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Title: Applying Machine Learning to Explore What Drives Biases in Fission Experiments

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NATIONAL LABORATORY

Applying Machine Learning to Explore What Drives Biases in Fission Experiments

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FIESTA2024 Nov. 22, 24

LA-UR-24-

We are applying machine learning to accelerate progress in understanding fission physics.

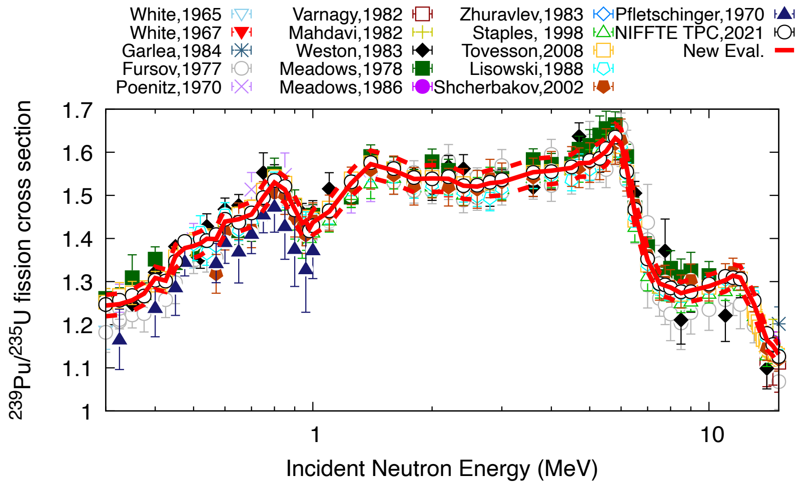
The big questions we are after:

- **What is the physical root cause for experimental discrepancies?**
- **What experiment can we perform to reduce scatter in experimental database?**

Benefit of answering questions:

- More targeted experiments reducing spread in an experimental data. This accelerates progress in understanding fission physics.
- Reduced uncertainties and better means for nuclear data that in turns lead to more reliable application simulation and better model fitting.

Background: Neutron Data Standards introduced unrecognized sources of uncertainties to account for discrepancies in data.



Carlson, NDS 148 (2018); Capote, NDS 163 (2020).

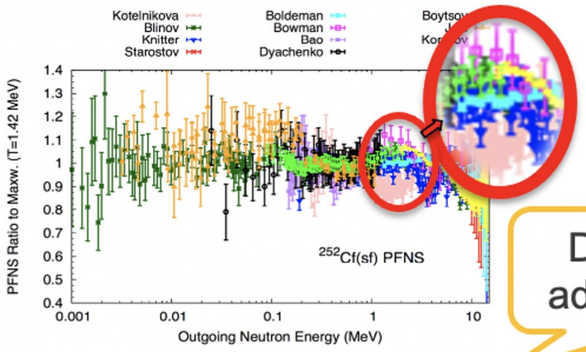
<u>The good</u>: we are quantifying obviously missing uncertainties in data.

<u>The ugly:</u> unc. based on the spread of data covering up our missing understanding physics root causes of discrepancies.

<u>The bad:</u> large unc. on quantities depending on standards with no way forward to reduce unc. if defined based on the spread of data.

<u>The solution:</u> We (AIACHNE and standards) try to uncover physics root causes driving discrepancies and either reject data with justification or correct them.

AIACHNE created a ML capability to explore discrepancies in past ^{252}Cf(sf) PFNS exp. & measures new data.



