

Unique Questions and Answers Revealed in Automated Resonance Fitting and Demonstrated on Ta-181

Noah Walton¹, Vladimir Sobes¹, Oleksii Zivenko¹, Jesse Brown², Jake Forbes¹, Cole Fritsch¹, Aaron Clark¹

Collaborators: Dave Brown³, Denise Neudecker⁴, Mike Grosskopf⁴

The University of Tennessee¹

Oak Ridge National Laboratory²

Brookhaven National Laboratory³

Los Alamos National Laboratory⁴

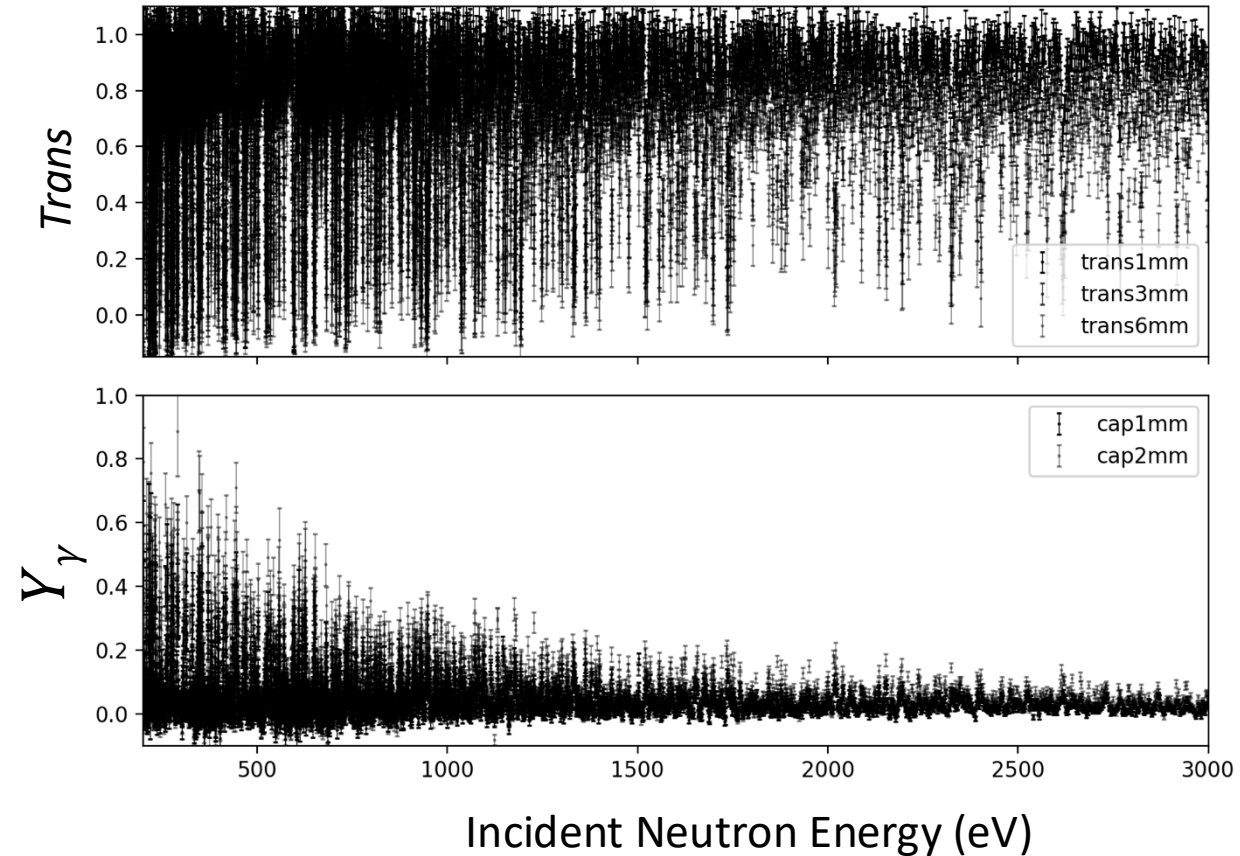
Unique Questions and Answers Revealed in Automated Resonance Fitting and Demonstrated on Ta-181

1. Does differential data have information on the spin group of resonances?
2. Quantitatively assess the impact of the PPP correction for Data Covariance Matrix
3. Smooth deterioration of evaluation performance approaching the URR

Can automation help?

- Manual effort and reproducibility
- Prior evaluations
- Uncertainty quantification

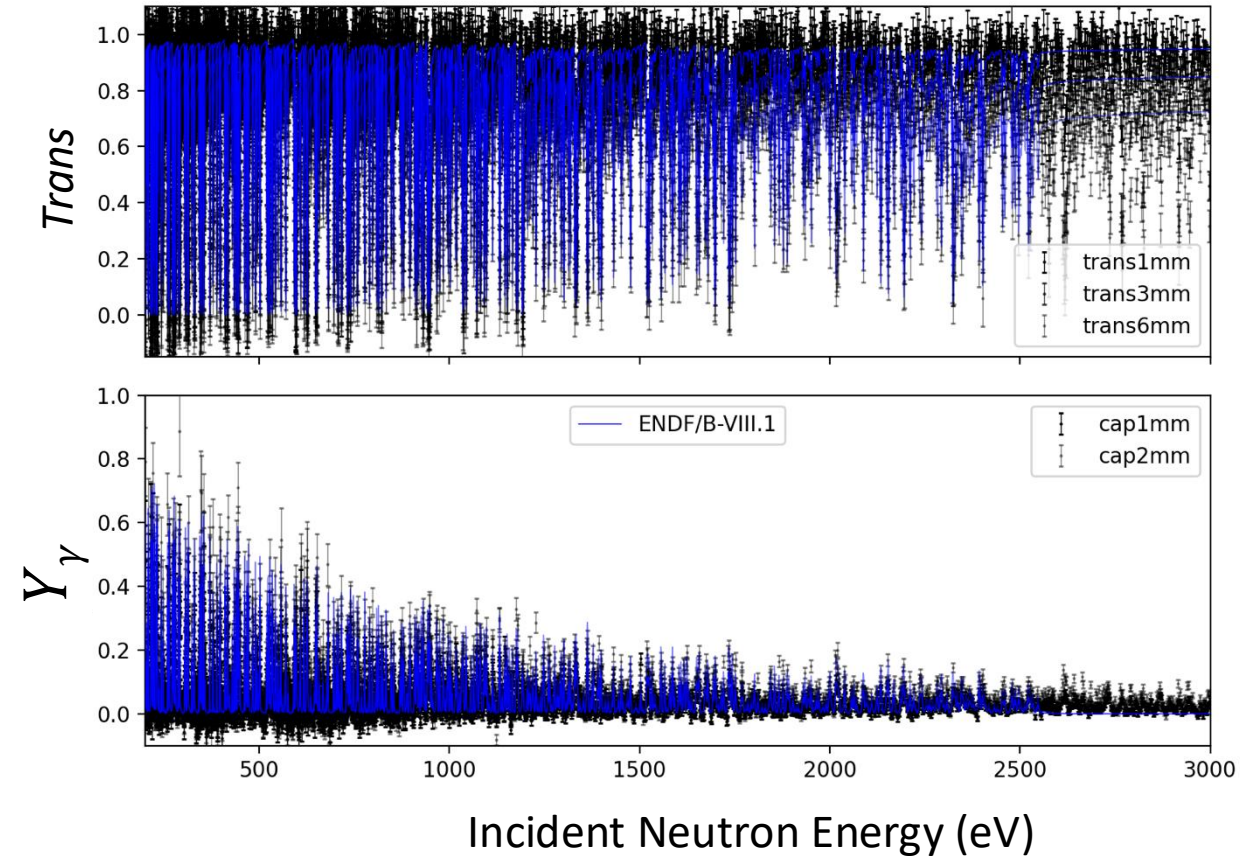
Composite observables used to infer resonance parameters



