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Title: Bias Identification in Nuclear Data Measurements for Experiment Design

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Intended for: Internal presentations as well as presentations to Noah's university

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Bias Identification in Nuclear Data Measurements for Experiment Design

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08/10/23

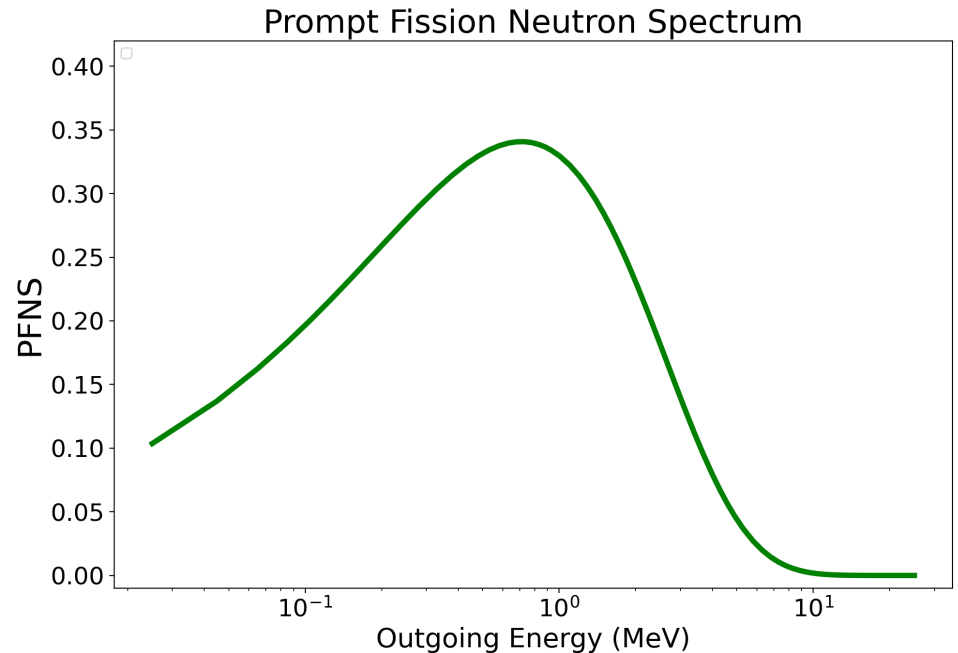
Noah Walton (CCS-6, XCP-5, and UTK)

- Education
 - BS Nuclear Engineering, 2020, University of Tennessee
 - PhD Nuclear Engineering, 2024, University of Tennessee
- Computer, Computational, & Statistical Sciences Division
 - CCS-6, Mentor: Mike Grosskopf
- X Computational Physics Division
 - XCP-5, Mentor: Denise Neudecker
- Summer project: Bias identification in nuclear data measurements
- PhD: Cross section evaluation for reproducibility, reliability, and uncertainty quantification in the resolved resonance region



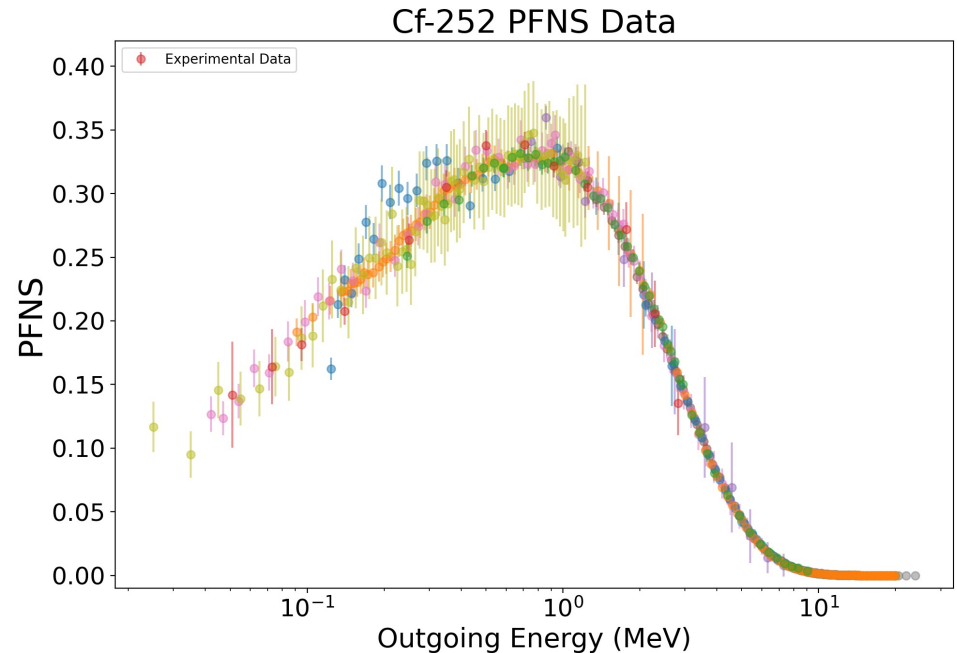
The Prompt Fission Neutron Spectrum (PFNS) is an important nuclear data quantity

- Gives the distribution of neutrons emitted promptly from fission as a function of outgoing neutron energy



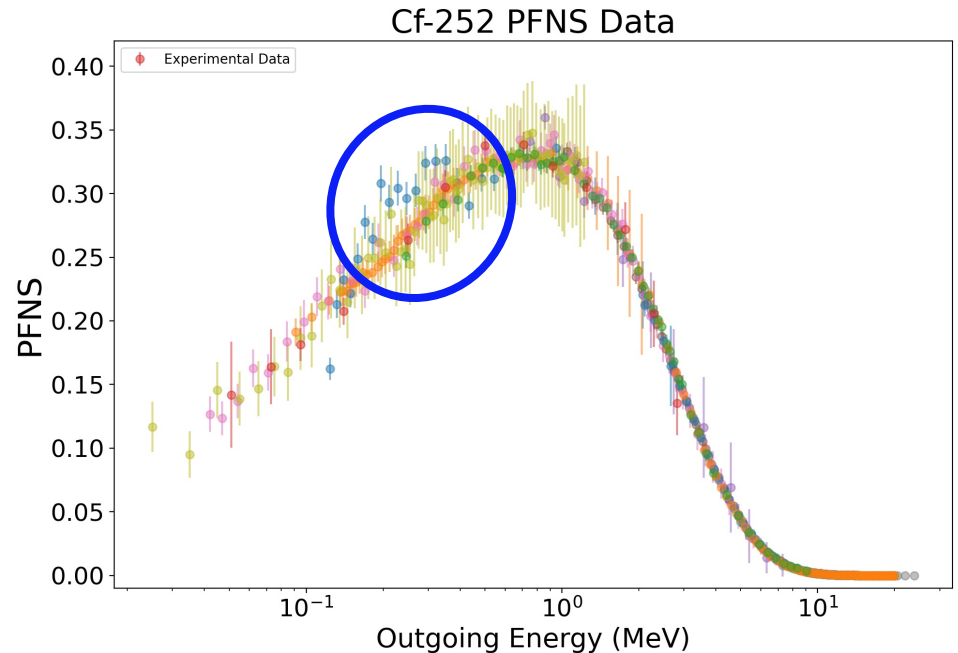
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- It is not that pretty!
 - noisy, uncertain, and biased/discrepant measurement data