Developing advanced ML

Using state-of-the-art LANSCE equipment

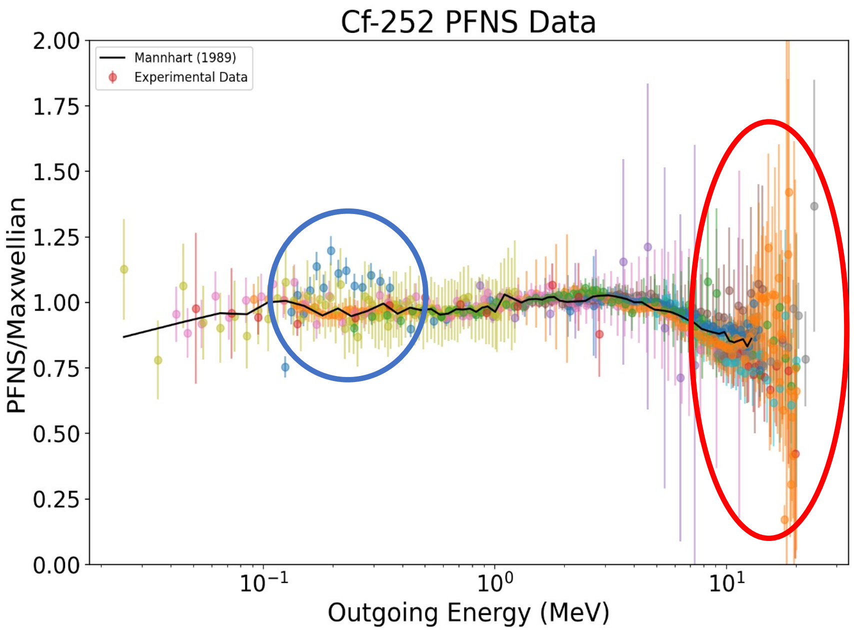
Correcting past data and assessing impact

Discrepant experiments (exp.) → ML indicates features of exp. related to bias → Simulations explore features and bias → Low-bias exp / Low-bias exp. + feature related to bias → Correction factor → Improved ND

Simulated correction factors

To that end, we used a ML capability to pin-point measurement features likely related to bias and choose most impactful experiments based on MCNP studies.

The problem at hand: Experimental ^{252}Cf PFNS have a wide systematic scatter of data at low and high energies.



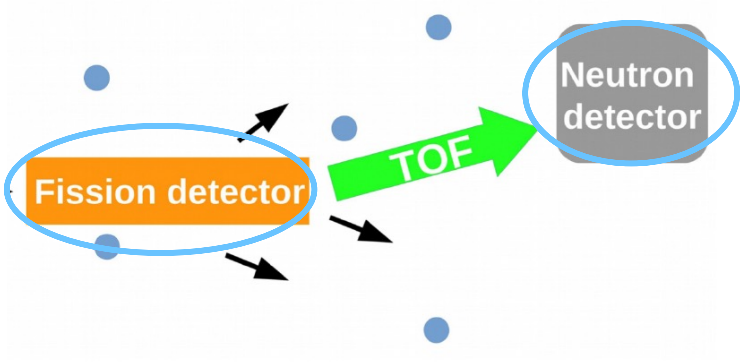
Discrepancies at low E_{out} understood: caused by incorrect resolution of ^{6}Li resonance for detector response.

Discrepancies at high Eout **not** understood:

- Background?
- Time resolution?
- Fission fragment issues?
- Neutron detector response?

Root cause of discrepancies must be tied to set-up issue or analysis technique encoded in measurement features.

Here, we analyze features related to neutron and fission detectors.



	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		

This is a *filtered* list of feature categories!!!

These metadata are retrieved from EXFOR in a by-hand process.

AIACHNE is using a sparse Bayesian model to identify potential sources of bias in ^{252}Cf PFNS data.

We are extending the Bayesian model with an energy-dependent, multiplicative bias. Sparsity ensures no bias for most energies but the term is active when the data indicate the need. A horseshoe prior reduces the number of potential biases.

