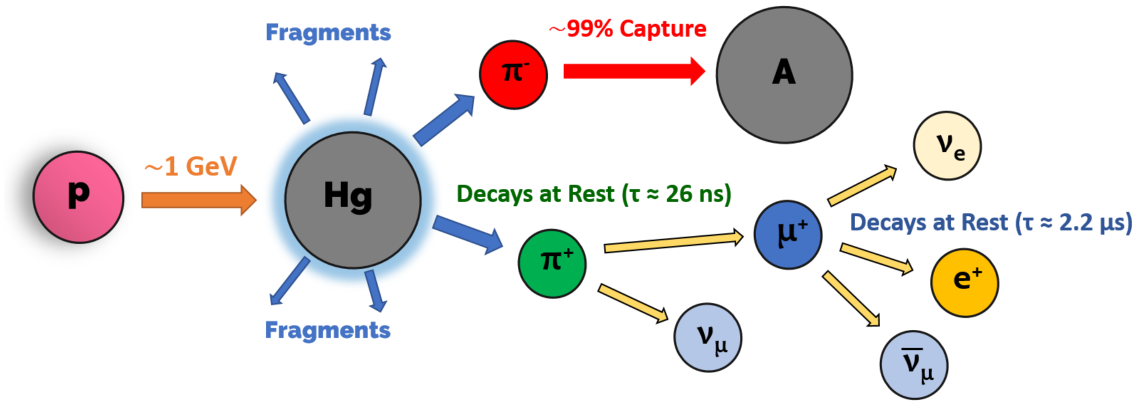


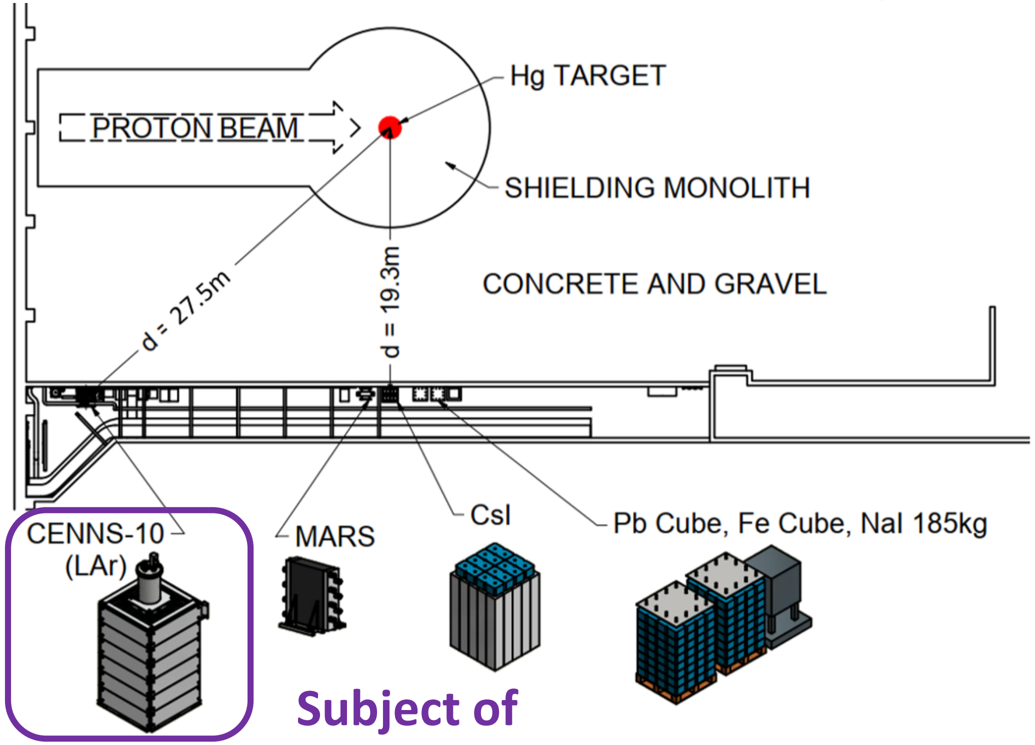
Cross section may be high, but the signal is in the form of a low-energy nuclear recoil!

$$\sigma_{tot} = \frac{G_F^2 E_\nu^2}{4\pi}\left[Z\left(1-4\sin^2\theta_W\right)-N\right]^2 F^2(Q^2)$$

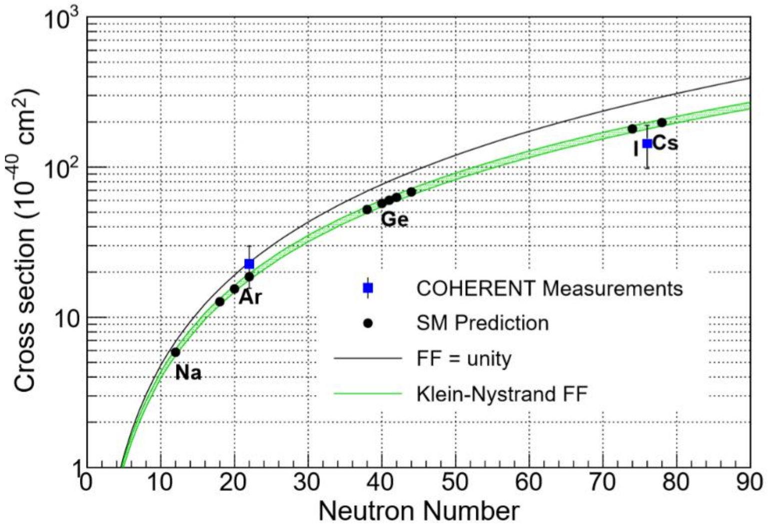
- Clean prediction from the Standard Model – D. Freedman 1974
- Cross-section increases with energy as long as coherence condition is satisfied ($q \leq \sim R^{-1}$)
- Largest of all SM neutrino cross-sections at 1-100 MeV scale
- NC mediated: all flavors of neutrino can scatter via CEνNS
- **Sensitive Standard Model Probe**
- **Applications: Dark Matter Experiments, Supernovae, Monitoring**

COHERENT at the SNS





Subject of This Talk!



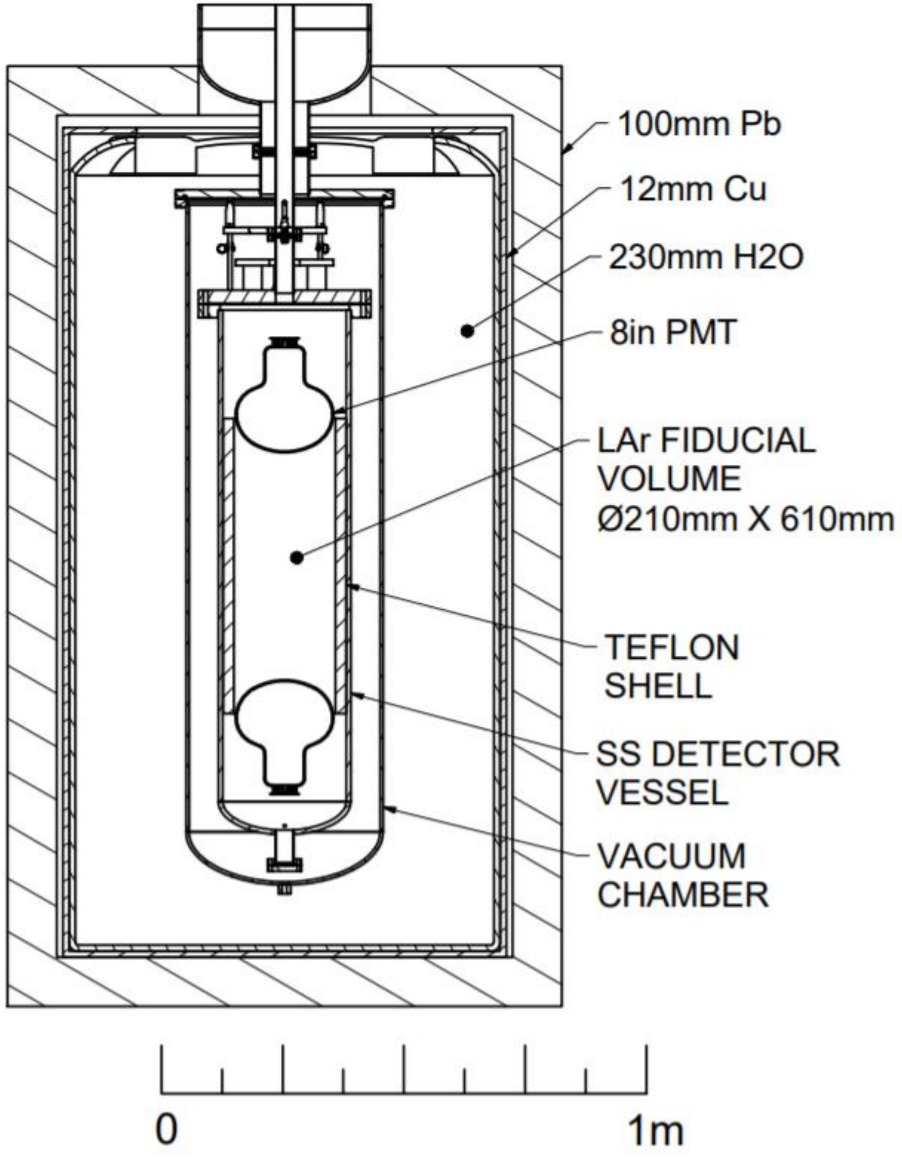
Staged approach: ***Observation -> Precision***

- Spallation Neutron Source (SNS):
  - **1.4 MW** pulsed 1 GeV proton beam on Hg target
  - Pulsed at 60 Hz with 400 ns FWHM
  - Pion decay-at-rest (DAR) neutrino source.
- Detectors located between 20-30 m from target in neutron quiet basement corridor (Neutrino Alley).
- Multiple detectors currently operating measuring either CEvNS or backgrounds.

CENNS-10

- Loaned from J. Yoo *et al* from Fermilab.
- Single-phase liquid Ar scintillation detector located 28 m from SNS target (~2 x 10^7 ν / s)
- **Engineering Run:** Dec 2016 -> May 2017
  - 80 keVnr threshold
  - No Pb shielding
  - Analysis Results -> Phys. Rev. D100 (2019) no. 11, 115020
- **First Production Run:** July 2017 -> December 2018
  - Dramatically improved light yield results in lower threshold (20 keVnr)
  - 2x 8" Hamamatsu PMTs with 18% eff @ 400 nm
  - Tetraphenyl butadiene (TPB) wavelength shifter coating Teflon walls and PMT glass.
  - 24 kg fiducial volume.

arXiv:*2003.10630*



Event Discrimination

- Use of PoT signal from SNS greatly reduces steady-state backgrounds, BUT 1 Hz/kg of ^{39}Ar events still a large background:

Data Events	3752
Fit CEvNS	159 ± 43 (stat.) ± 14 (syst.)
Fit Beam Related Neutrons	553 ± 34
Fit Beam Unrelated Background	3131 ± 23
Fit Late Beam Related Neutrons	10 ± 11
2Δ(-lnL)	15.0
Null Rejection Significance	3.5σ (stat. + syst.)