Challenges in resonance parameter inference

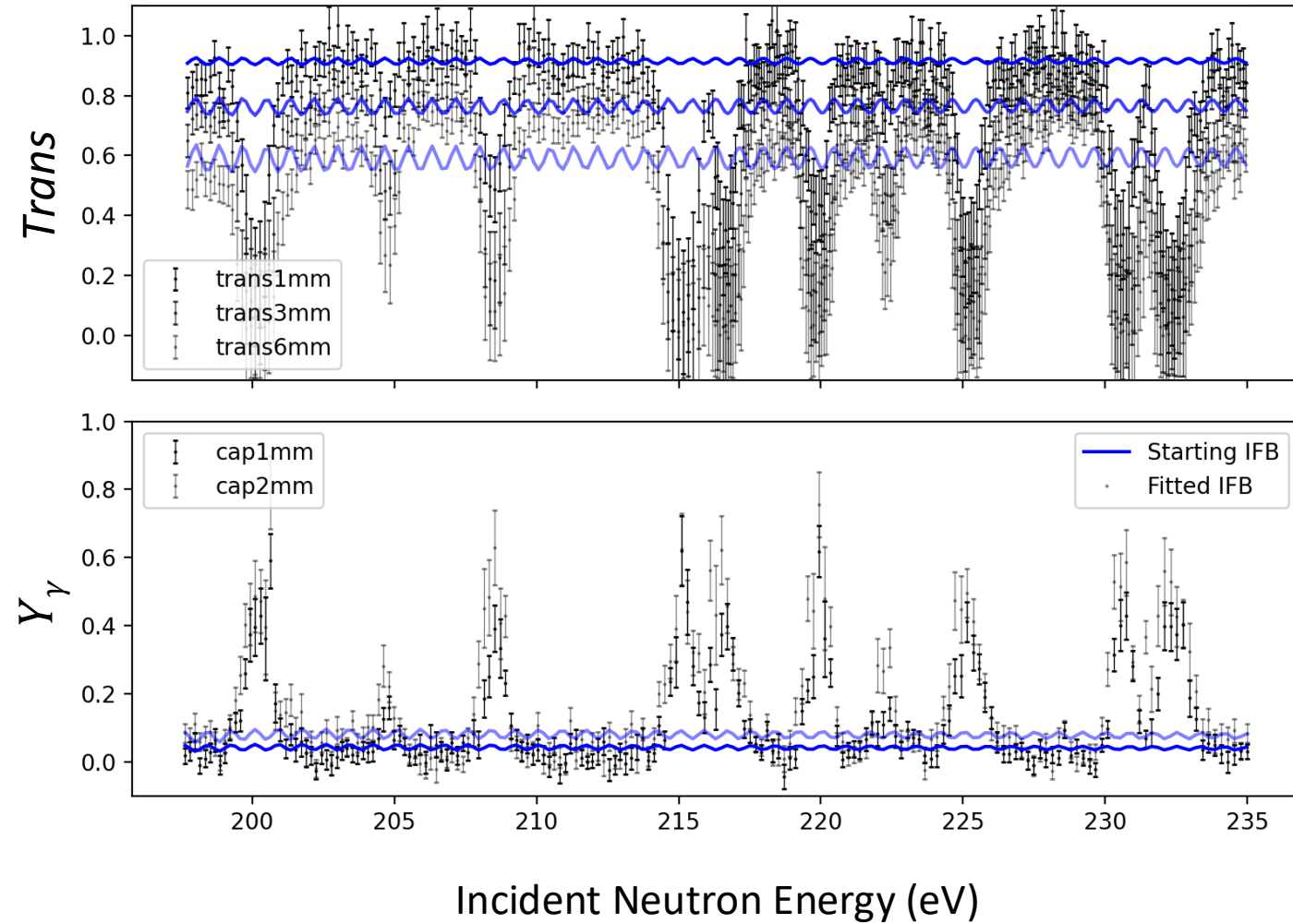
- Manual effort and reproducibility
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Composite observables used to infer resonance parameters