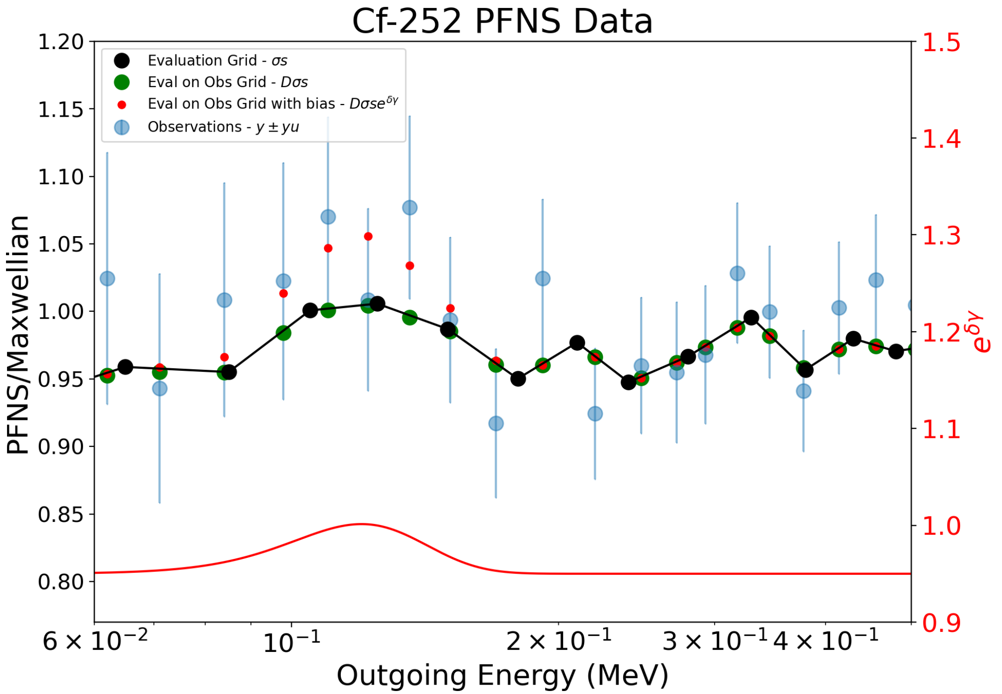
$$\boldsymbol{y} = \ \boldsymbol{D\sigma} \cdot \boldsymbol{e^{\delta}} + \boldsymbol{\varepsilon}$$

$\boldsymbol{\delta} =$ $\boldsymbol{B\gamma} =$ **relative bias**

$\mathbf{B} =$ **bias basis matrix**

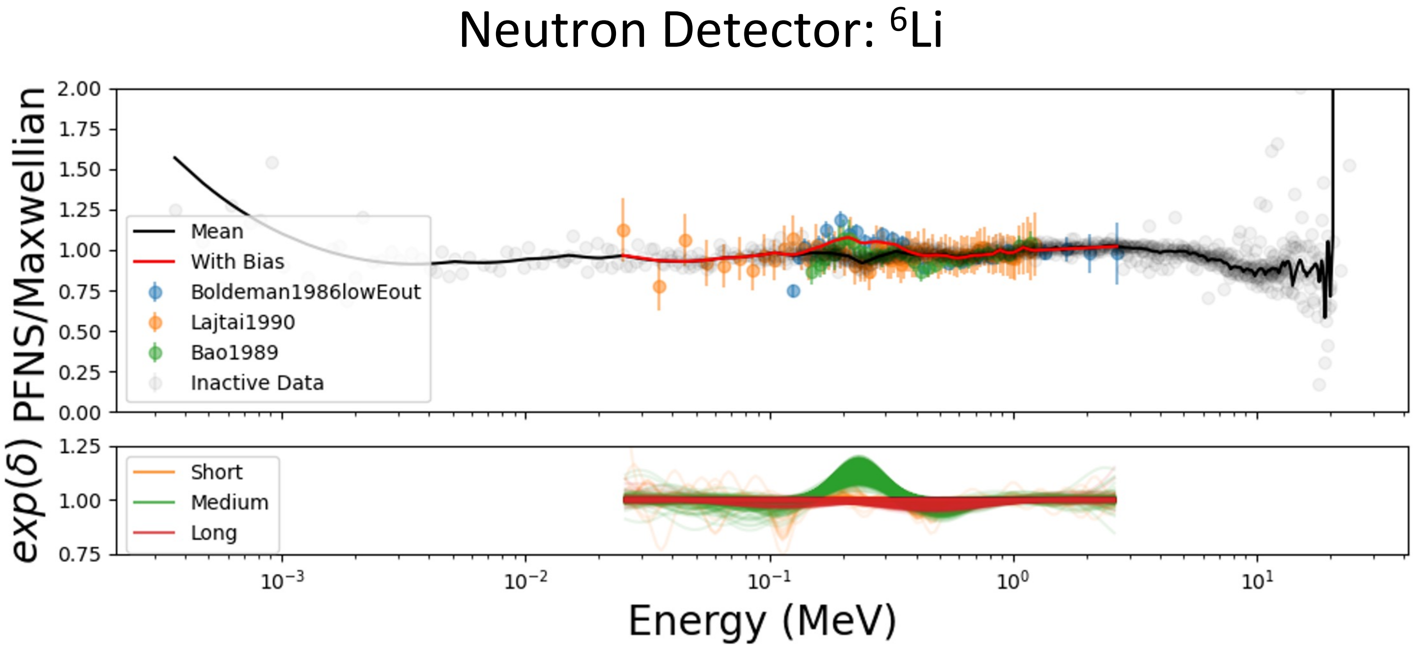
$\boldsymbol{\gamma} =$ **bias coefficients**