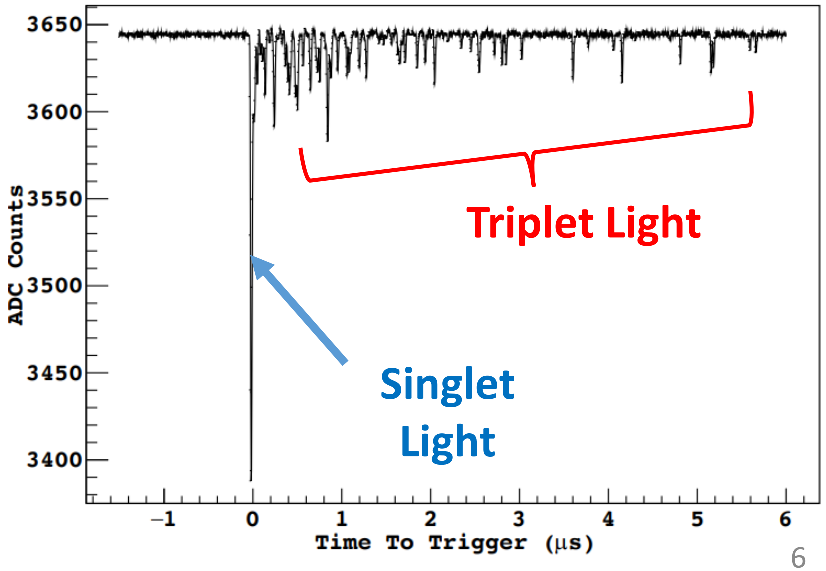
Analysis A Fit Results

- Standard PSD technique for Ar scintillation is ratio of integral in first 90 ns to total integral (F90)

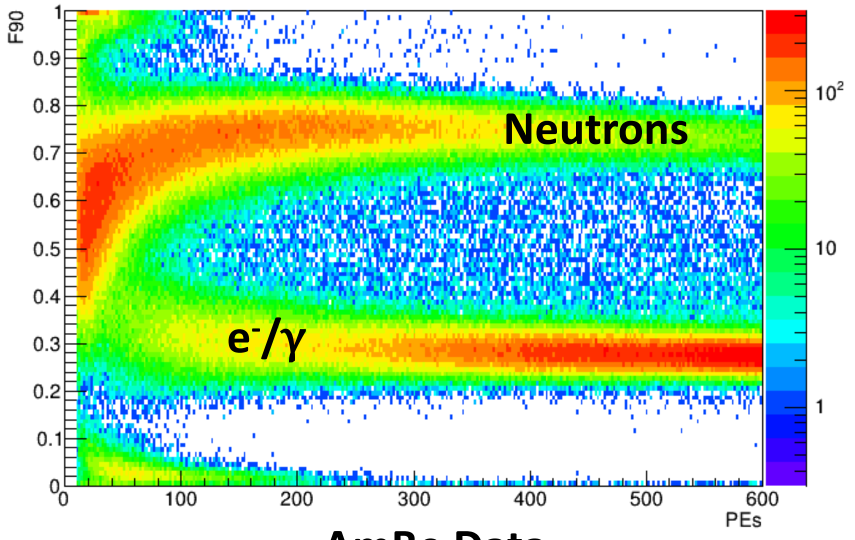
- Potential issues near threshold:
  - Discrete photon pulses widen dispersion of band.
  - Value of F90 much more susceptible to fluctuations.

- Can we use more (all) waveform information?

Example waveform



Total PEs vs F90



AmBe Data

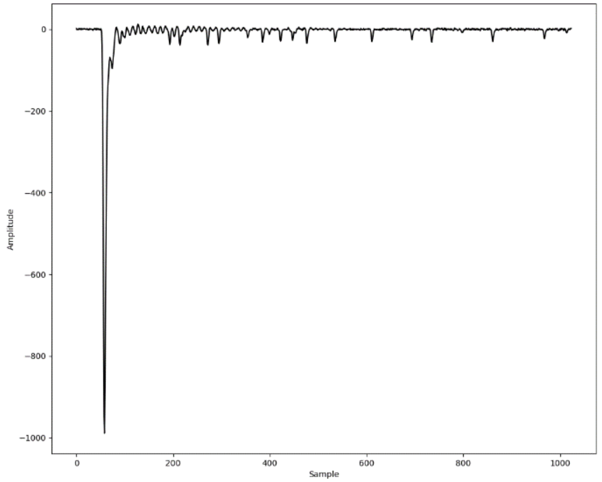
Applying a 2D CNN

- Convolutional neural networks typically work on 2-d images; but there is some support for 1d neural network in pyKeras.
- Relative paucity of 1D examples, so first attempt works on 2D images of waveforms instead.
- Recurrence plots are often used to visualize periodic features in N-dimensional phase spaces.

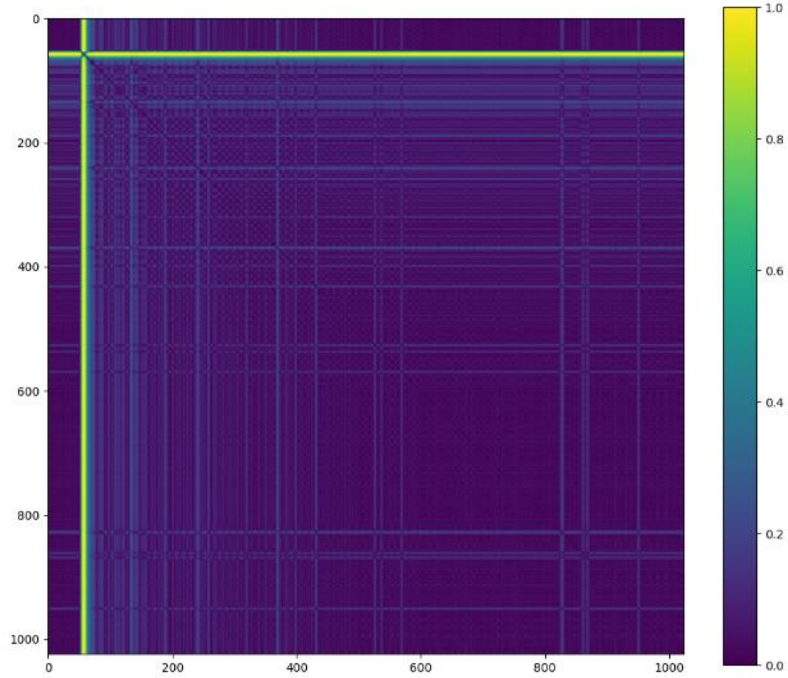
$$R(i,j) \quad = \|\vec{x}(i) - \vec{x}(j)\|$$

- Distance is limited to some number of gradations which in the following instances is set to 128.
- Due to large size of peak w.r.t. other samples, square root of distance was used instead.