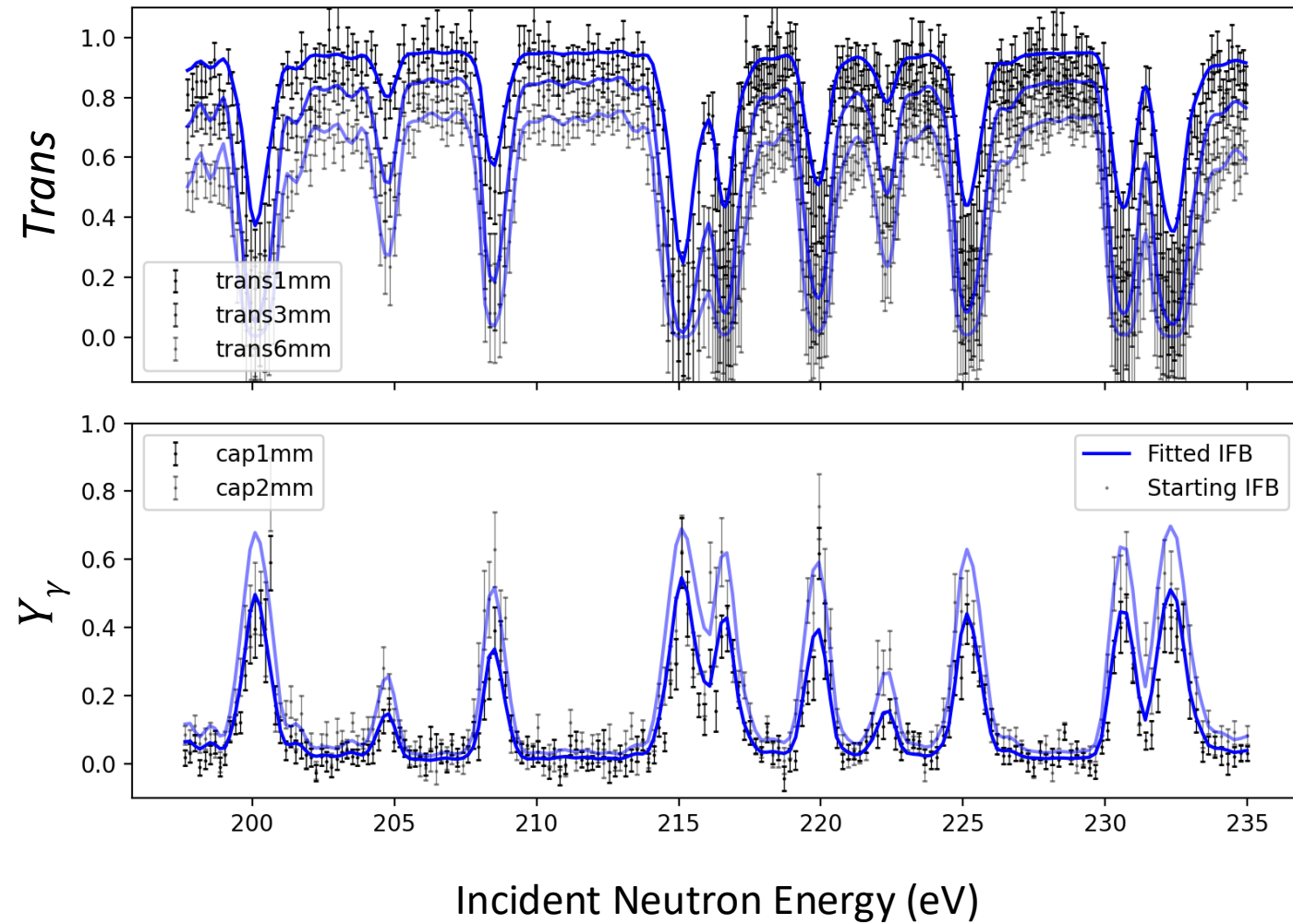
1. Design initial feature bank

Composite observables used to infer resonance parameters



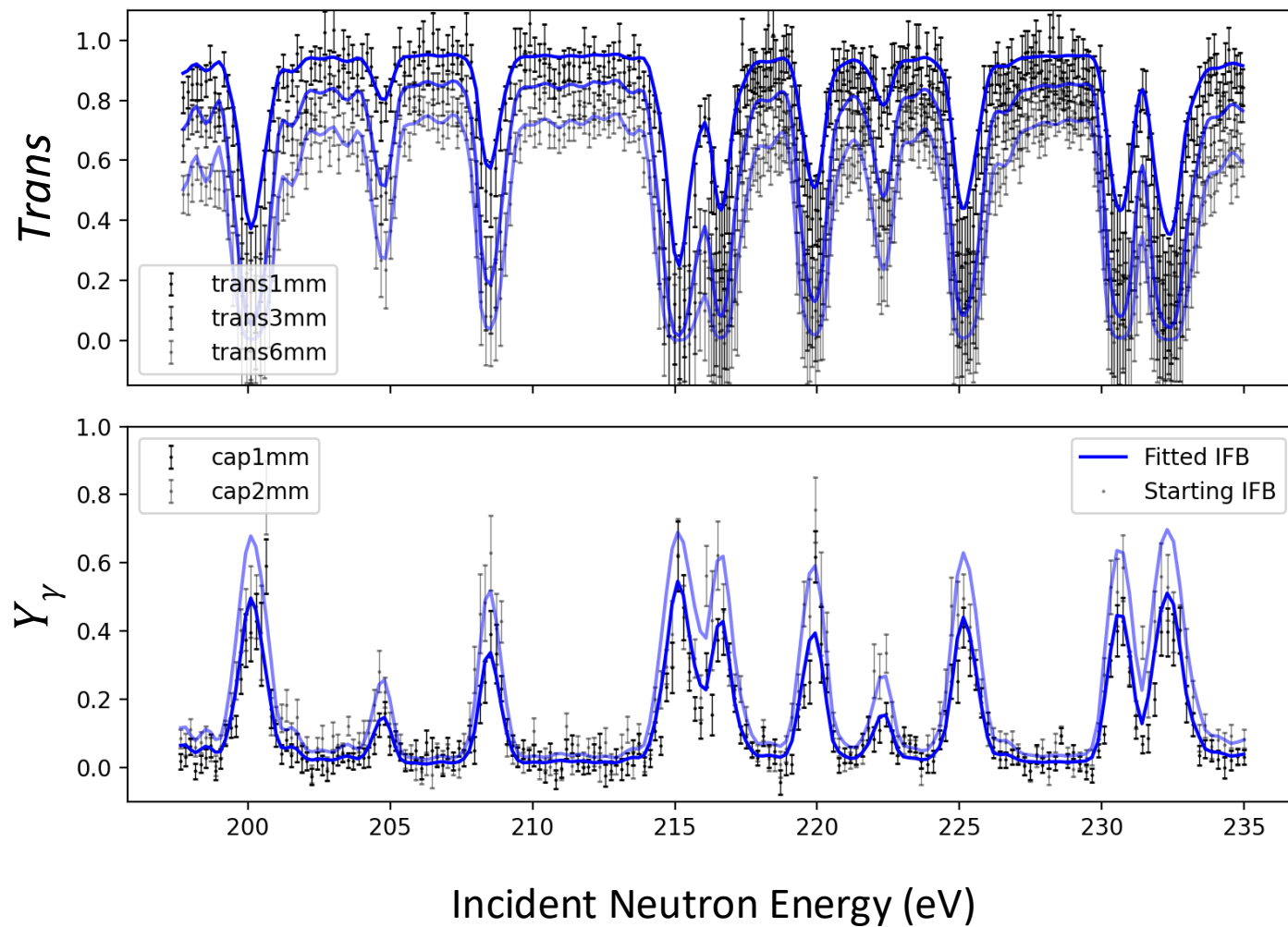
1. Design initial feature bank
2. Non-linear optimization