$\cdot =$ **element-wise product**



The algorithm deals well with a large number of correlated features compared to experimental data.

Validation example: does the algorithm correctly identify expected bias due to ^{6}Li peak? – Yes, it does!



Study is documented in paper: N. Walton, LA-UR-24-29607 (2024), submitted.

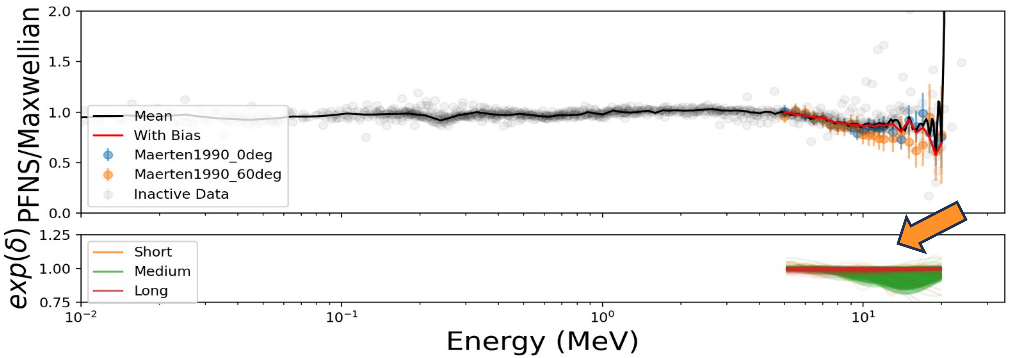
Advantage of algorithm: Enables to more quantitatively identify bias in exp. data as a function of energy to be included in evaluation algorithm.

Another example: High-E bias identified across several feature groups, less obvious but experimentally explainable.

Effect at high energies was attributed to many features. Detailed expert discussion and analysis of data pointed to fission detection (angular dependence of fission fragments).

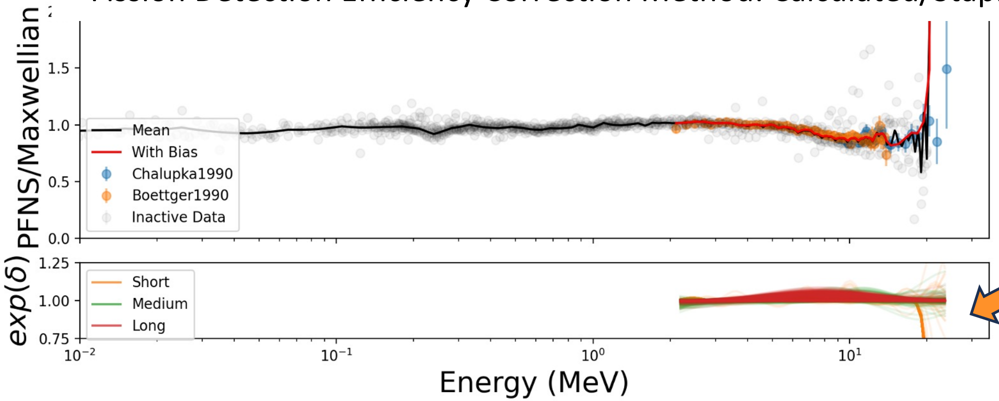
The algorithm finds features related to bias experts might have otherwise overlooked. The algorithm results require expert interpretation.