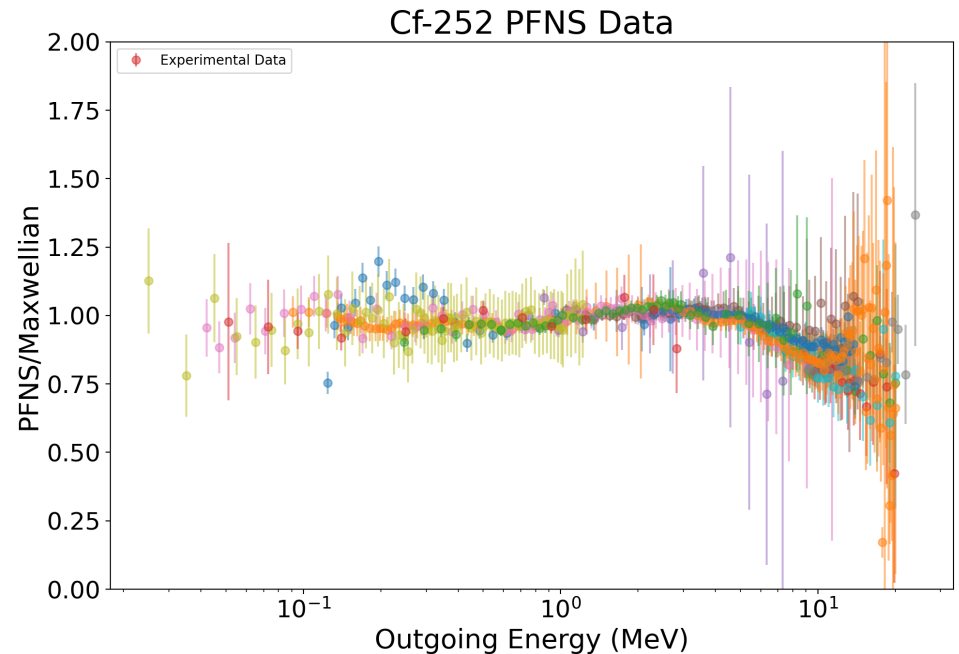
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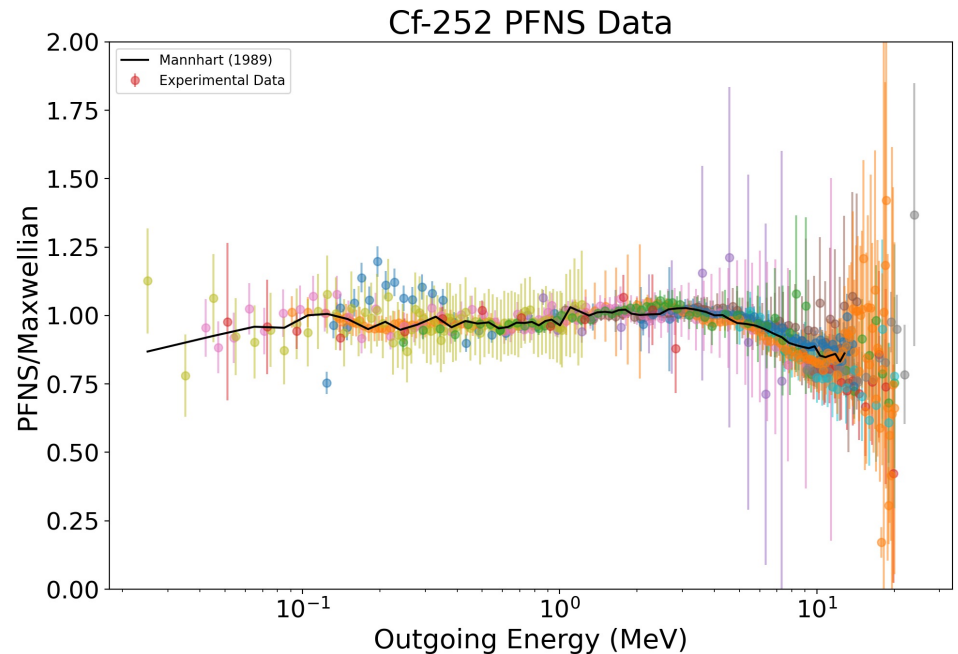
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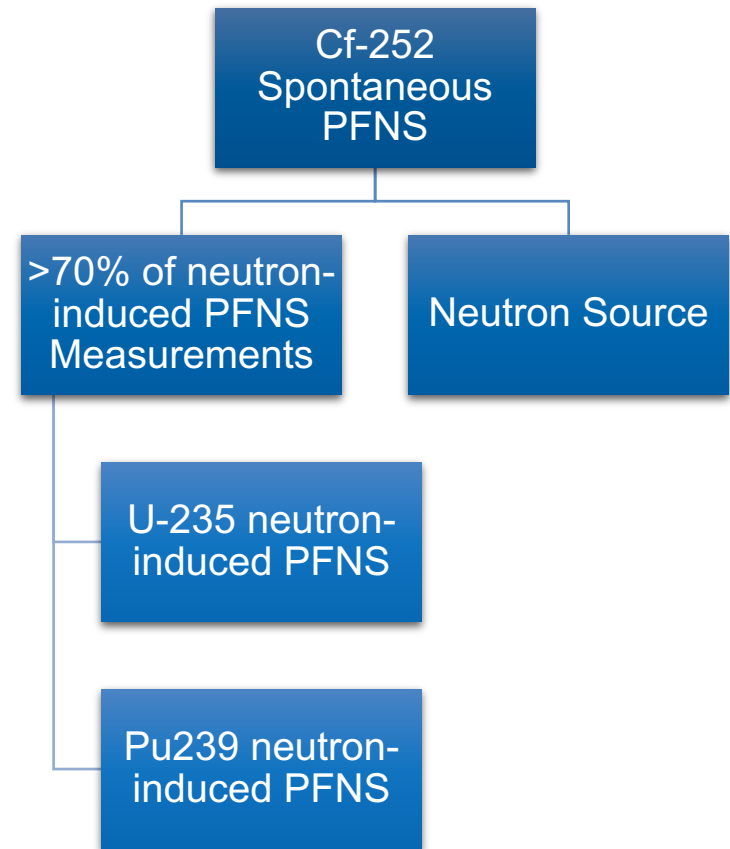
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- Gives the distribution of neutrons emitted promptly from fission as a function of outgoing neutron energy
- It is not that pretty!
 - noisy, uncertain, and biased/discrepant measurement data
- It is the role of the evaluator to suggest a pretty curve from the measurement data at hand
 - Last evaluation was in 1989

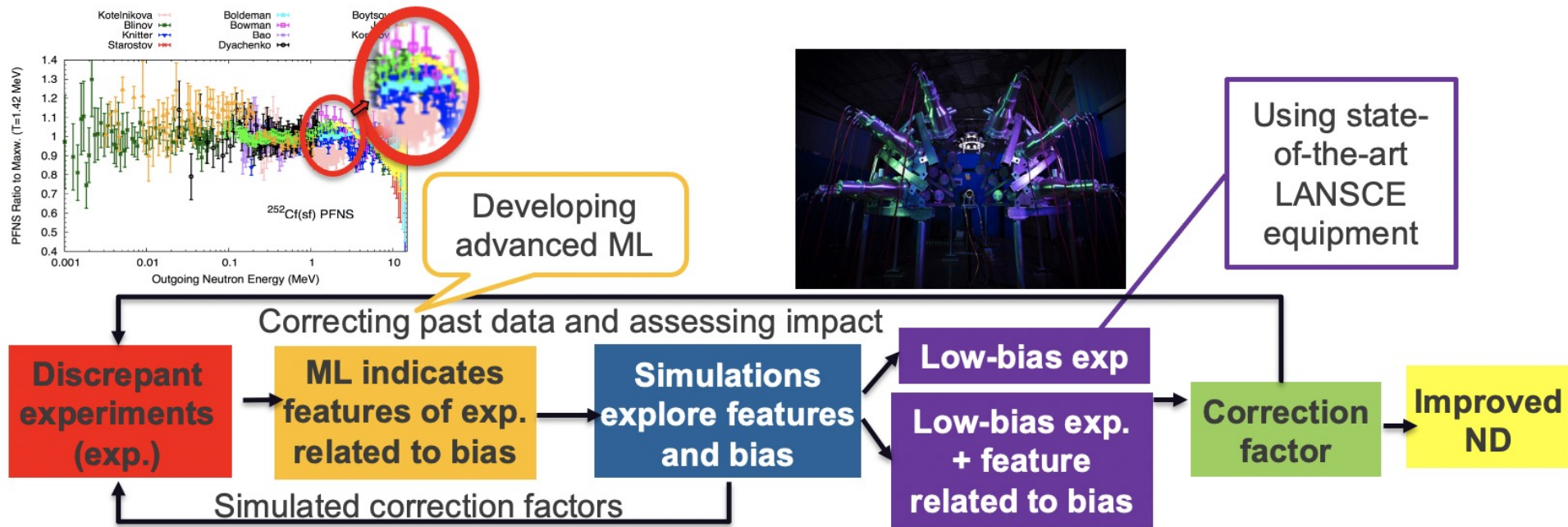


Cf-252 Spontaneous PFNS is a neutron data standard and a particularly important one