Composite observables used to infer resonance parameters



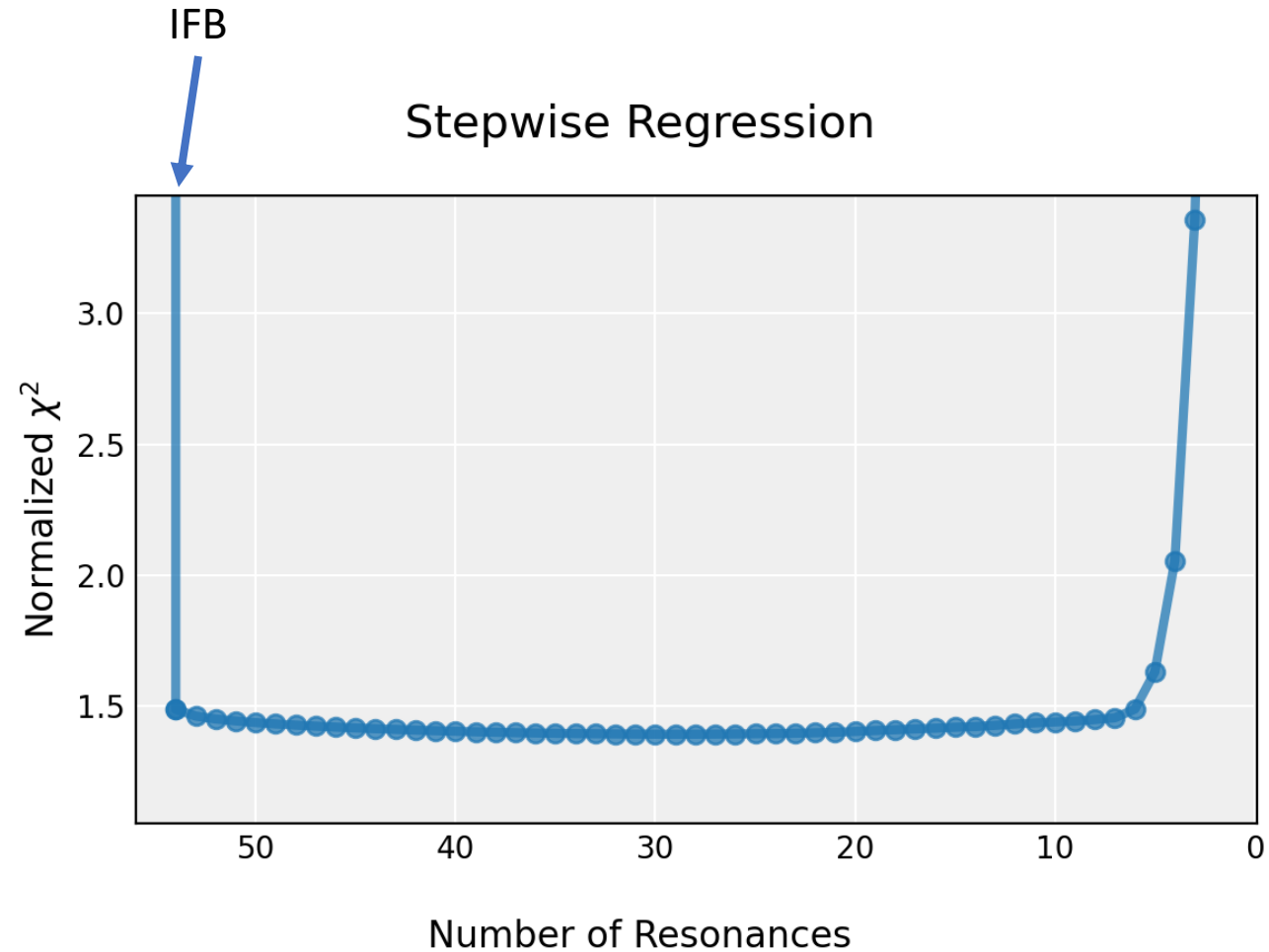
1. Design initial feature bank
2. Non-linear optimization
3. Stepwise variable selection

Composite observables used to infer resonance parameters



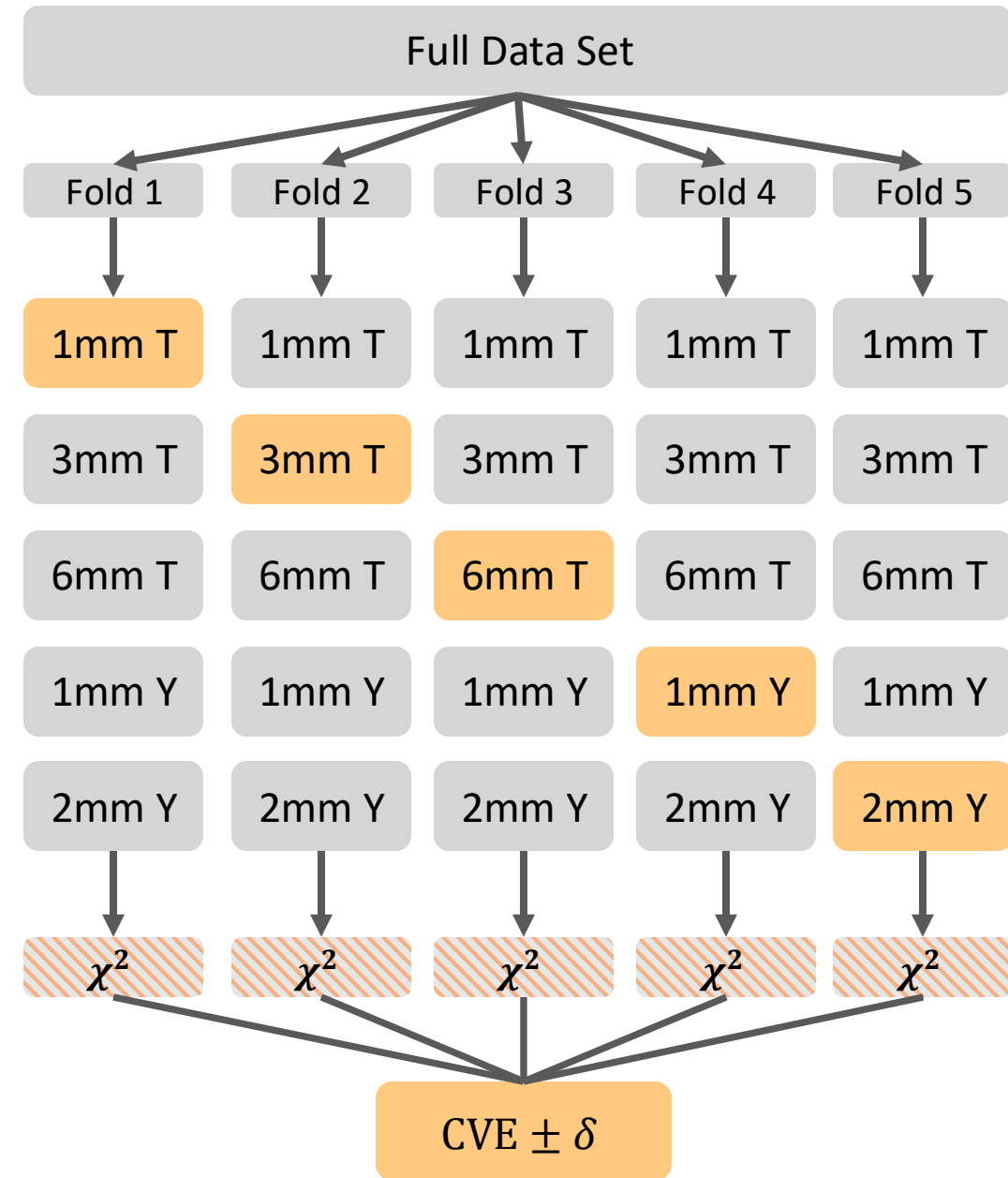
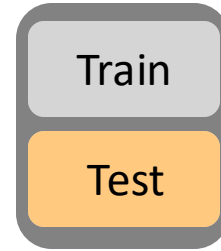
Automated parameter inference