Waveform

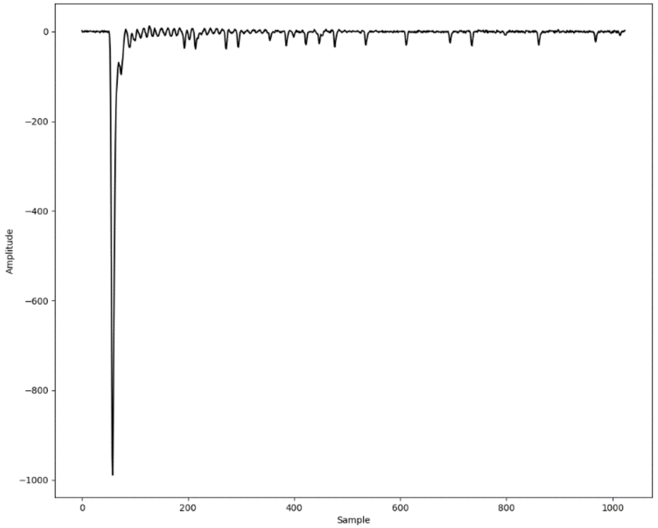


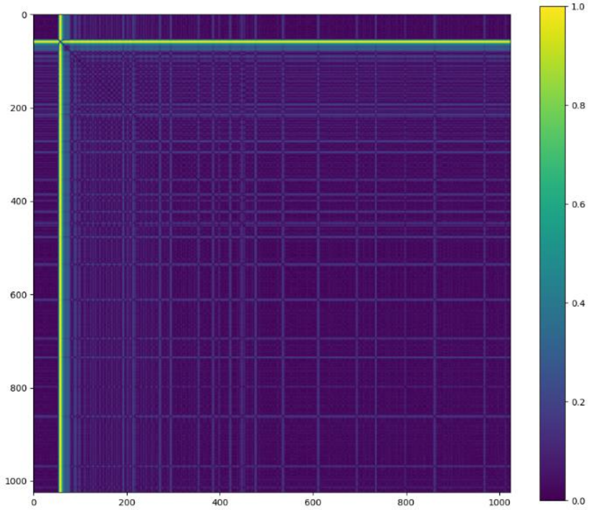
Recurrence Plot



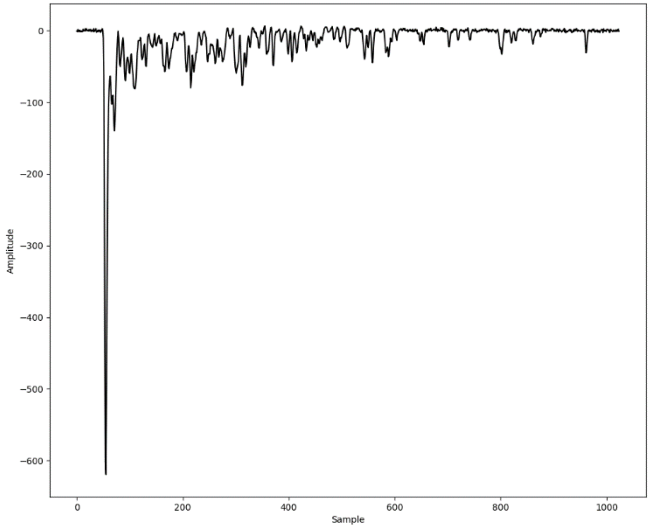
Creating Waveform Images

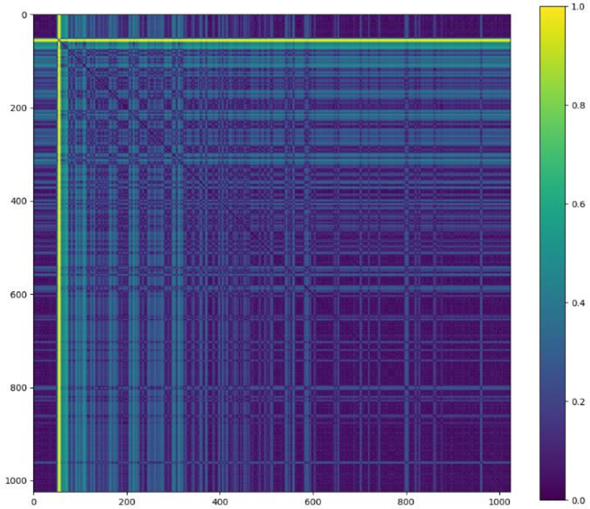
NR





ER





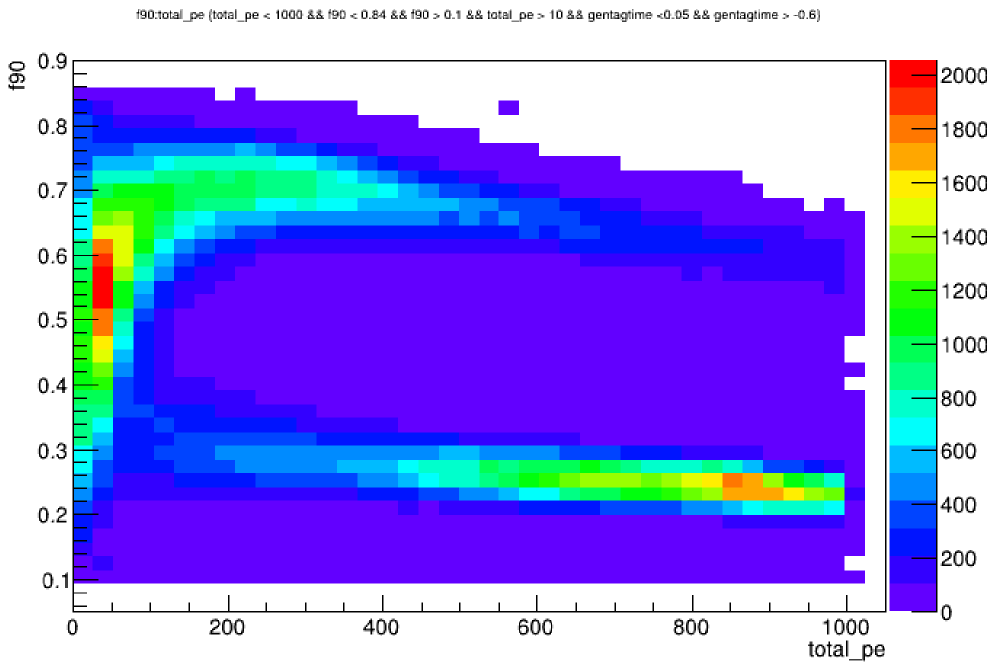
Training the Network

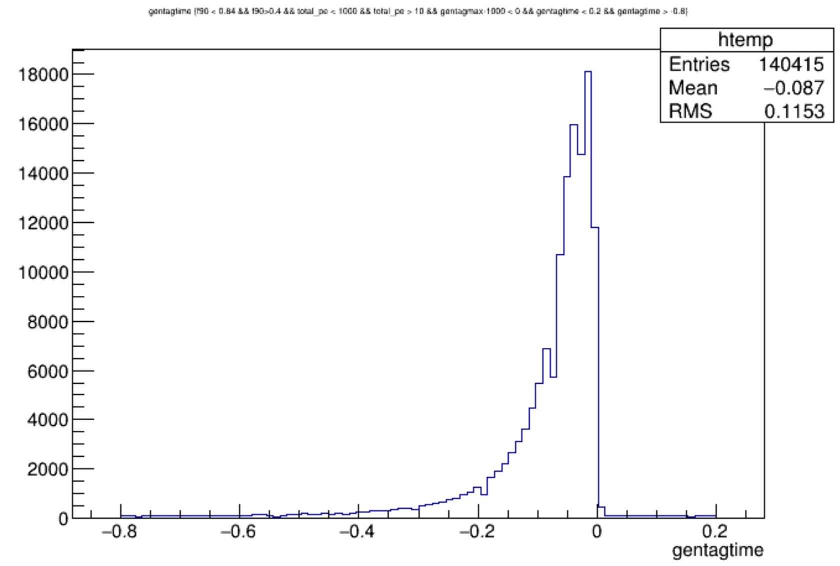
- Time-tagged DT data makes for an excellent source of NR waveforms with little accidentally contamination form ER band.
- Selection criteria for training samples:

  NR
  - 20 < NPE < 600
  - 0.4 < F90 < 0.81
  - -0.6 < Tag Time < 0.1

  ER
  - 40 < NPE < 600
  - 0.15 < F90 < 0.4
  - ^{57}Co calibration data

- Approximately 1e5 events for both event samples.





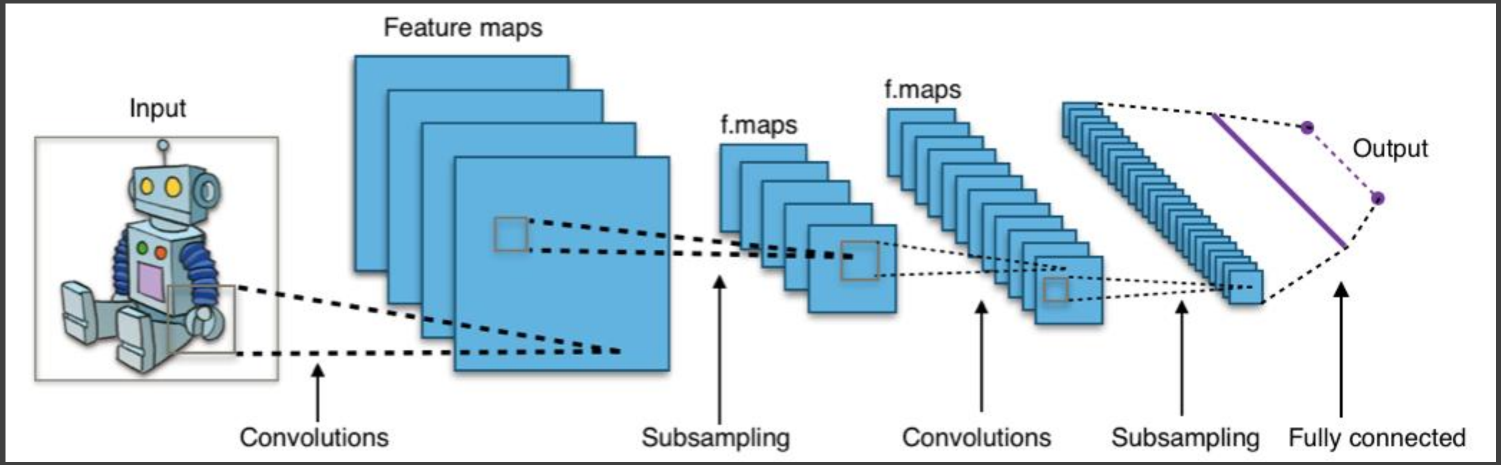
Training the Network

- Event waveforms are truncated to 1024 samples, and then down sampled twice to yield an array of 256 samples.

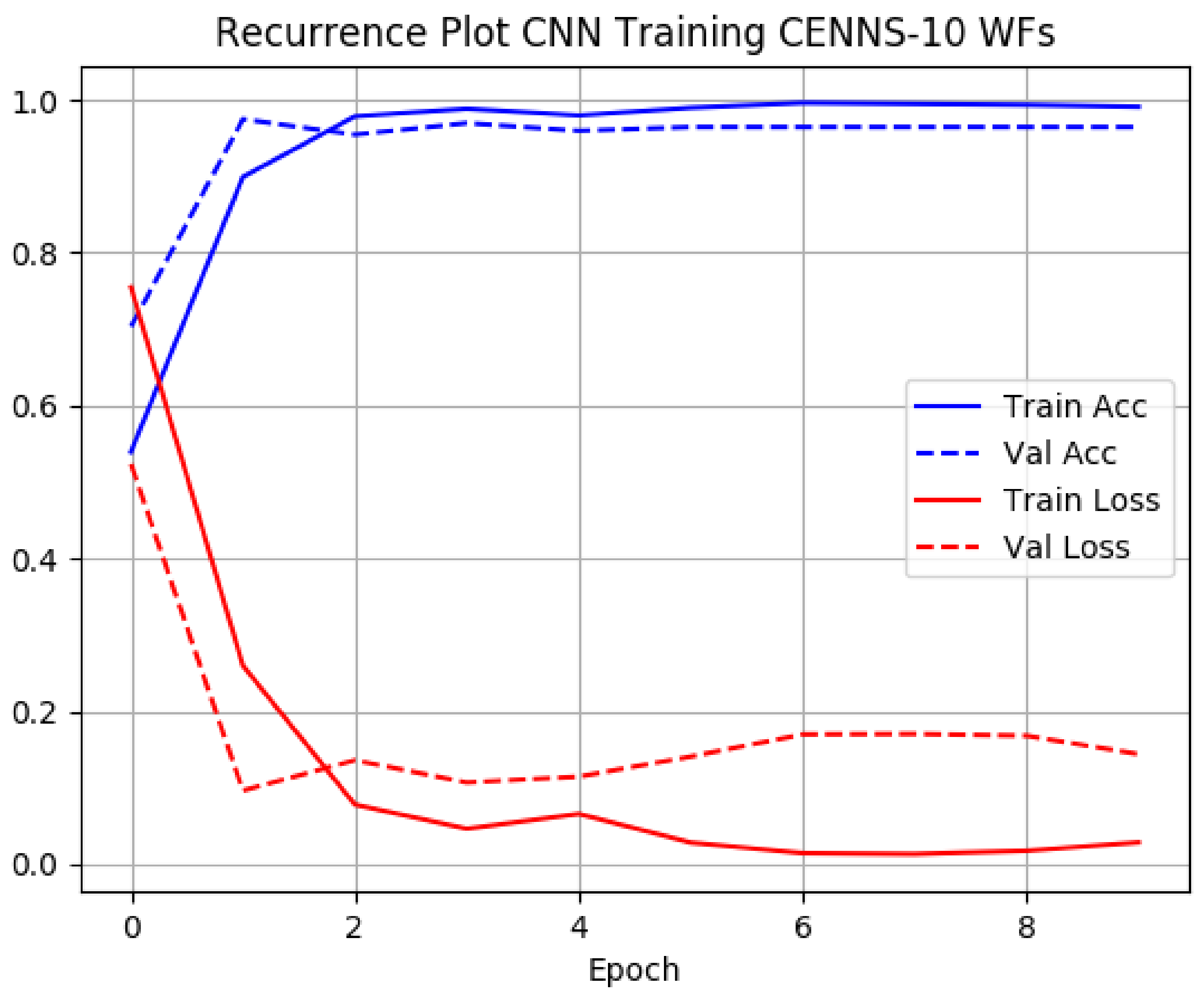
- Recurrence map then generated which has shape (256,256), which is fed to the CNN.

```
initializer = initializers.glorot_normal()

model = Sequential()
model.add(Conv2D(64,kernel_size=(3,3),activation='relu',input_shape=(256,256,1)))
model.add(MaxPooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(32,kernel_size=(3,3),activation='relu'))
model.add(Flatten())
model.add(Dense(128,activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(2,activation='sigmoid'))
model.compile(loss="sparse_categorical_crossentropy",optimizer='adam',metrics=['accuracy'])
```



Training the Network

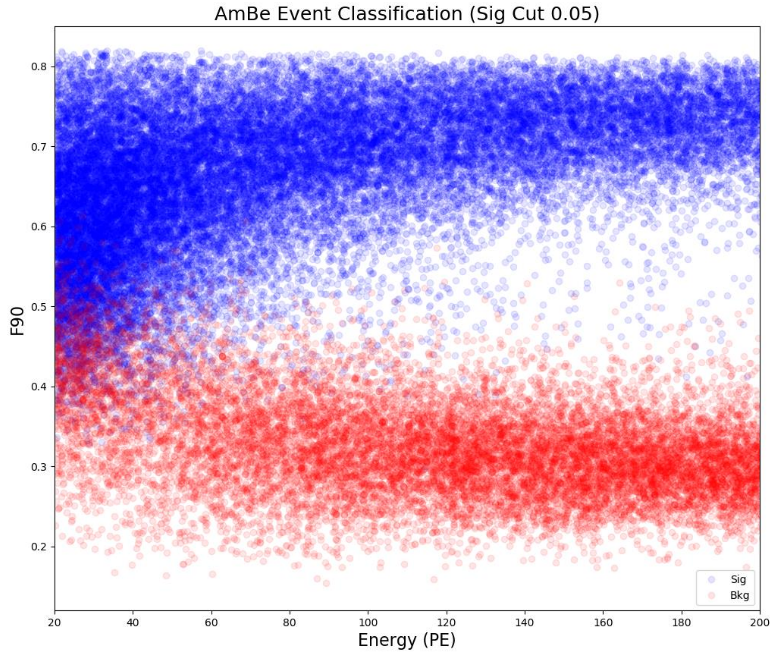


- Few epochs required to train on this dataset.
- Can use model output to classify new data.
- Classification results are either binary class decision (Sig,Bkg)
  OR
- Score for each category (0->1) where summation of scores equals unity.
- Variable used for cuts: Signal Score – Bkg Score (-1->1 with > 0 being signal classification).