- >70% of PFNS measurements (both spontaneous and neutron-induced) are made relative to Cf-252
 - Includes Pu-239 and Uranium-235
- Improvement in Cf-252 PFNS propagates to other isotopes PFNS
- These improvements then propagate to a broad range of applications through modelling and simulation

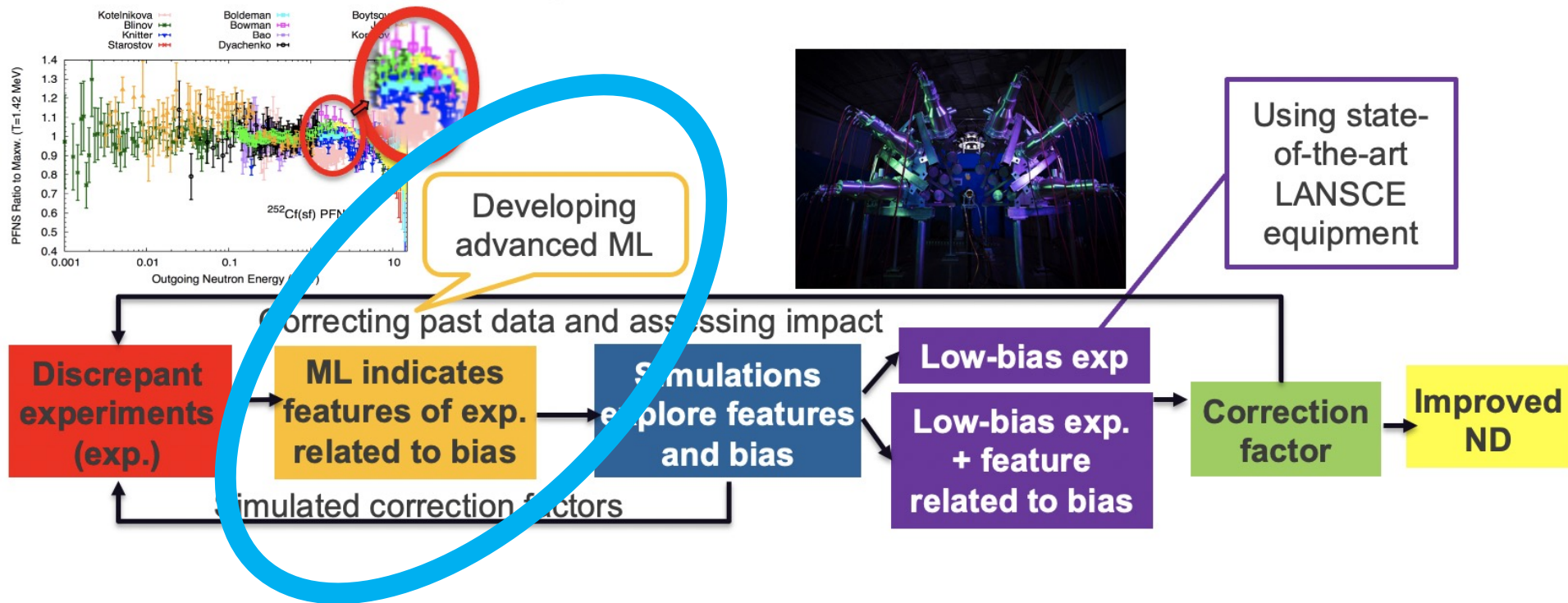


AIACHNE seeks to design an experimental campaign to explore systematic biases in the differential data



Improves the Cf-252 spontaneous PFNS standard by improving the quality of measurement data → One measurement will have minimal bias while the other will help to characterize bias in a past dataset

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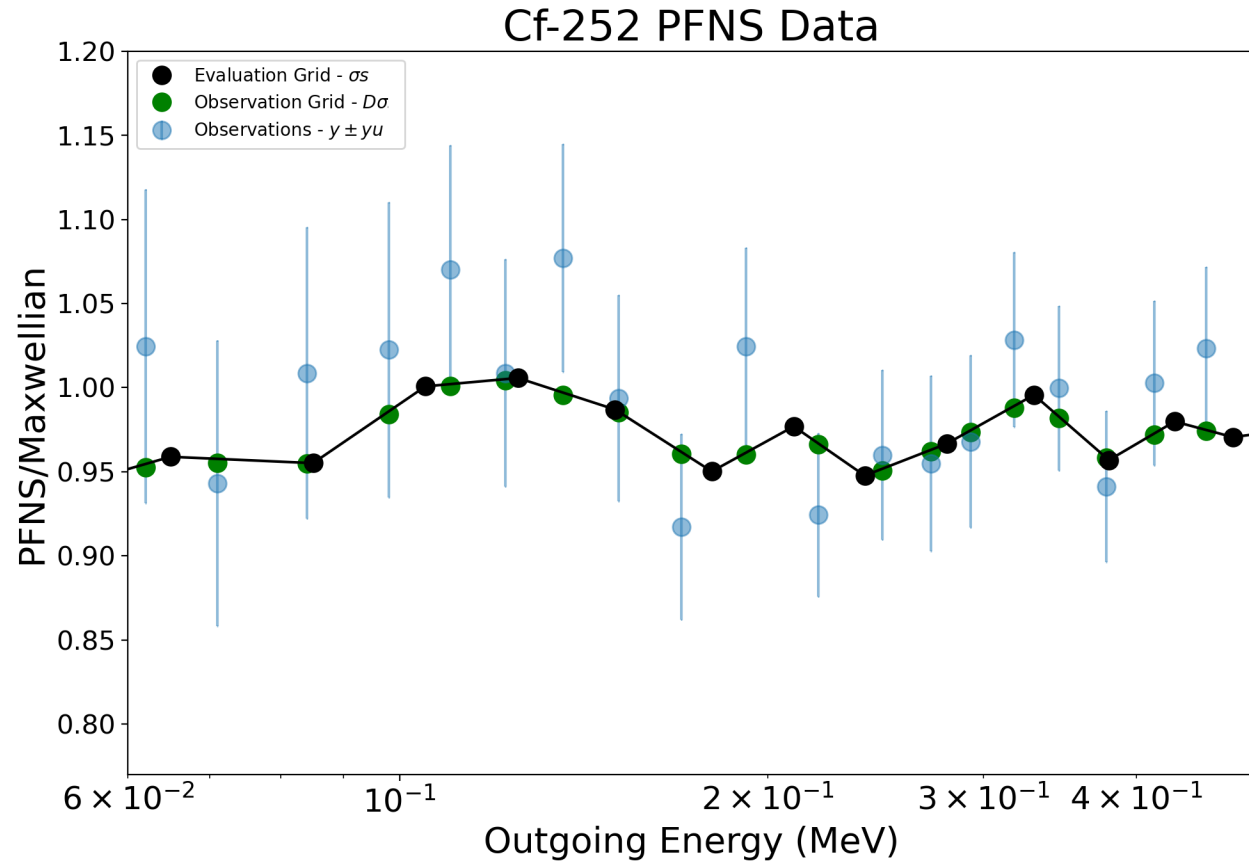
Improves the Cf-252 spontaneous PFNS standard by improving the quality of measurement data → One measurement will have minimal bias while the other will help to characterize bias in a past dataset

Traditional Bayesian model for generalized least squares evaluation

$$y = D\sigma + \varepsilon$$

$$\varepsilon \sim N(\mathbf{0}, (D\sigma u)^2)$$

D	Linear interpolation matrix
σ	PFNS Evaluation
y	Observational Data
u	Observational uncertainty
δ	Gaussian basis functions
γ	Basis function scaling factor