1. Design initial feature bank
2. Non-linear optimization
3. Stepwise variable selection

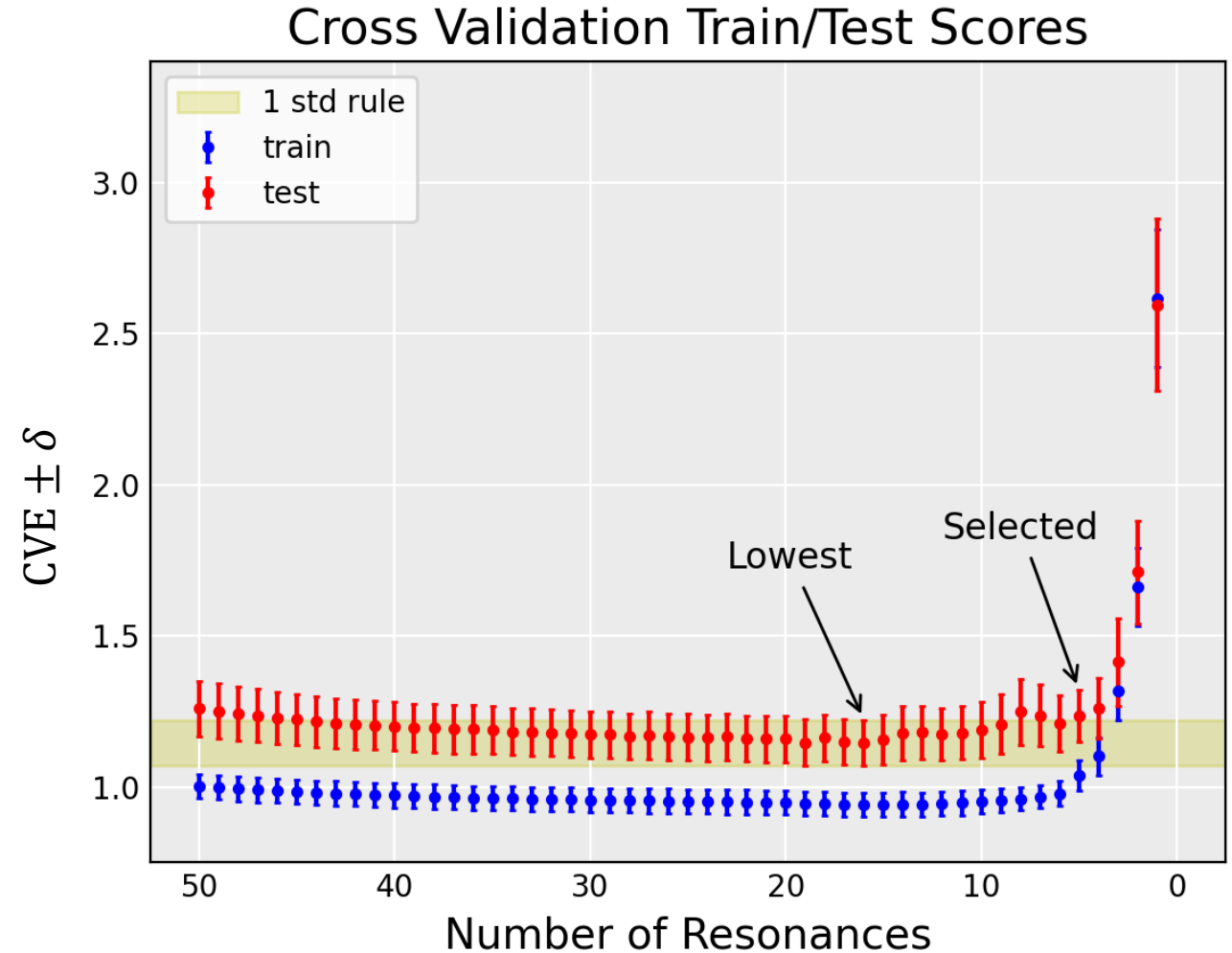


Automated parameter inference

1. Design initial feature bank
2. Non-linear optimization
3. Stepwise variable selection
4. Cross validation for model selection

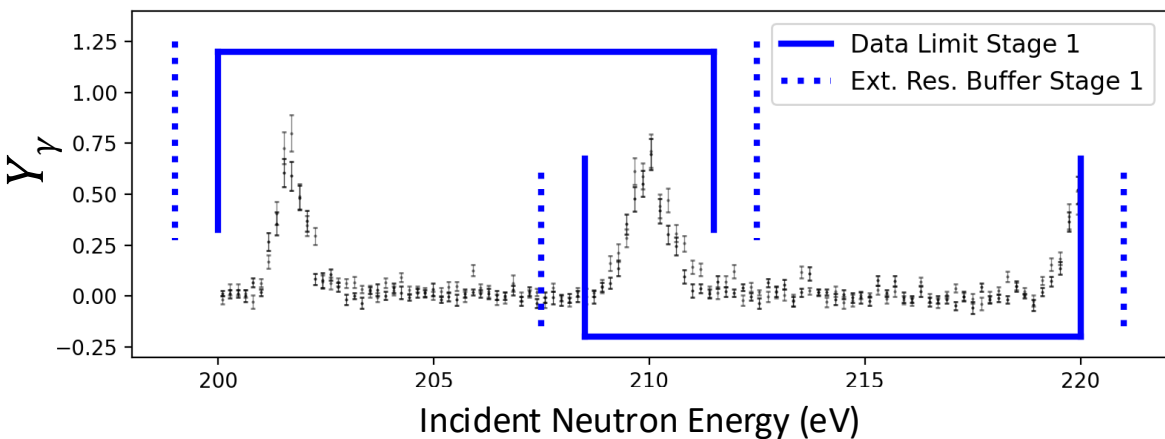
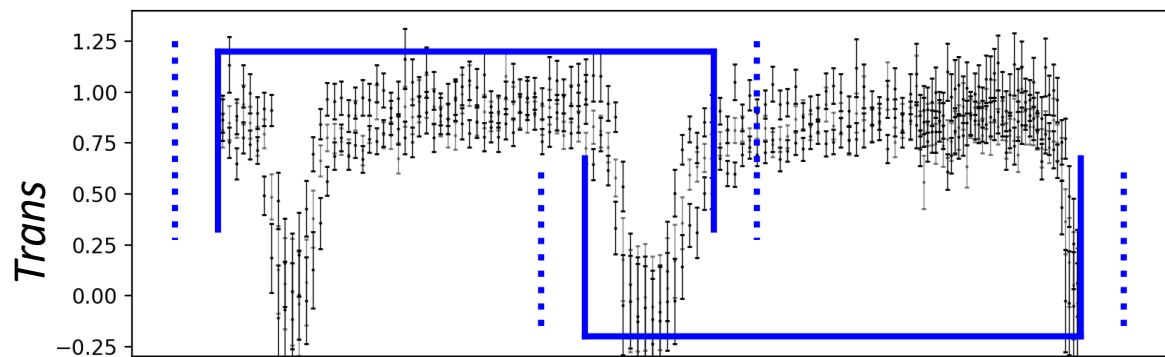