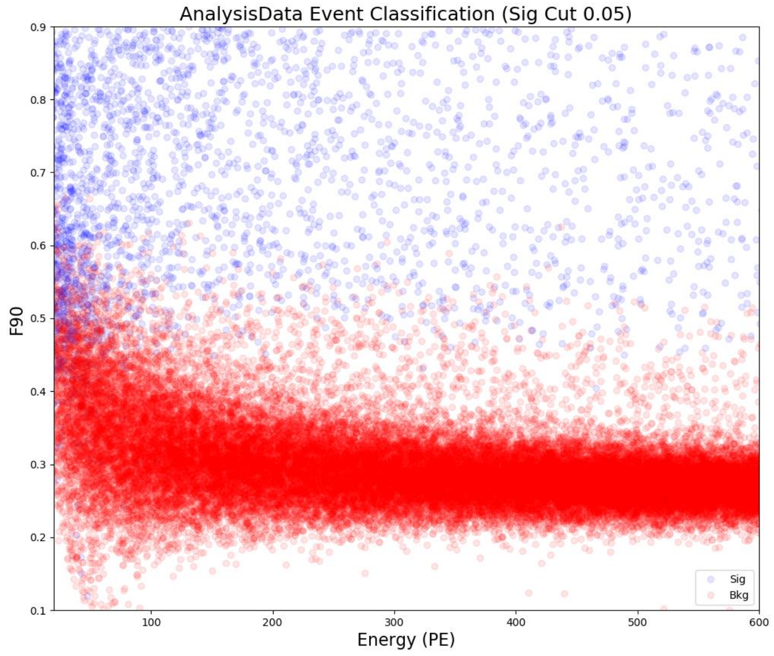
Evaluation on Calibration Data

- **Sig**
- **Bkg**

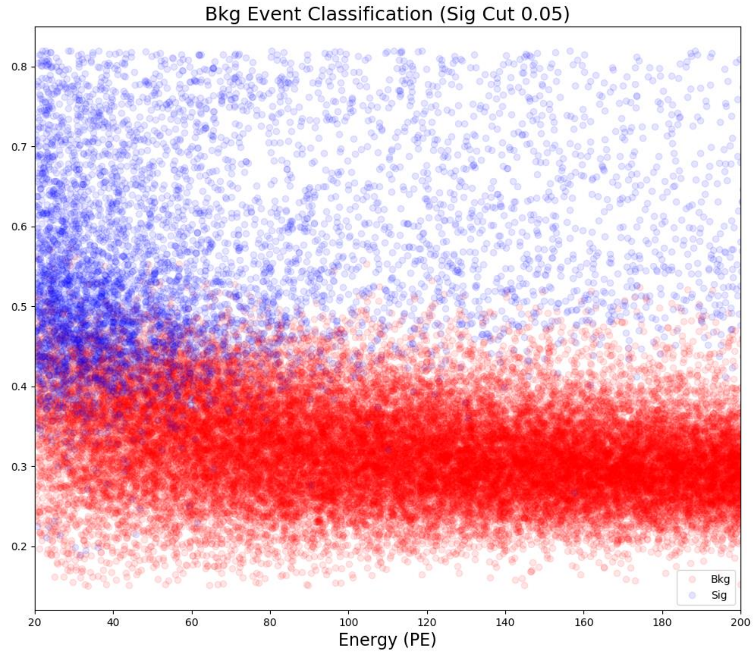
AmBe



Analysis Dataset (Beam OFF)