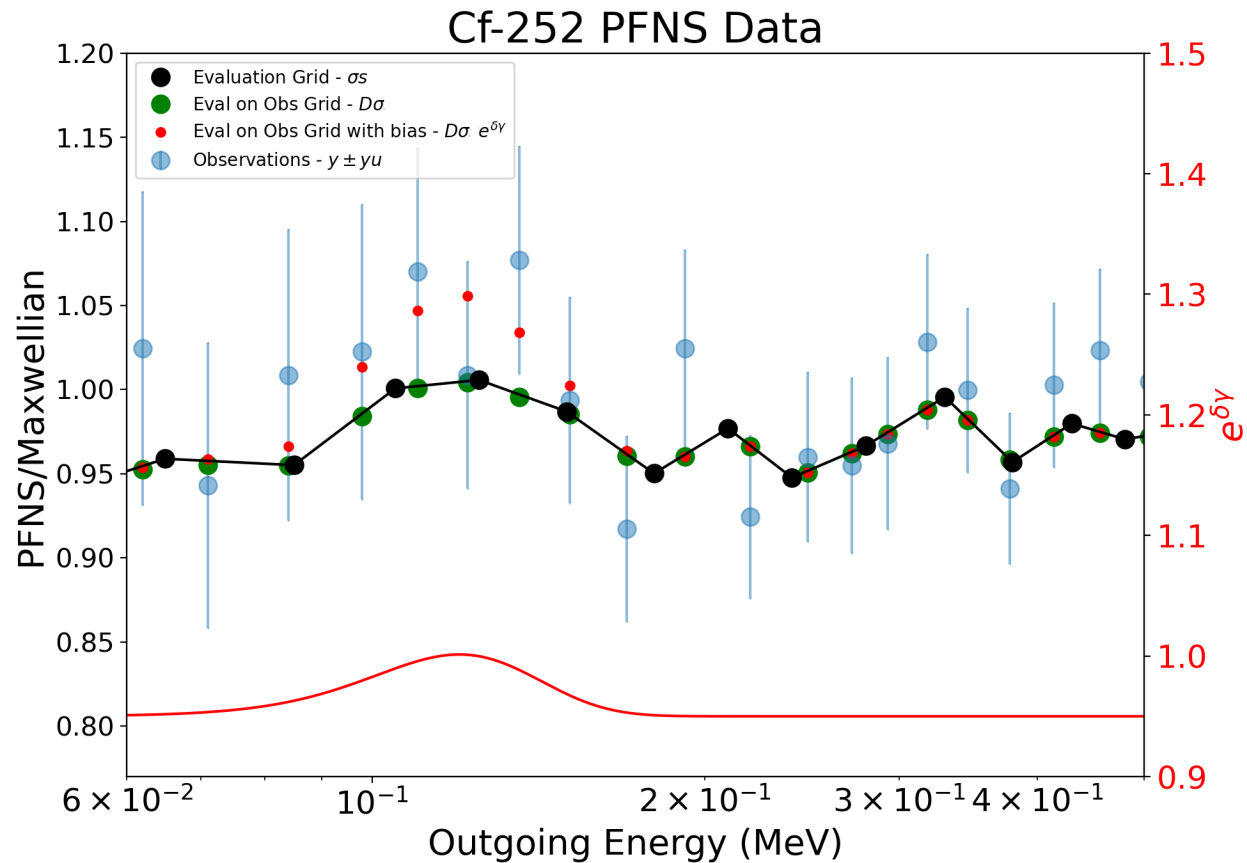


Multiplicative basis functions used to account for bias in the model

$$y = D\sigma e^{\delta\gamma} + \varepsilon$$

$$\varepsilon \sim N(0, (D\sigma u)^2)$$

D	Linear interpolation matrix
σ	PFNS Evaluation
y	Observational Data
u	Observational uncertainty
δ	Gaussian basis functions
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Multiplicative basis functions used to capture bias

$$y = D\sigma e^{\delta\gamma} + \varepsilon$$

$$\varepsilon \sim N(0, (D\sigma u)^2)$$

$$\delta = \{B_s, B_m, B_l\}$$

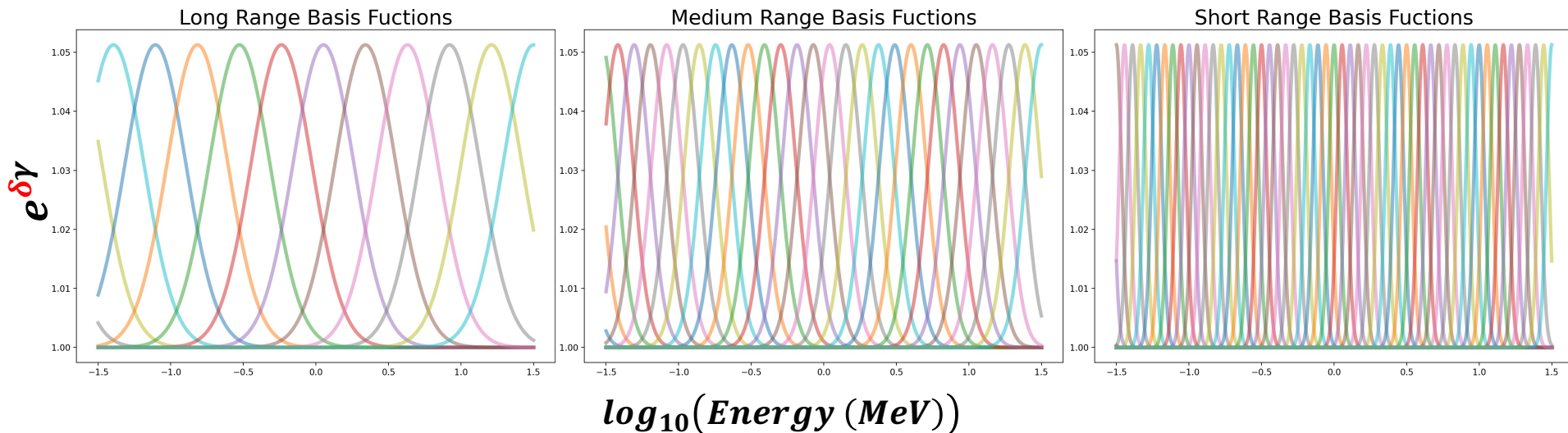
$$B_x = e^{-\frac{(E-\zeta_x)^2}{(x)^2}}$$

$$x = \{0.3, 0.15, 0.05\}$$

$$\zeta_s = \{\text{logspace}(\text{min}/\text{max}, 100)\}$$

$$\zeta_m = \{\text{logspace}(\text{min}/\text{max}, 50)\}$$

$$\zeta_l = \{\text{logspace}(\text{min}/\text{max}, 10)\}$$



Sparse Bayesian inference – horseshoe prior on γ induces sparsity in these bias terms

$$y = D\sigma e^{\delta\gamma} + \varepsilon$$

$$\varepsilon \sim N(0, (D\sigma u)^2)$$

$$\gamma \sim H.S.(\tau)$$

$\tau \propto$ sparsity level

$$\delta = \{B_s, B_m, B_l\}$$

$$B_x = e^{-\frac{(E-\zeta_x)^2}{(x)^2}}$$

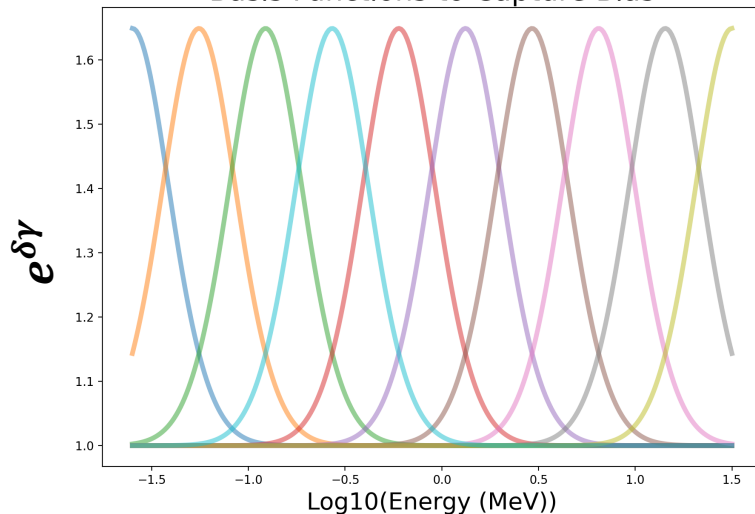
$$x = \{0.3, 0.15, 0.05\}$$

$$\zeta_s = \{\text{logspace}(-1.5, 1.5, 100)\}$$

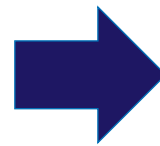
$$\zeta_m = \{\text{logspace}(-1.5, 1.5, 50)\}$$