1. Design initial feature bank
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4. Cross validation for model selection

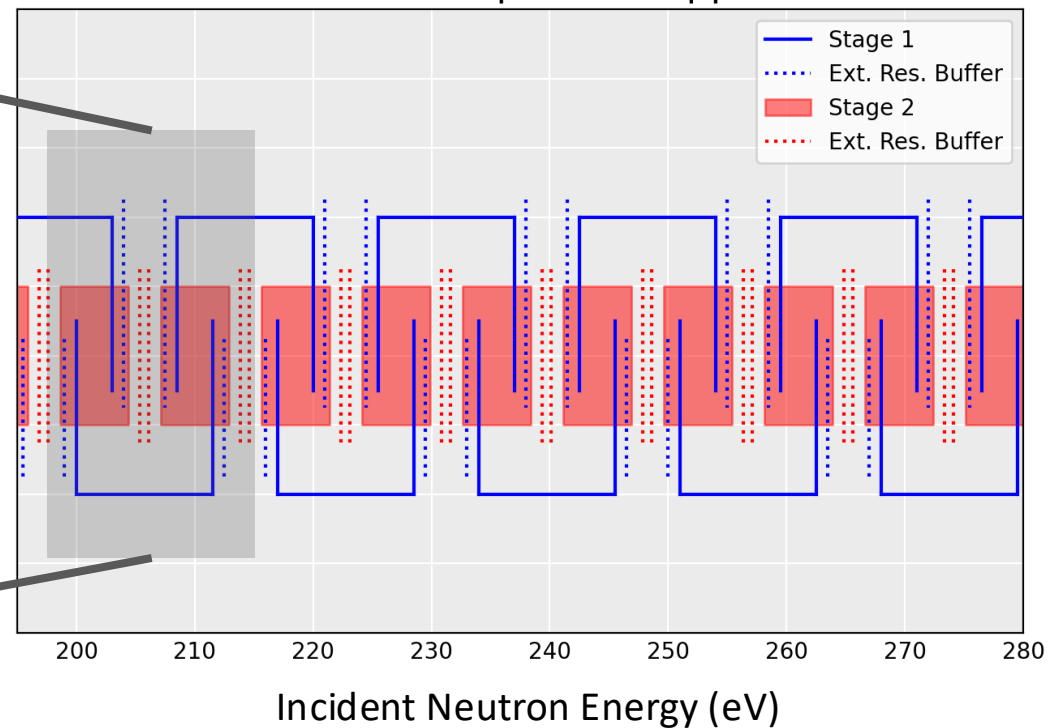


Solved in overlapping windows

20 eV Window



Window Decomposition Approach



AutoFit “Hyperparameters”

- Few inputs \Rightarrow reproducible estimates
- Intuition for good settings
- Initial feature bank can integrate with prior knowledge

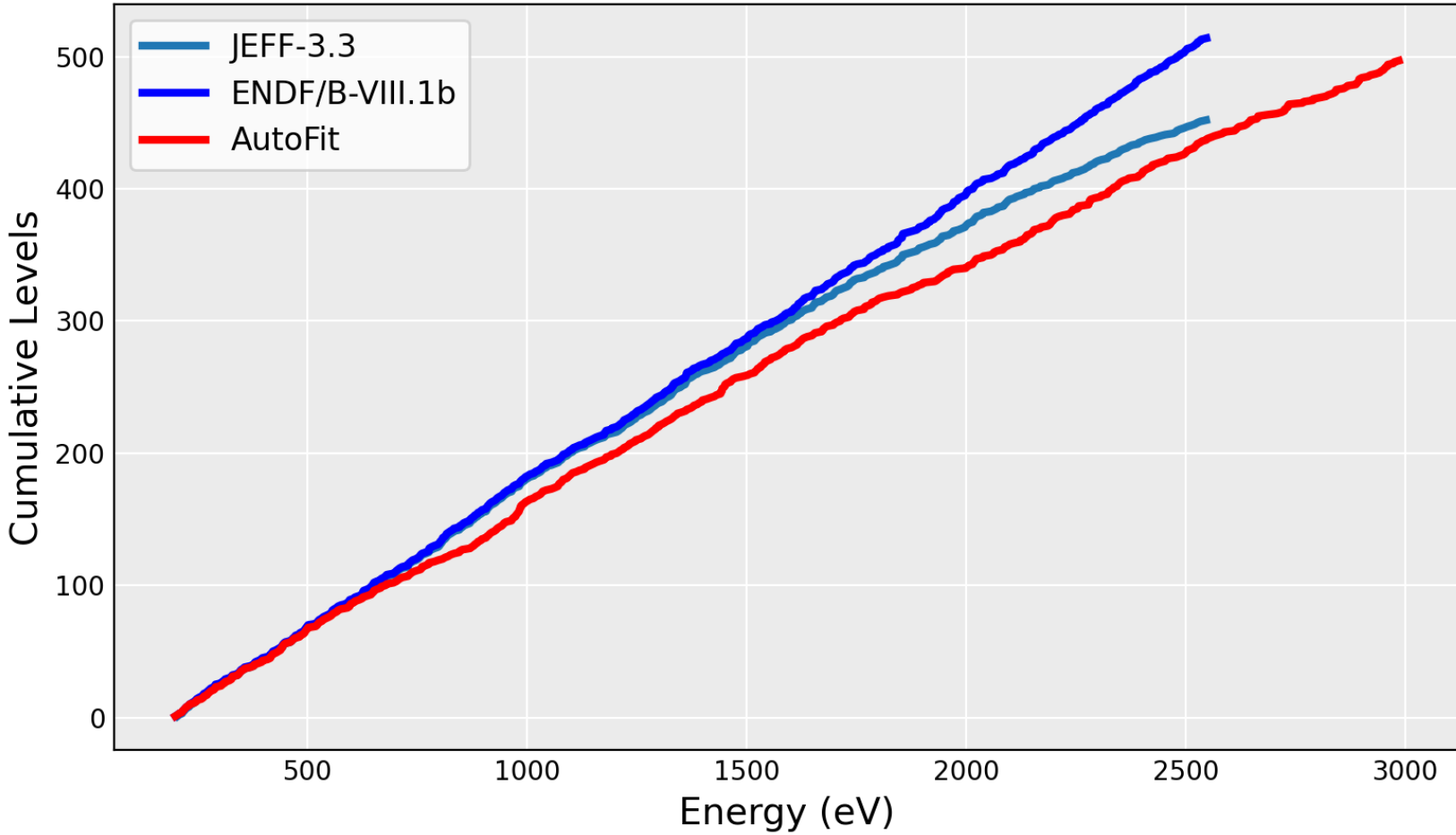
Parameter	Setting
Initial feature bank design	$\Delta E_\lambda = Q_W(0.01)$
	$\Gamma_\gamma = \langle \Gamma_\gamma \rangle$
	$\Gamma_n = Q_{PT}(0.1)$
Fitting precision	$\frac{\Delta\chi^2}{N_d} < 0.01$
Stepwise greediness	Low
CV window size	20 eV