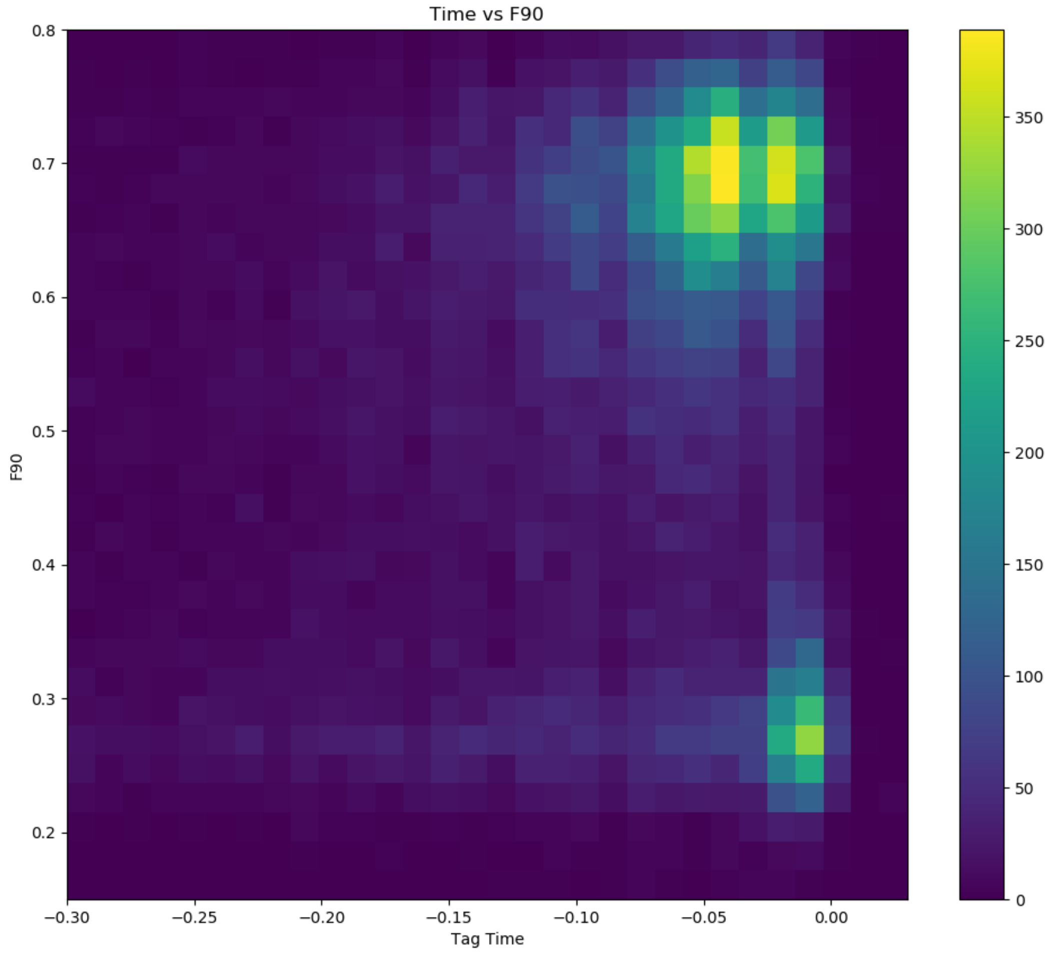
Internally Triggered Bkg



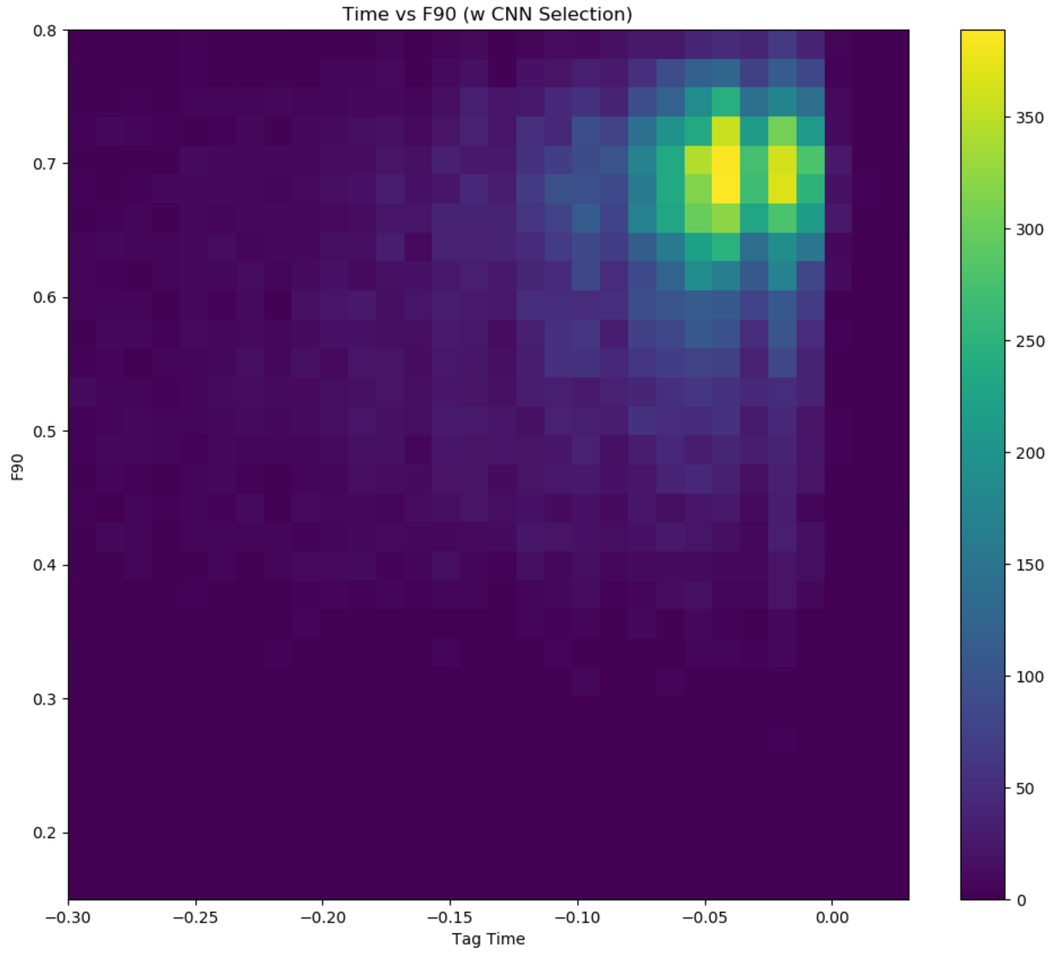
Signal Score – Bkg Score > 0.05

Evaluation on Separate DT Dataset

Tagged Data – No Cut

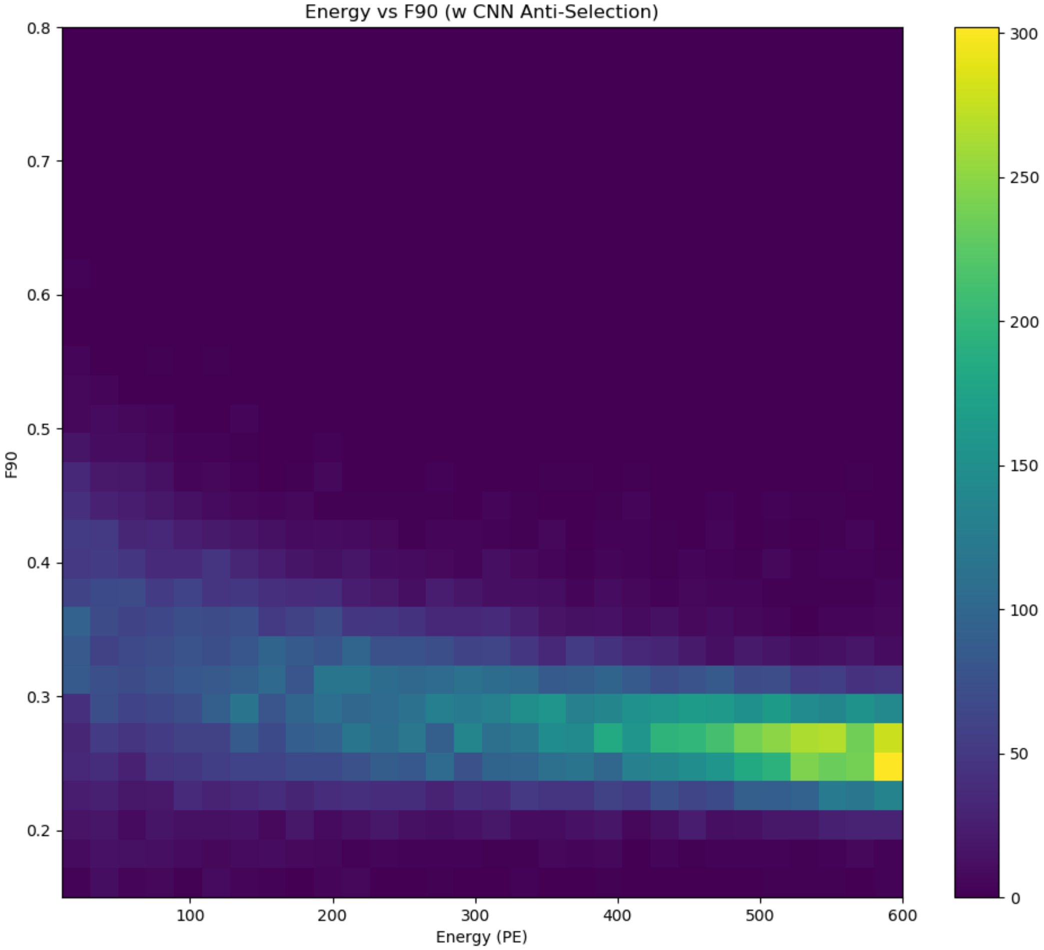


Tagged Data – Score > 0.01

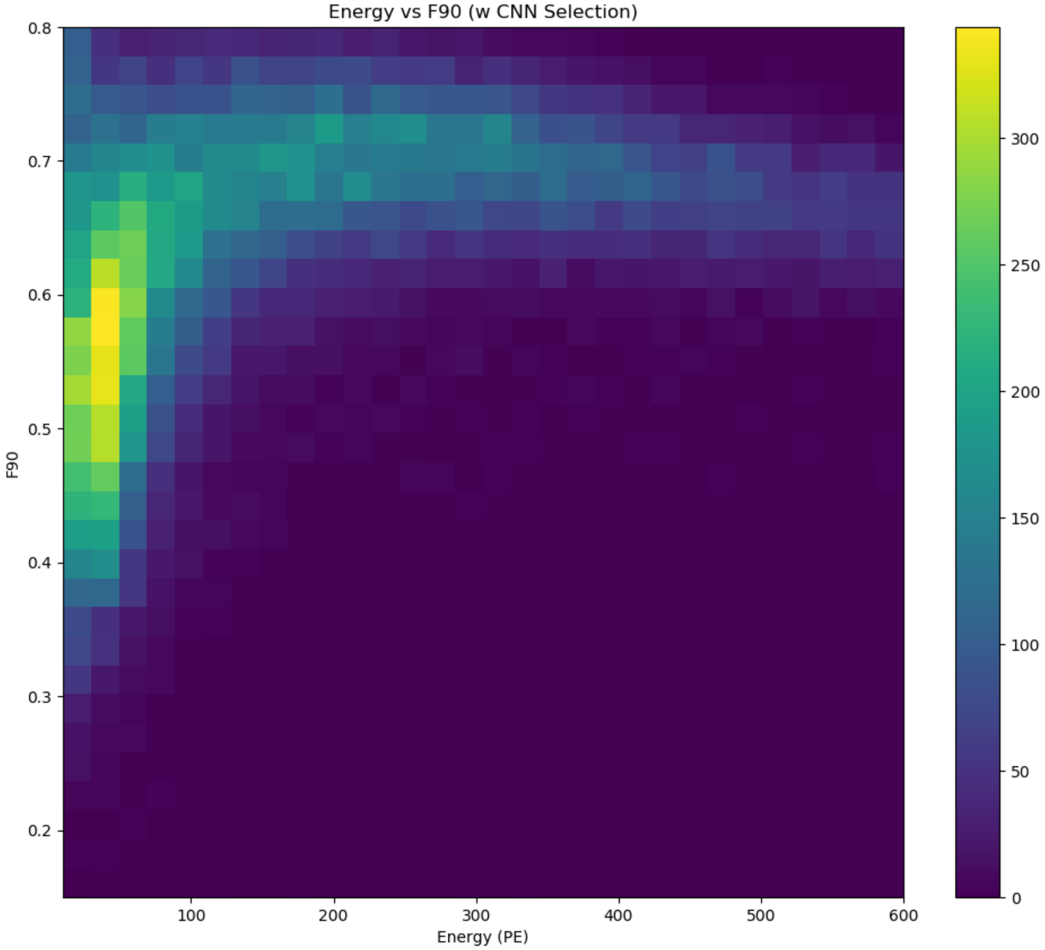


Evaluation on Separate DT Dataset

Bkg Classified

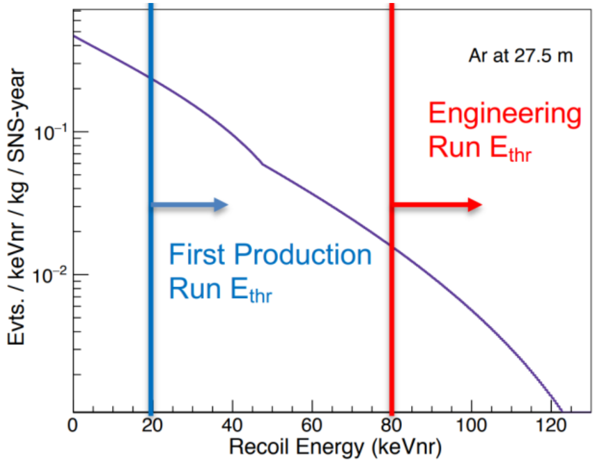


Sig Classified



Summary and Outlook

- Standard PSD methods in LAr scintillation detectors begin to degrade with low photo-statistics.
- Signal spectrum for CEvNS (and other NR signals) is steeply rising at low energy; harsh F90 cuts eliminate potential signal.
- CNN trained using time-tagged DT data is able to distinguish events at low energy without strict cut in F90-space.
- Results are still preliminary; work to be done to see how much this may improve sensitivity of CENNS-10.
- If successful, begin to incorporate ML approaches to other COHERENT subsystems.



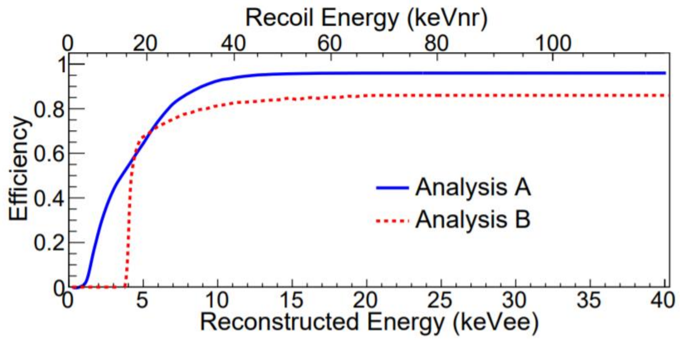
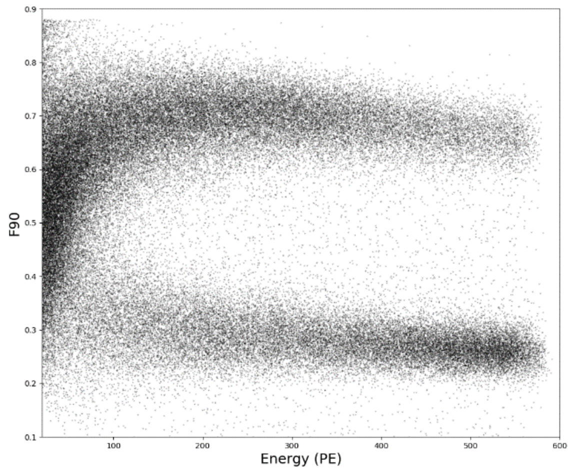
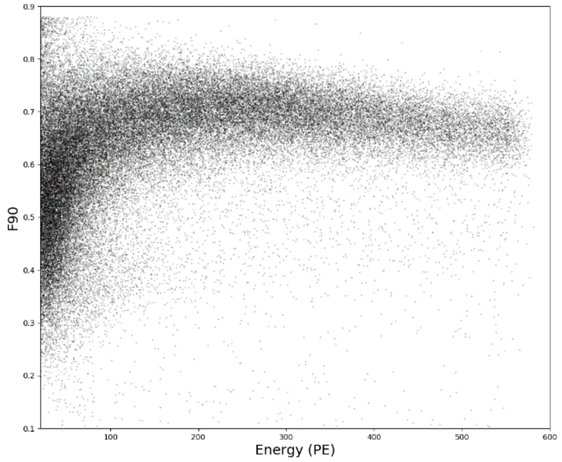


FIG. 3. Energy-dependent reconstruction efficiency estimated for CEvNS events to pass the data selection criteria for each of the two analyses.