$$\zeta_l = \{\text{logspace}(-1.5, 1.5, 10)\}$$

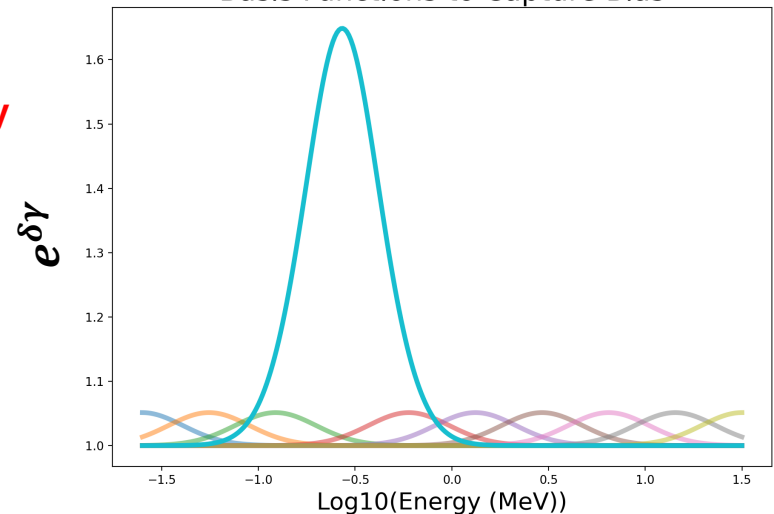
Basis Functions to Capture Bias



Induce sparsity on γ



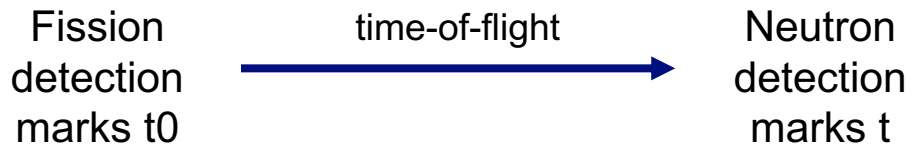
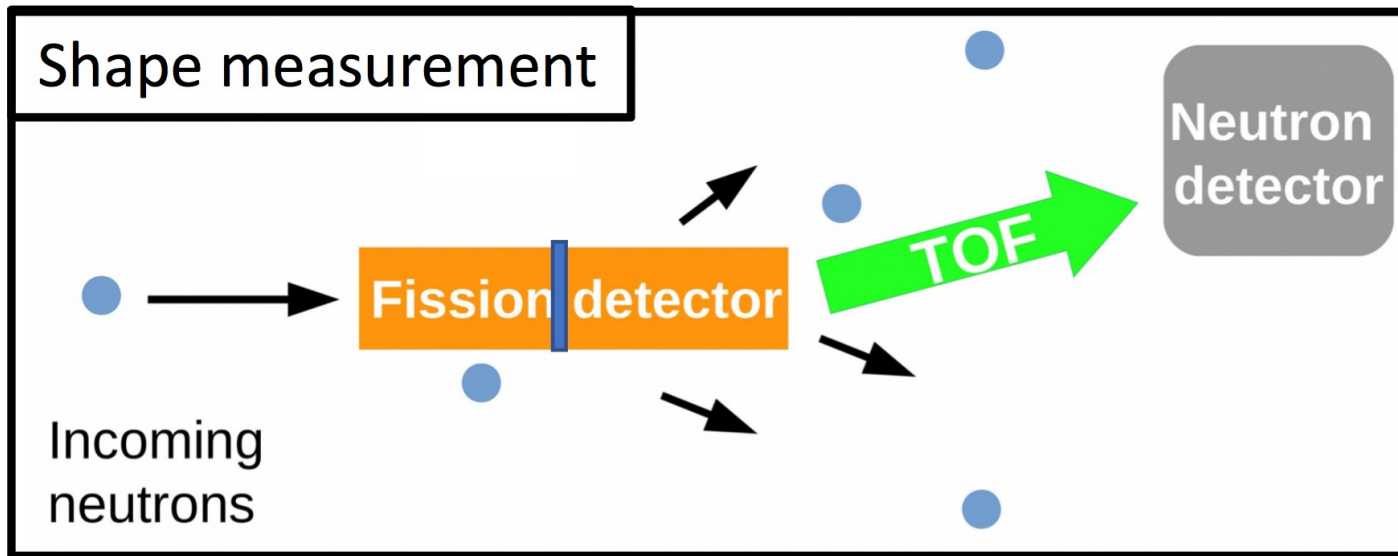
Basis Functions to Capture Bias



There are many more features than datasets – and this is a filtered list!

	Correction Features	Hardware Features	Method Features
0	ShadowBarBackground	FissionDetector1_raw	RandomCoincidence
1	BackgroundCorrected	FissionDetector1_caseA	BackgroundGeneral
2	RandomCoincidenceBackground	FissionDetector1_caseB	BackgroundAlpha
3	GammaBackground	FissionDetector1_caseC	GammaBackground
4	AlphaBackground	FissionParticleDetected	MSinSample
5	WrapAroundBackground	FissionFragmentDetectorEfficiency	MSinSurrounding
6	MultipleScatteringSampleBackingCorrected	FissionDetectorGas_raw	FissionDetectorEfficiencyMethod
7	MultipleScatteringSurroundingCorrected	FissionDetectorGas_caseA	FFAbsorptionAngularDistributionMethod
8	AttenuationSampleBackingCorrected	AngularAcceptanceofFFDetector	NeturonDetectorResponseMethod
9	AttenuationSurroundingCorrected	NeutronDetector_raw	NeturonDetectorEfficiencyMethod
10	FissionDetectionEfficiencyCorrected	NeutronDetector_caseA	DeadtimeDeterminationMethod
11	NeutronDetectionEfficiencyCorrected	AngularCoverageofNeutronDetector	
12	NeutronDetectionResponseCorrected	NeutronDetectorSizeCM	
13	SampleDecayCorrected	NeutronDetectorStructuralMaterialAu	
14	FissionFragmentAbsorptioninSampleCorrected	NeutronDetectorStructuralMaterialAl	
15	SignalPulsePileupCorrected		
16	DeadtimeCorrected		
17	AngularDistributionFissionFragmentsCorrected		
18	ImpuritiesCorrected		

Two primary experimental features in a PFNS measurement are the hardware and methods associated with neutron and fission detection