Differences in evaluation methods

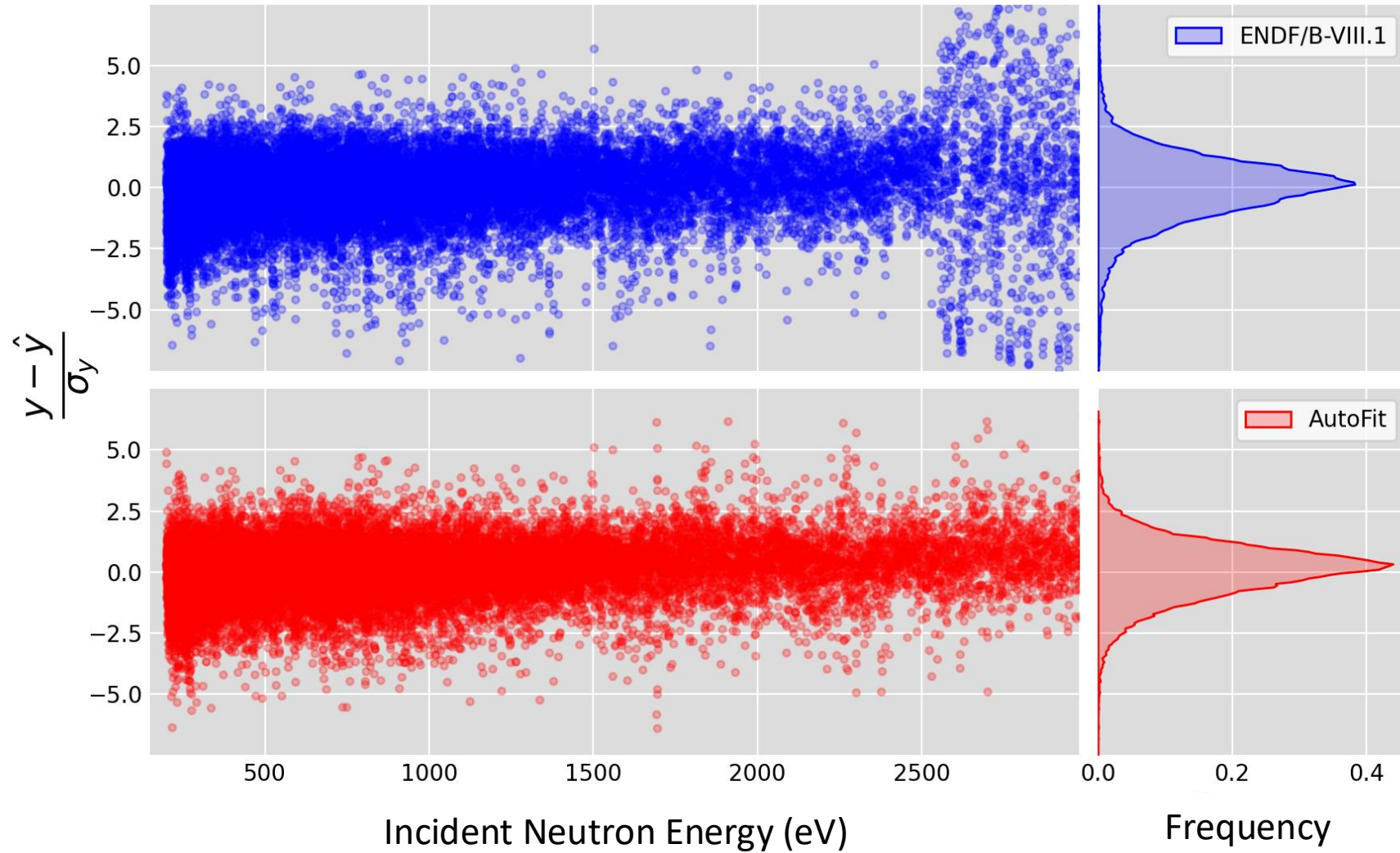
	AutoFit	ENDF/B-VIII.1
Spin group selection	χ^2	Atlas/resonance statistics
Fitting method	Simultaneous	Sequential
Small fake resonances added	No	Yes
Datasets used in 200-2550eV	5	6
Fit Γ_γ	Average +/- 2%	Average +/- 2%
Prior evaluation	None	JEFF-3.3