Fission Detection Efficiency Correction Method: Calculated/Measured



~30% of samples

Fission Detection Efficiency Correction Method: Calculated/Stapre



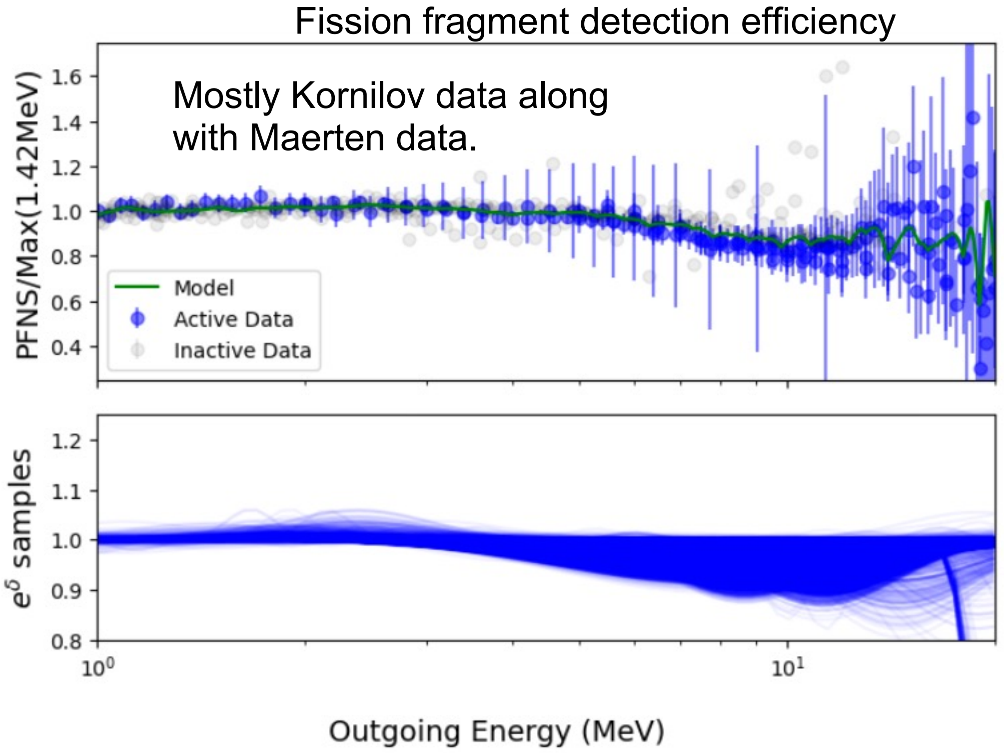
~10% of samples

ML results also list in several categories Kornilov data.

Bias in Kornilov data related to:

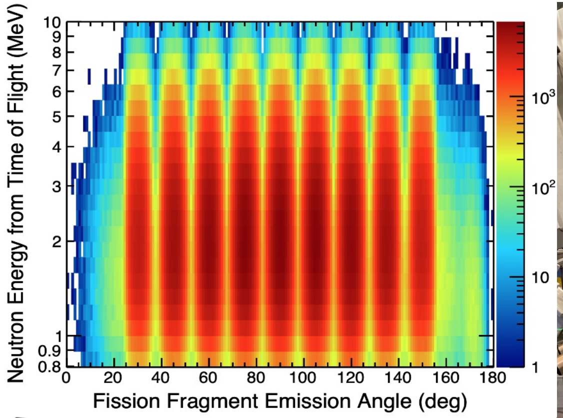
- Fission fragment efficiency,
- Various uncorrected background,
- Neutron detector components,
- ...