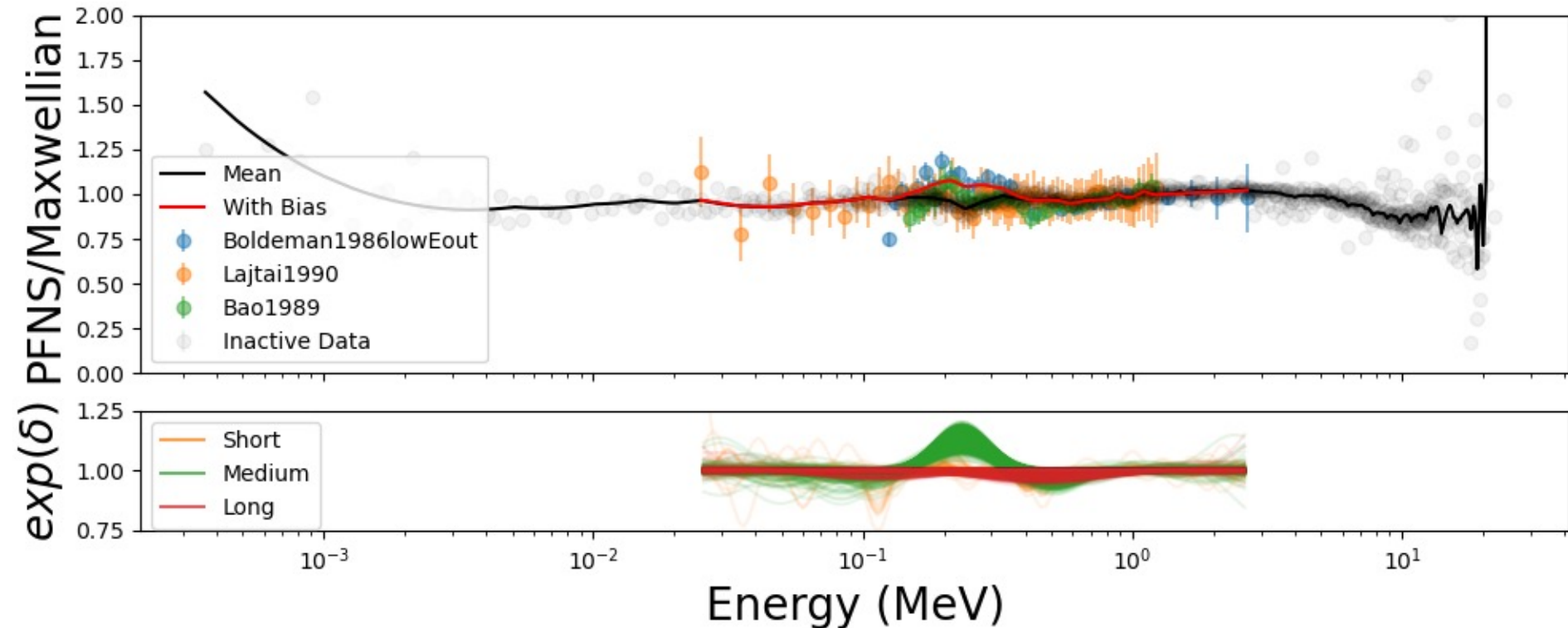


In order to investigate, we let the experimental features guide how we group datasets, for example:

Dataset	NeutronDetector_raw	NeutronDetector_caseA
Boldeman1986lowEout	Scin (6li)	(6li)
Lajtai1990	Glasd (6li)	(6li)
Blinov1973	loch (235u(n,f) chamber)	loch (235u(n,f) chamber)
Poenitz1982	Scin	Scin
Boytssov1983ant	Scin (anthracene)	Scin (anthracene)
Maerten1990_0deg	Scin (liquid)	Scin (liquid)
Maerten1984	Scin (liquid)	Scin (liquid)
Blain2017highEout	Scin (liquid)	Scin (liquid)
Chalupka1990	Scin (liquid)	Scin (liquid)
Maerten1990_60deg	Scin (liquid)	Scin (liquid)
Boettger1990	Scin (liquid)	Scin (liquid)
Kornilov2015	Scin (liquid)	Scin (liquid)
Boldeman1986highEout	Scin (plastic)	Scin (plastic)
Blain2017lowEout	Scin (plastic)	Scin (plastic)

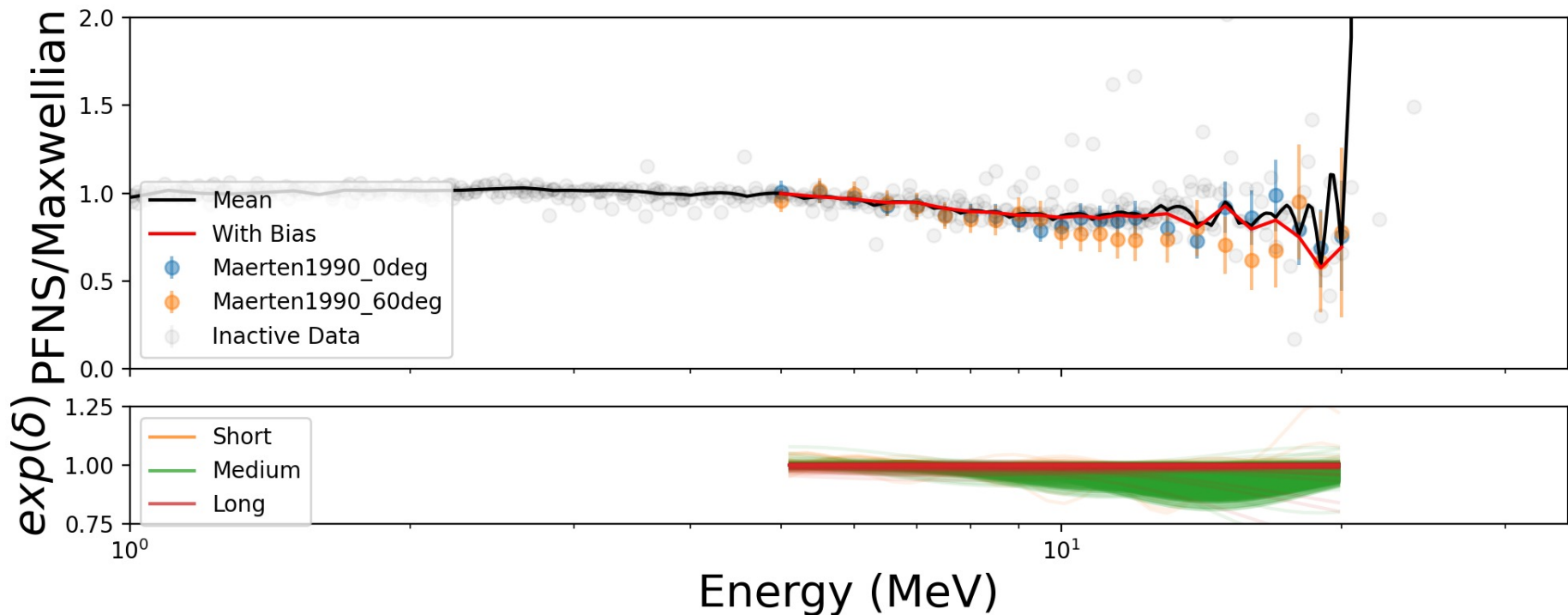
Results for Neutron Detector Case A – we find expected bias due to Li-6 peak