DT Data → **CNN Applied**





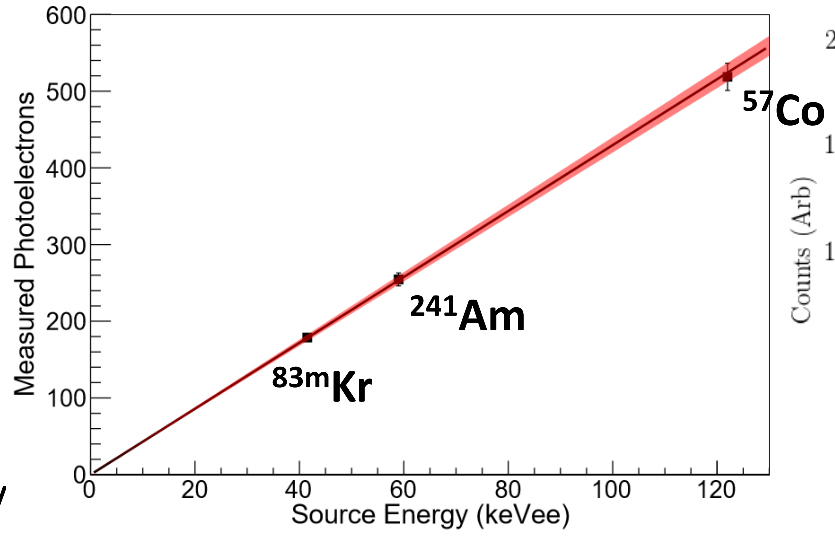
Auxiliary Slides

Calibrations

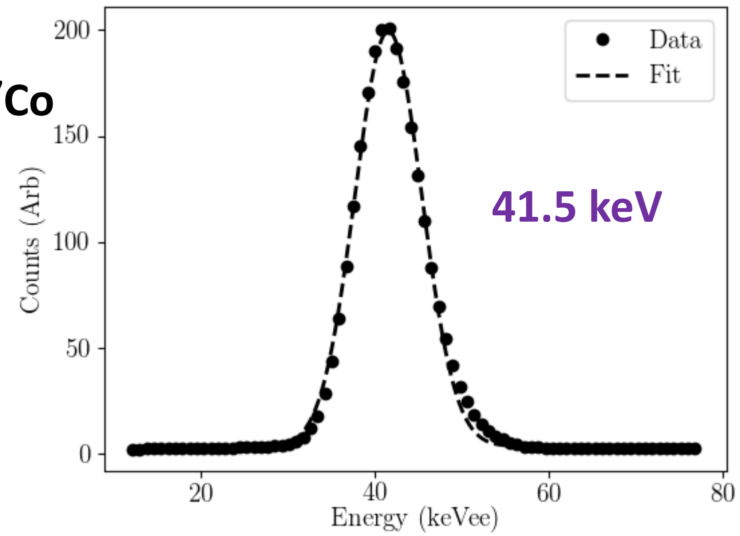
- Calibrations performed using multiple gamma sources (^{57}Co, ^{241}Am, ^{83m}Kr).
- Observed light yield: 4.6 ± 0.4 p.e./keVee
- 9.5% resolution at 41.5 keVee
- Linearity of detector response over energy range of interest.
- Global fit to LAr nuclear quenching data to provide keVnr->keVee conversion.

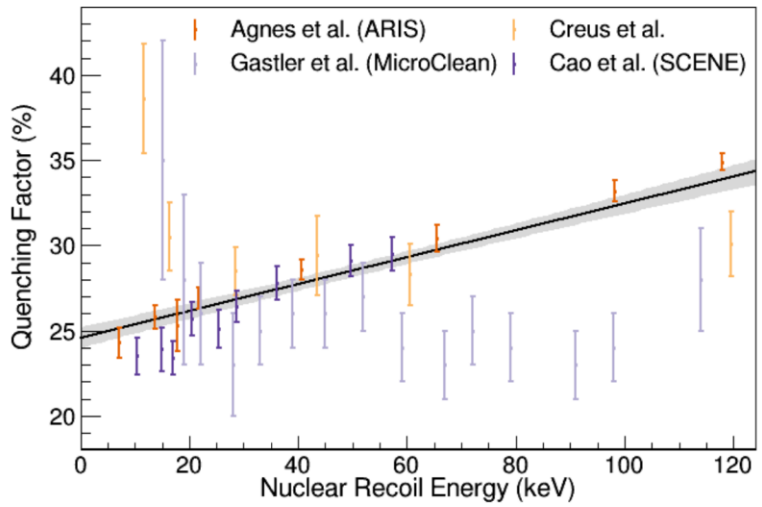
Neutron Calibrations

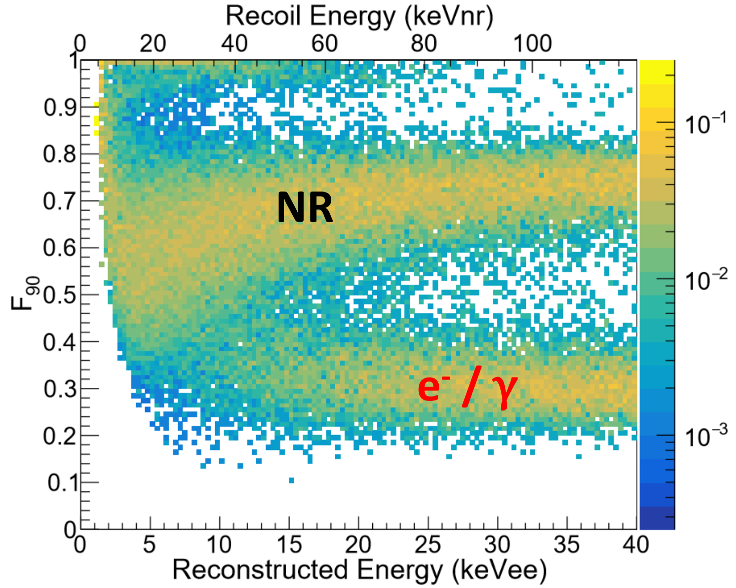
- **AmBe** – Used to measure NR response in detector and model CEvNS signal.
- **DT Generator** – Used to confirm veracity of external neutron simulations



^{83m}Kr Calibration

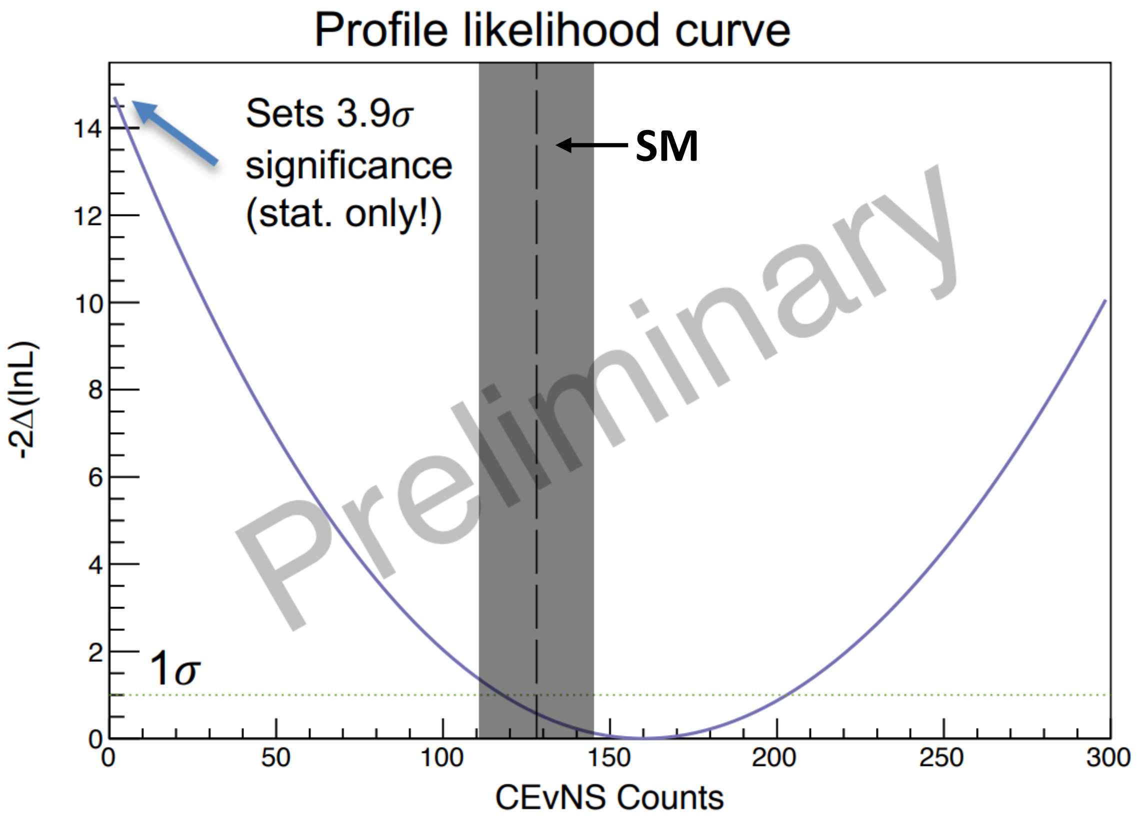






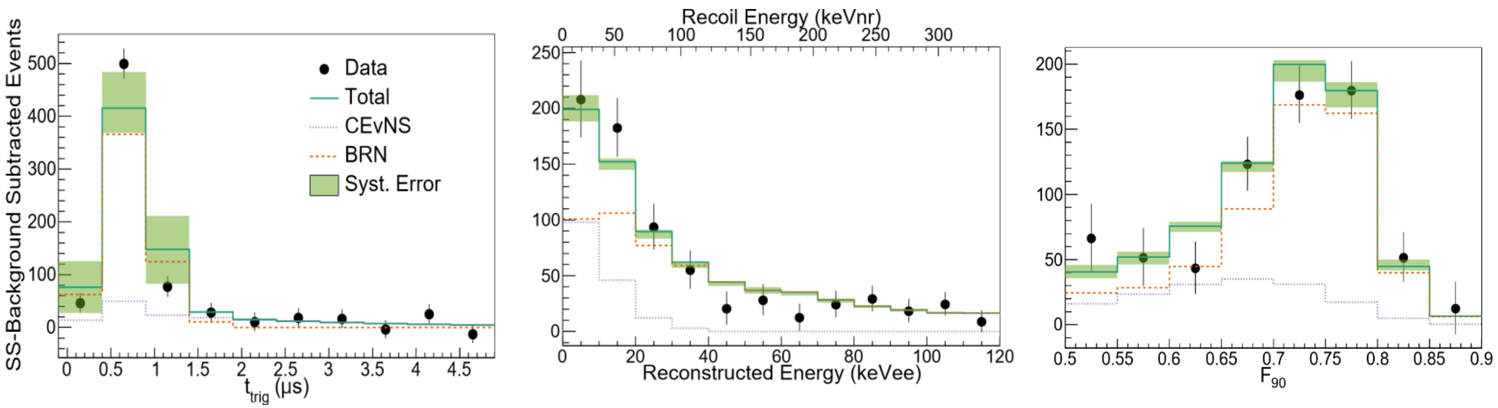
Fit Results

- Best fit for N CEvNS is **159** ± 43 (stat) ± 14 (syst)
- Null hypothesis rejected at 3.9σ (stat only)
- Null hypothesis rejected at **3.5σ** (stat+syst)
- Validity of Wilks' theorem checked with pseudo-data.
- **Result within 1-σ of SM prediction.**