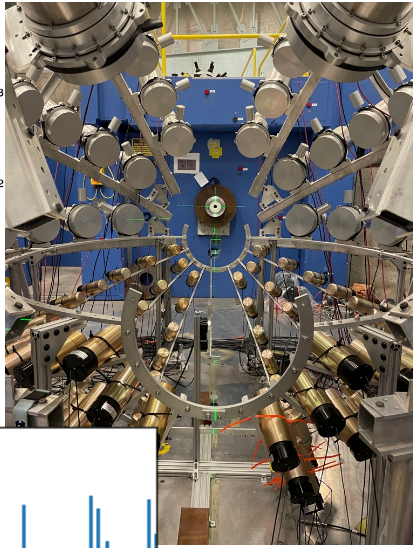
In essence, the algorithm told us to go and look more at the data. ☺

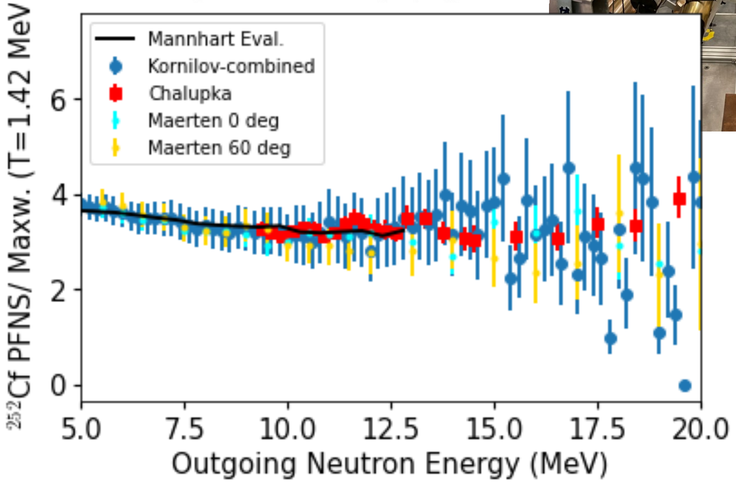


It is key for experts to take a second look at ML results. We are doing that via exp. and simulations.