Neutron Detector: Li-6

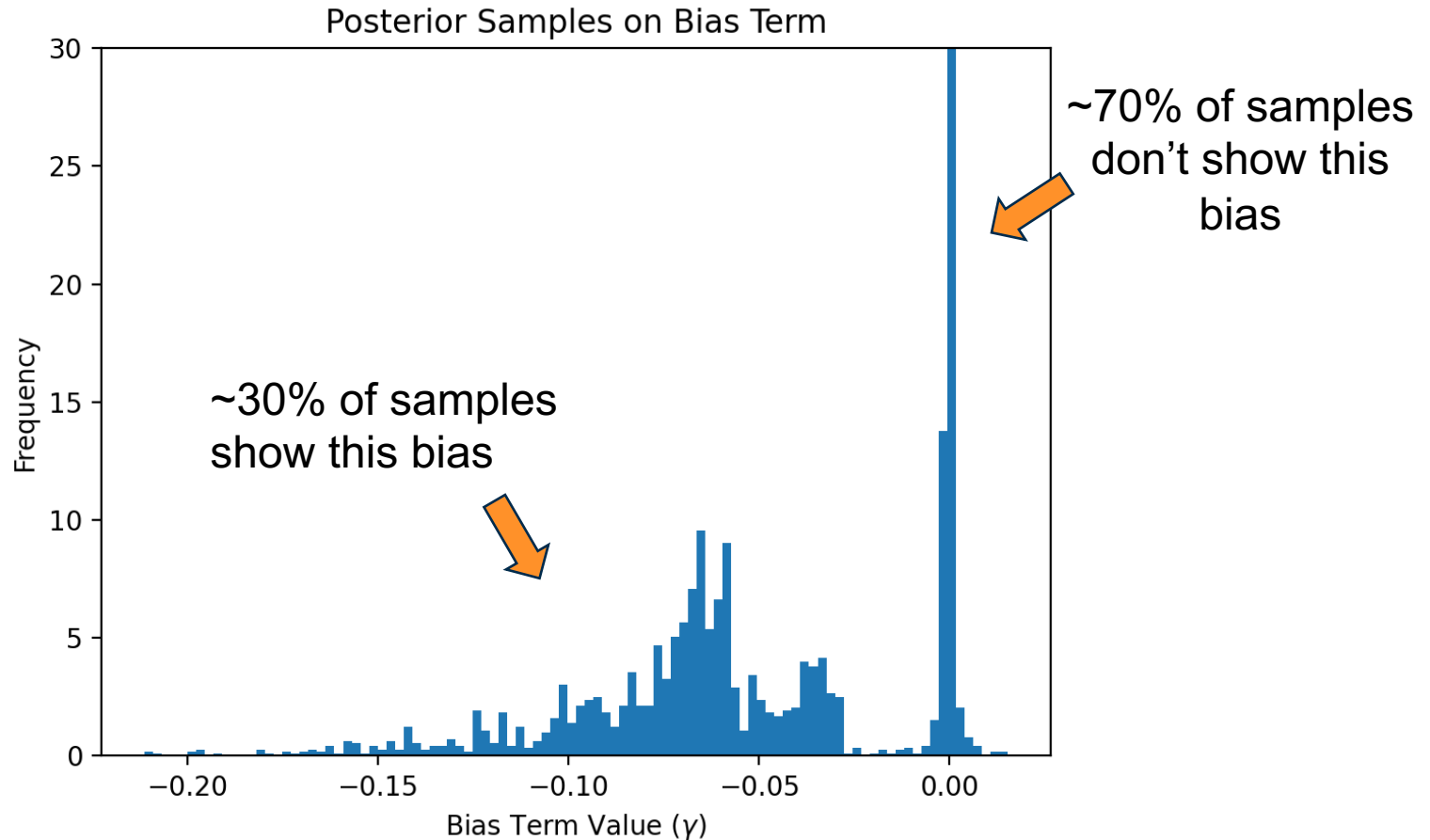


High-E bias identified across several feature groups, less obvious but experimentally justified

Fission Detection Efficiency Correction Method: Calculated/Measured

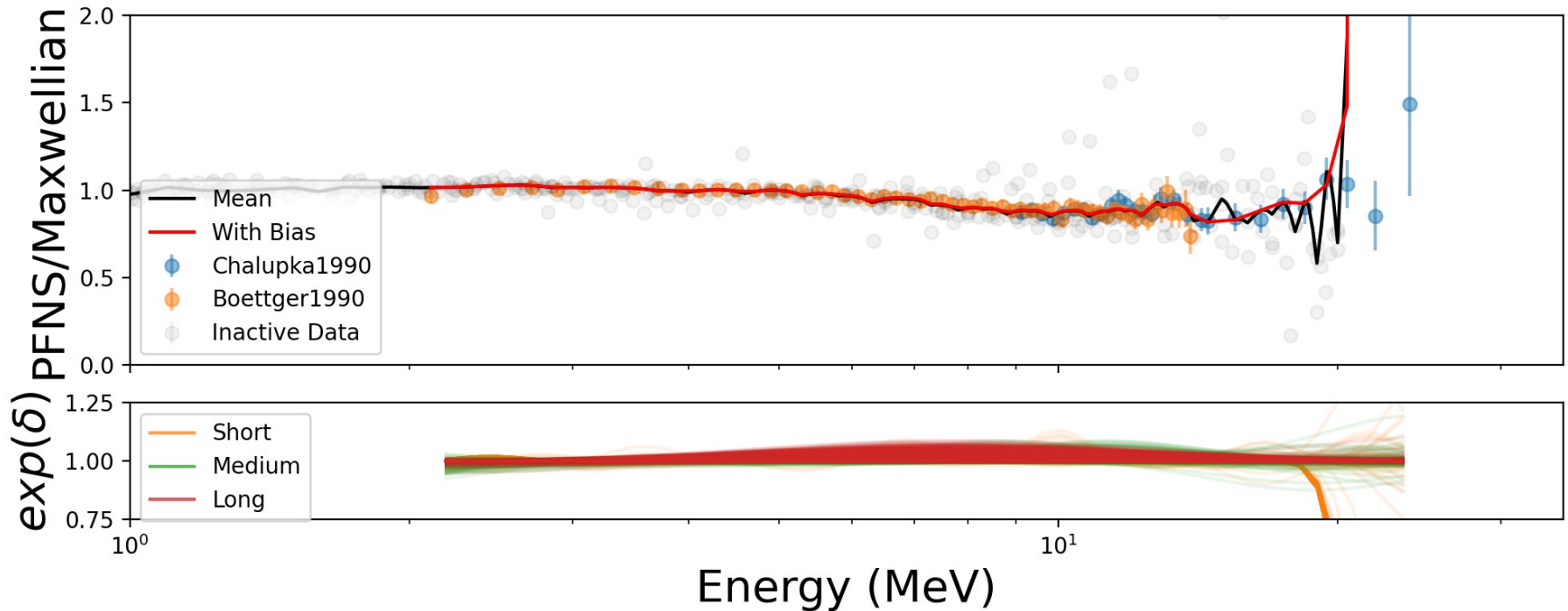


The strength of the bias term can be characterized by looking at the posterior samples

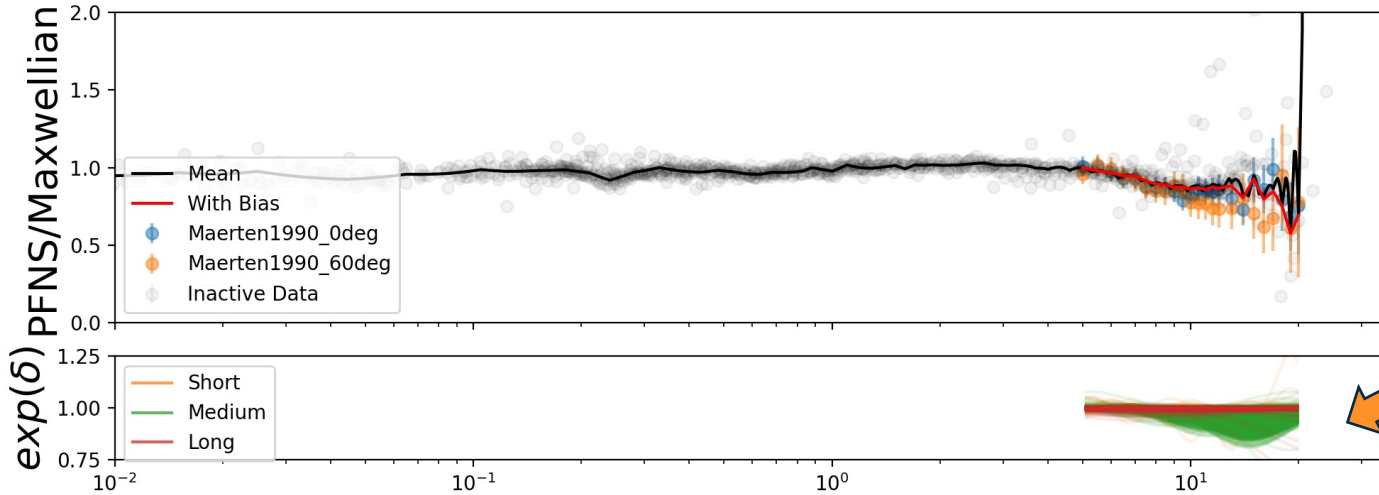


High-E bias identified in several feature groups, less obvious but experimentally justified