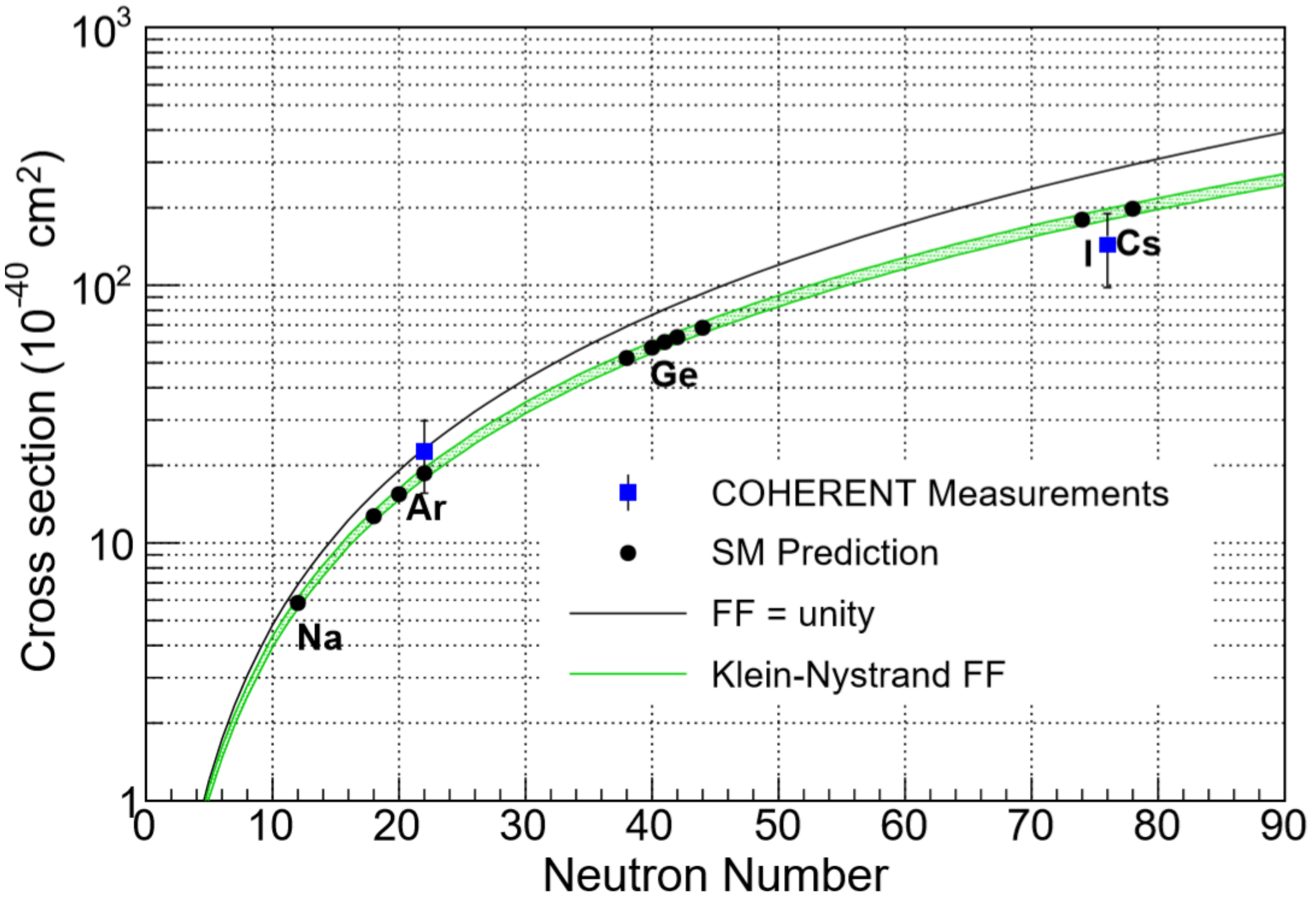


Predicted SM CEvNS	128 ± 17
Predicted Beam Related Neutrons	497 ± 160
Predicted Beam Unrelated Background	3154 ± 25
Predicted Late Beam Related Neutrons	33 ± 33

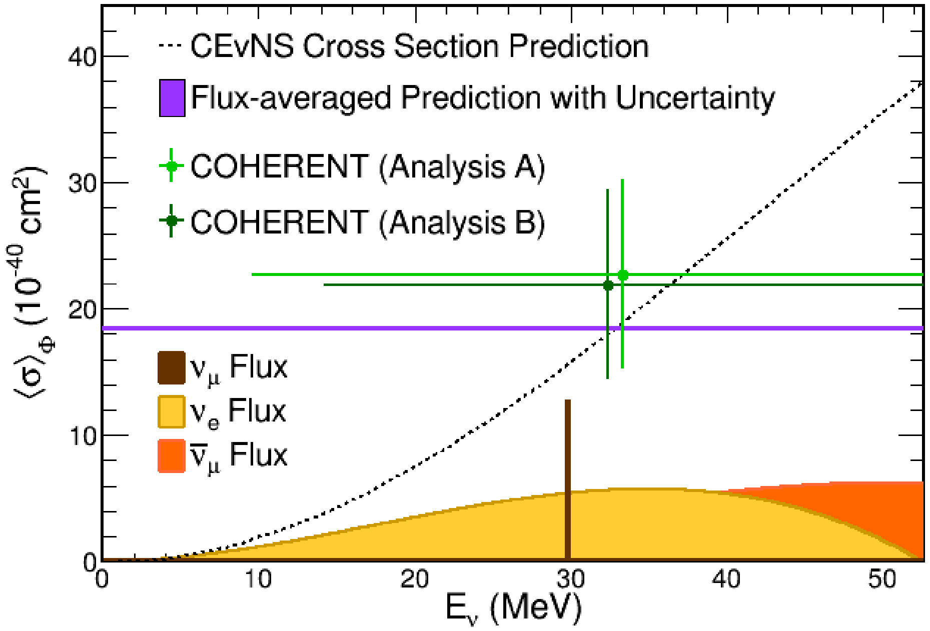
Data Events	3752
Fit CEvNS	159 ± 43 (stat.) ± 14 (syst.)
Fit Beam Related Neutrons	553 ± 34
Fit Beam Unrelated Background	3131 ± 23
Fit Late Beam Related Neutrons	10 ± 11
2Δ(-lnL)	15.0
Null Rejection Significance	3.5σ (stat. + syst.)



CEνNS Cross Section



arXiv:2002.10630; submitted to PRL



- Combine best fit CEvNS counts with flux, fid. volume, efficiency uncertainties.

$$\frac{N_{meas}}{N_{SM}} = 1.2 \pm 0.4$$

- Obtain flux-averaged cross section:

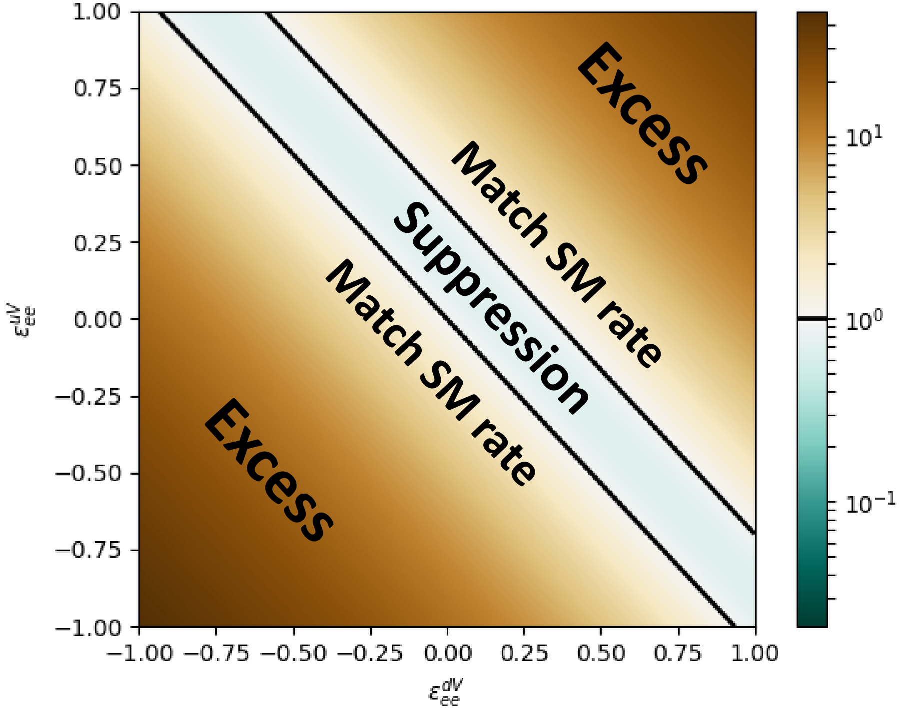
$$\sigma_{meas} = \frac{N_{meas}}{N_s \phi \epsilon} = (2.3 \pm 0.7) \times 10^{-39}\ cm^2$$

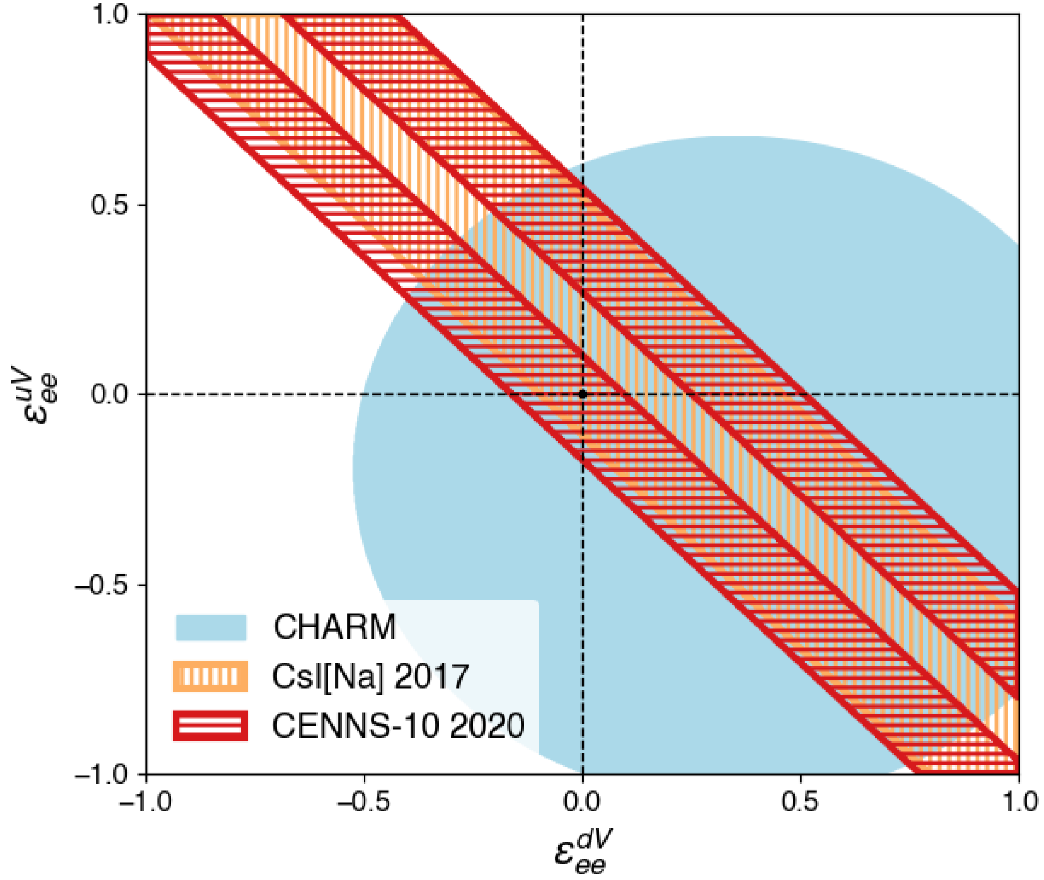
stat dominated

Constraints on Non-Std Interactions

Modified Cross Section

$$Q_W^2 \to Q_{\rm NSI}^2 = 4\left[N\left(-\frac{1}{2} + \epsilon_{ee}^{uV} + 2\epsilon_{ee}^{dV}\right) + Z\left(\frac{1}{2} - 2\sin^2\theta_W + 2\epsilon_{ee}^{uV} + \epsilon_{ee}^{dV}\right)\right]^2 + 4\left[N(\epsilon_{e\tau}^{uV} + 2\epsilon_{e\tau}^{dV}) + Z(2\epsilon_{e\tau}^{uV} + \epsilon_{e\tau}^{dV})\right]^2 .$$