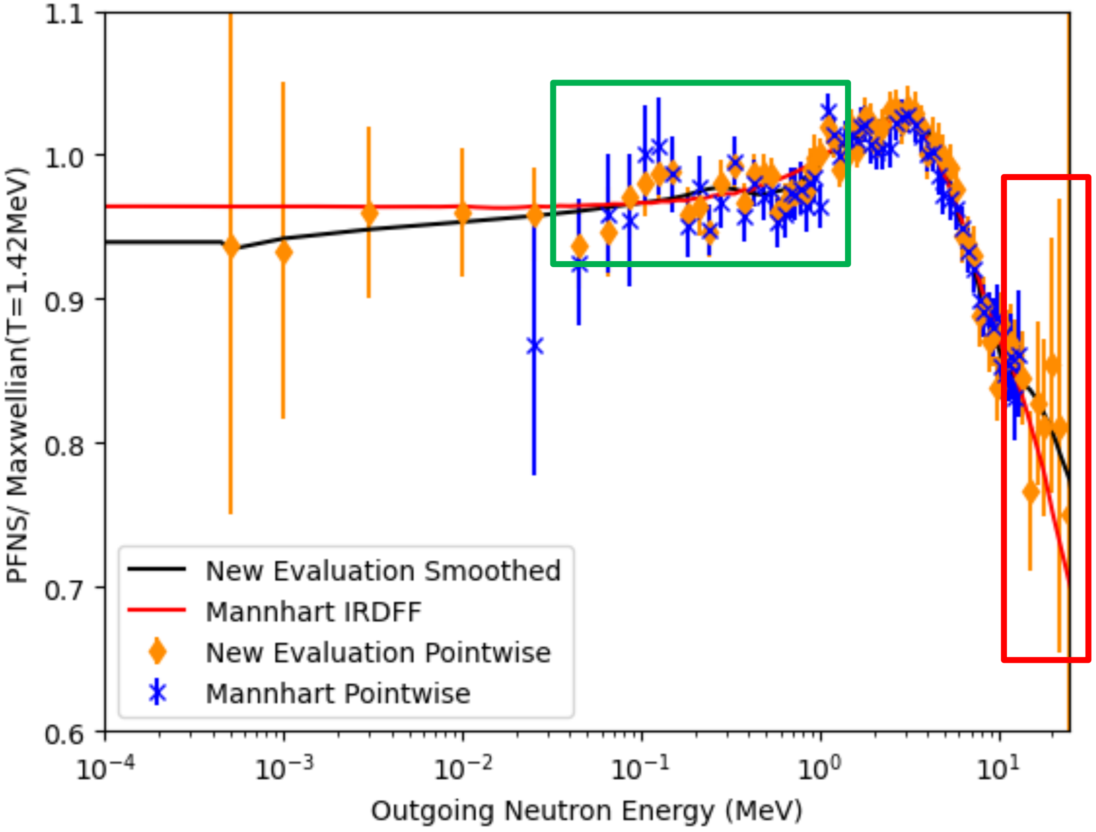
- Boldeman ^{6}Li bias: will be explored via CoGNAC ^{252}Cf PFNS experiment by K. Kelly.
- Kornilov bias: AIACHNE team worked with Tom Massey to identify issue (neutron detector response extrapolation) and removed biased run from data set.
- Maerten bias: will simulate fission fragment angular distribution for correction.

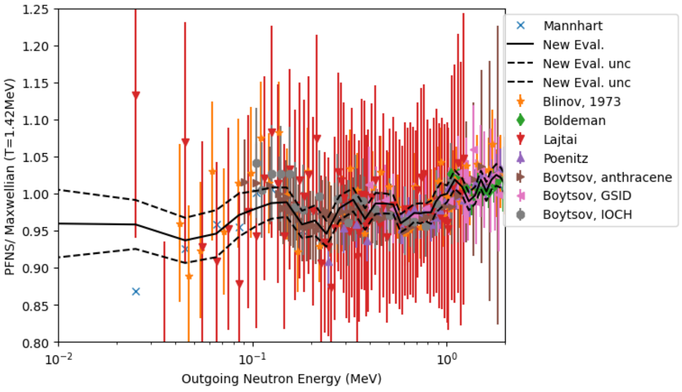


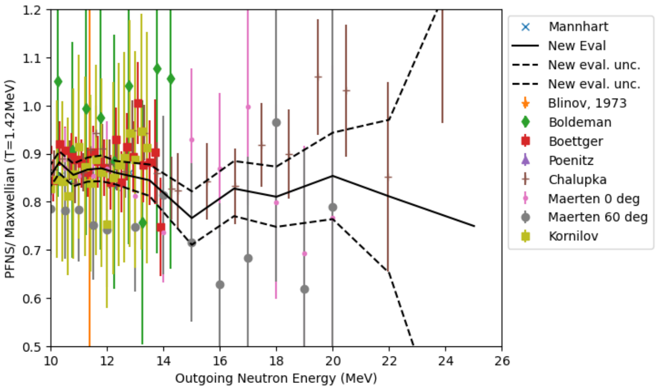




New evaluation reduces ^{6}Li peak but more work needed at high outgoing energies correcting data.







Summary: Sparse Bayesian model pointed us successfully to what drives discrepancies between experimental data.

Lesson learned:

- You can only progress in improving physics understanding if you question what is causing systematic discrepancies in exp. databases!
- Interplay between expert judgment and ML results can be key to tease out more understanding of physics information than each on their own.

Thank you for listening!

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