Fission Detection Efficiency Correction Method: Calculated/Stapre

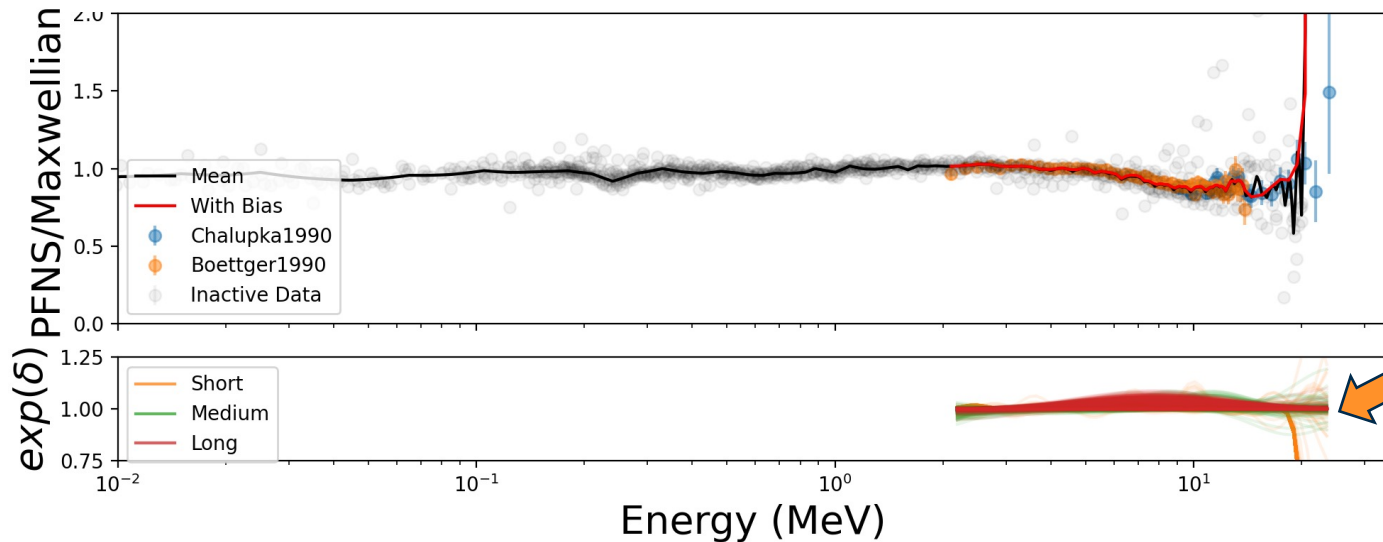


Fission Detection Efficiency Correction Method: Calculated/Maxwellian



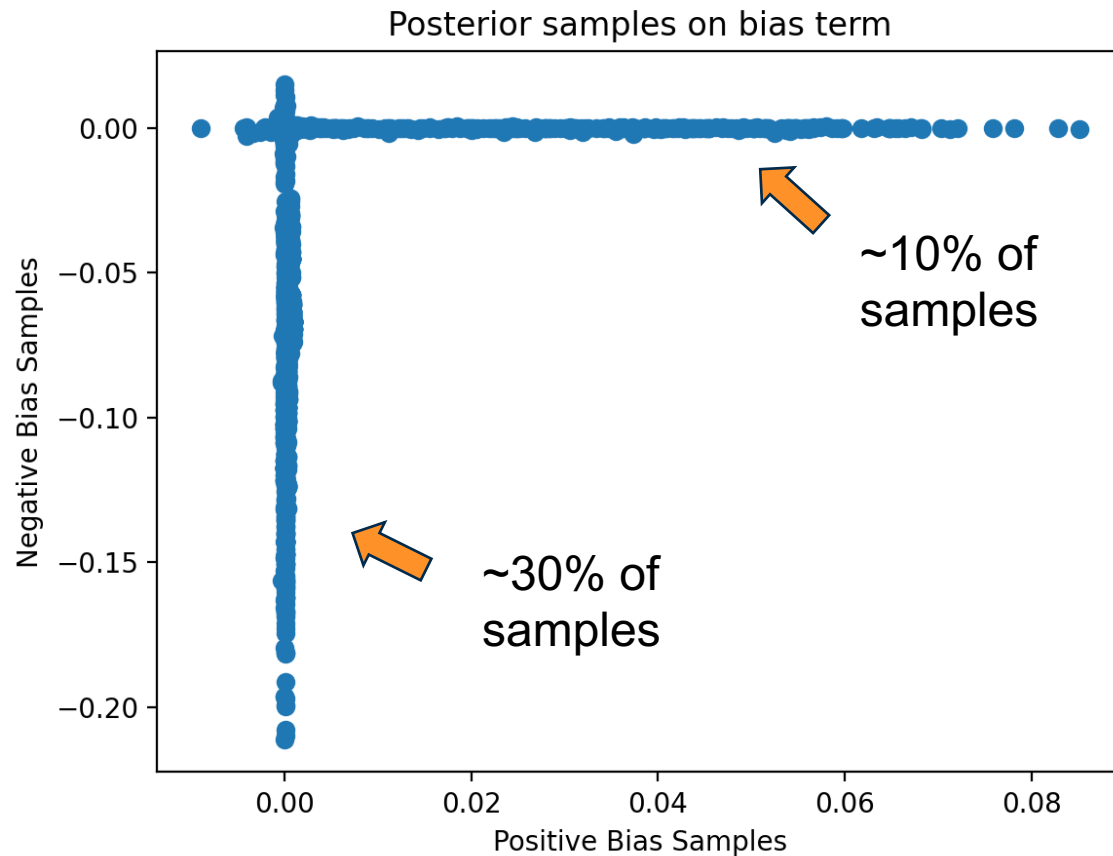
~30% of samples

Fission Detection Efficiency Correction Method: Calculated/Stapre



~10% of samples

Posterior samples for the negative and positive bias terms are strongly correlated



Main Point:

Method cannot tell us which group is biased, **only that a bias exists between the two**

In total, a bias seen in ~40% of samples

Potential bias causing groups agreed with expert judgement - but might not have thought of without ML

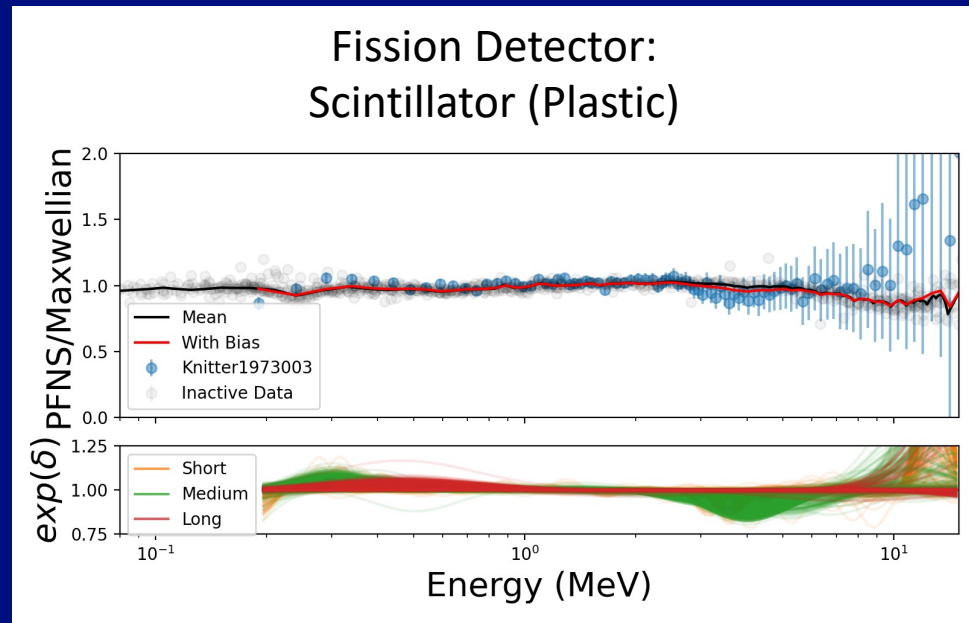
Correction Features	Hardware Features	Method Features
Shadow bar background	Fission detector type	Random coincidence
Alpha/gamma background	Fission fragment efficiency	Alpha/gamma background
Multiple scattering surrounding/sample	Fission detector gas	Multiple scattering surrounding/sample
Attenuation surrounding/sample	Fission fragment angular acceptance	Fission fragment angular distribution
Fission/neutron detection efficiency	Neutron detector type	Neutron detector response/efficiency
Neutron detector response	Neutron detector size/angular coverage	Deadtime determination
Sample decay/impurities	Neutron detector structural material	Fission detector efficiency
Fission fragment angular distribution/absorption		
Signal pulse pileup		
Deadtime		

Limitations of the method

- Significantly more features than datasets
 - Similar groupings of the datasets all show similar bias
 - It is important to interpret the identified biases with respect to the grouping of datasets
 - Further analysis and expert reasoning to deduce which features may be the root cause
- Global sparsity parameter (τ) will allow more/less bias terms to remain
 - Requires tuning to eliminate unnecessary bias terms while still allowing others
 - Expert judgement comes into play again

Conclusions and future applications

- Identified less-obvious discrepancies
 - Results agreed with (hidden) expert opinions on potential bias-causing features
- Narrows the set of features that could be the root cause of bias



- Allows for a more quantitative description of bias in measurement data
 - Energy range of impact
 - Used later for determination of bias correction factor
- Will result in a better evaluation for the Cf-252 PFNS neutron data standard and hopefully many other PFNS data!