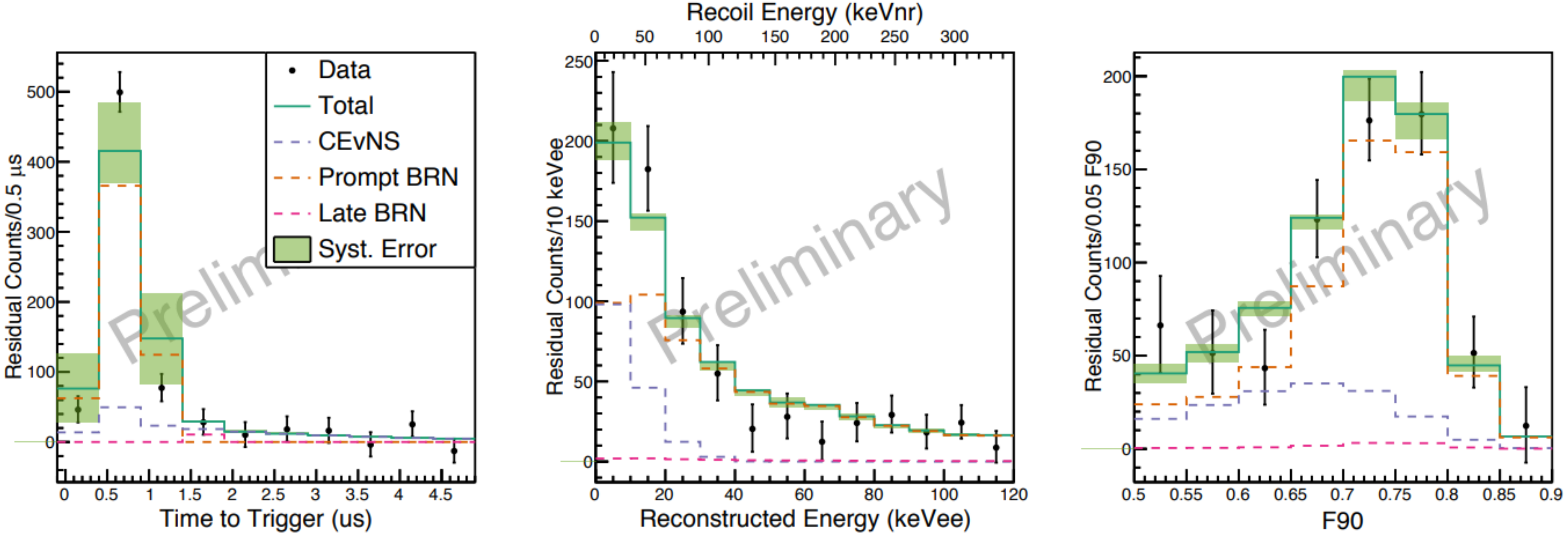




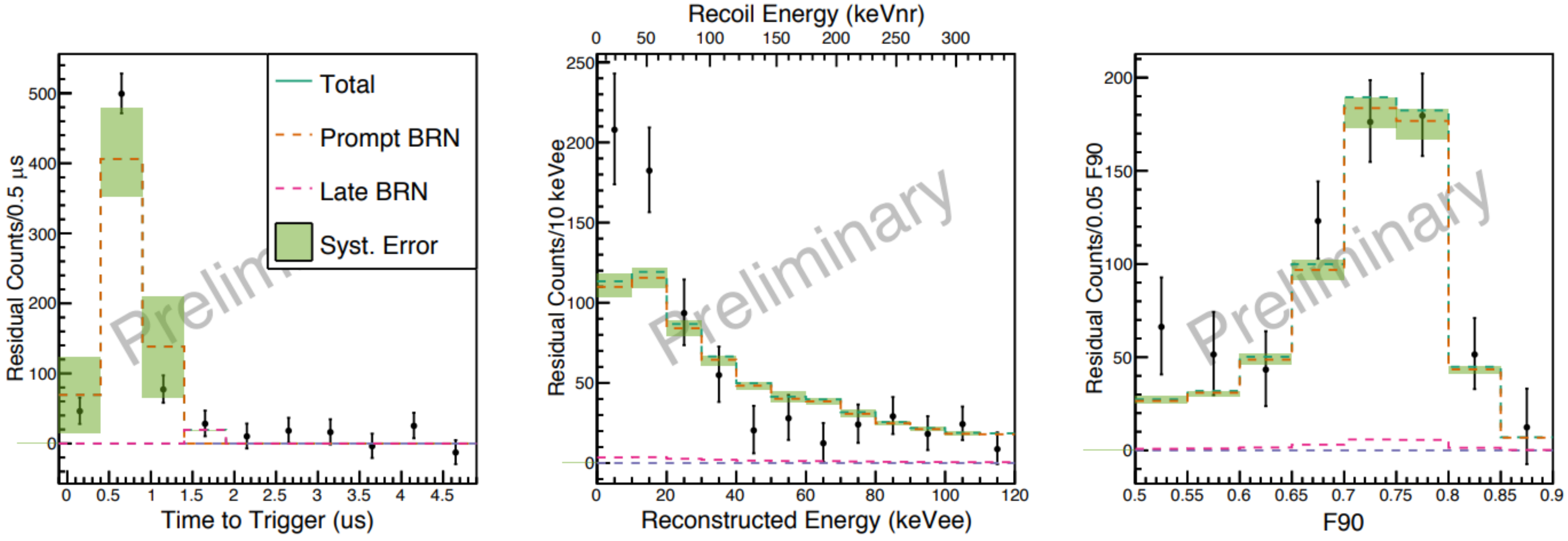
J. Barranco *et al*. Phys Rev D **76** (2007)
J. Billard, J. Johnston, B. Kavanagh. arXiv:1805.01798

Fit Projections

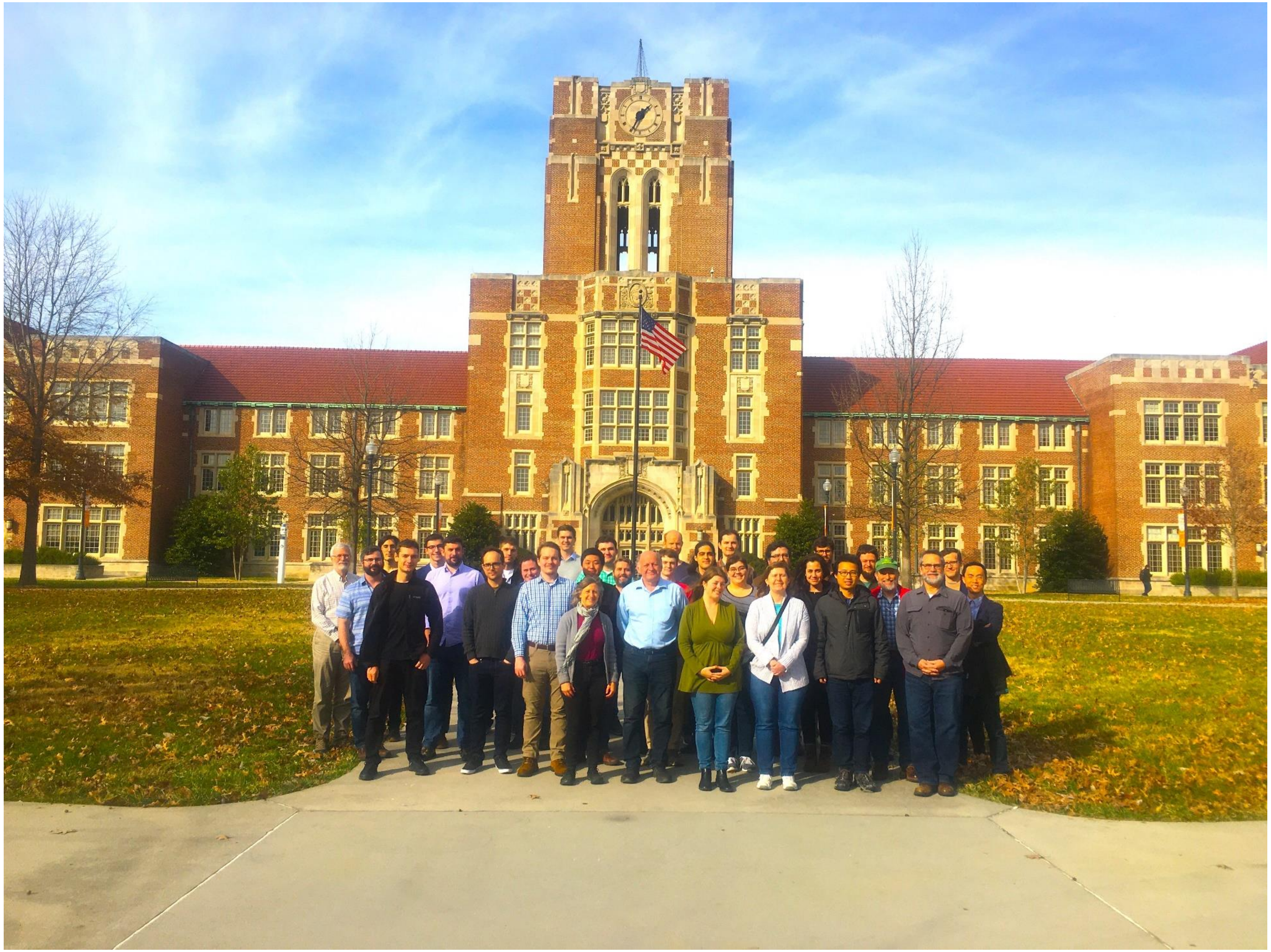
Best Fit 1-D Projections



Best Fit 1-D Projections with CEvNS = 0



The COHERENT Collaboration



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