AutoFit prefers parsimonious models

Cumulative Levels for Different Evaluations of ^{181}Ta



Normalized Residuals For Different Fitting Approaches

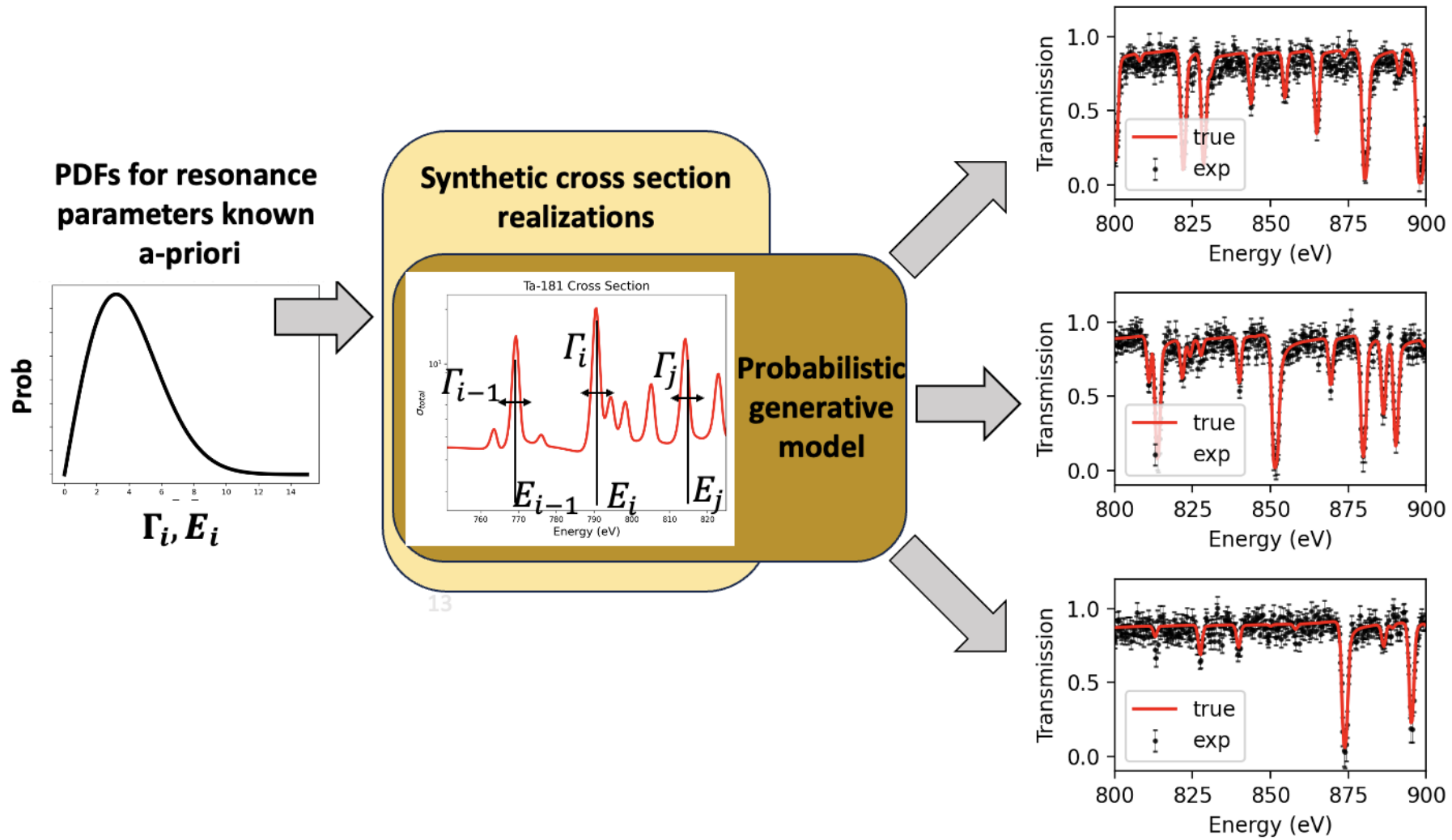


χ^2 calculated below 2500 eV

Fitting Method	χ^2/N_{data}
AutoFit	1.354
ENDF/B-VIII.1	1.698
ENDF/B-VIII.1 Fit	1.581

Synthetic Data Testing Framework

Sampled Resonance Ladders

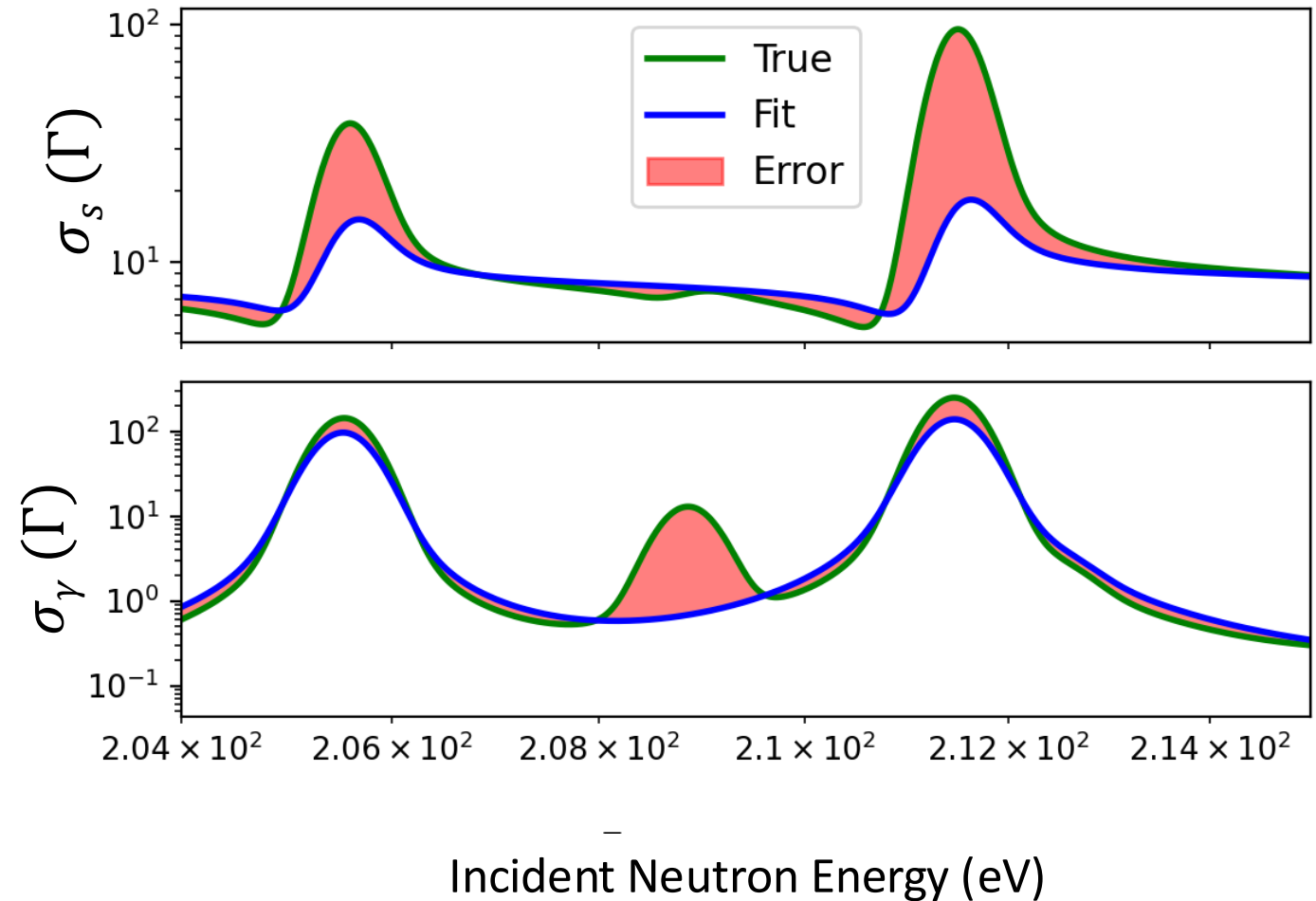


$$\text{True} = \sigma_{\text{rxn}}(\Gamma_{\text{True}})$$

$$\text{Fit} = \sigma_{\text{rxn}}(\Gamma_{\text{Fit}})$$

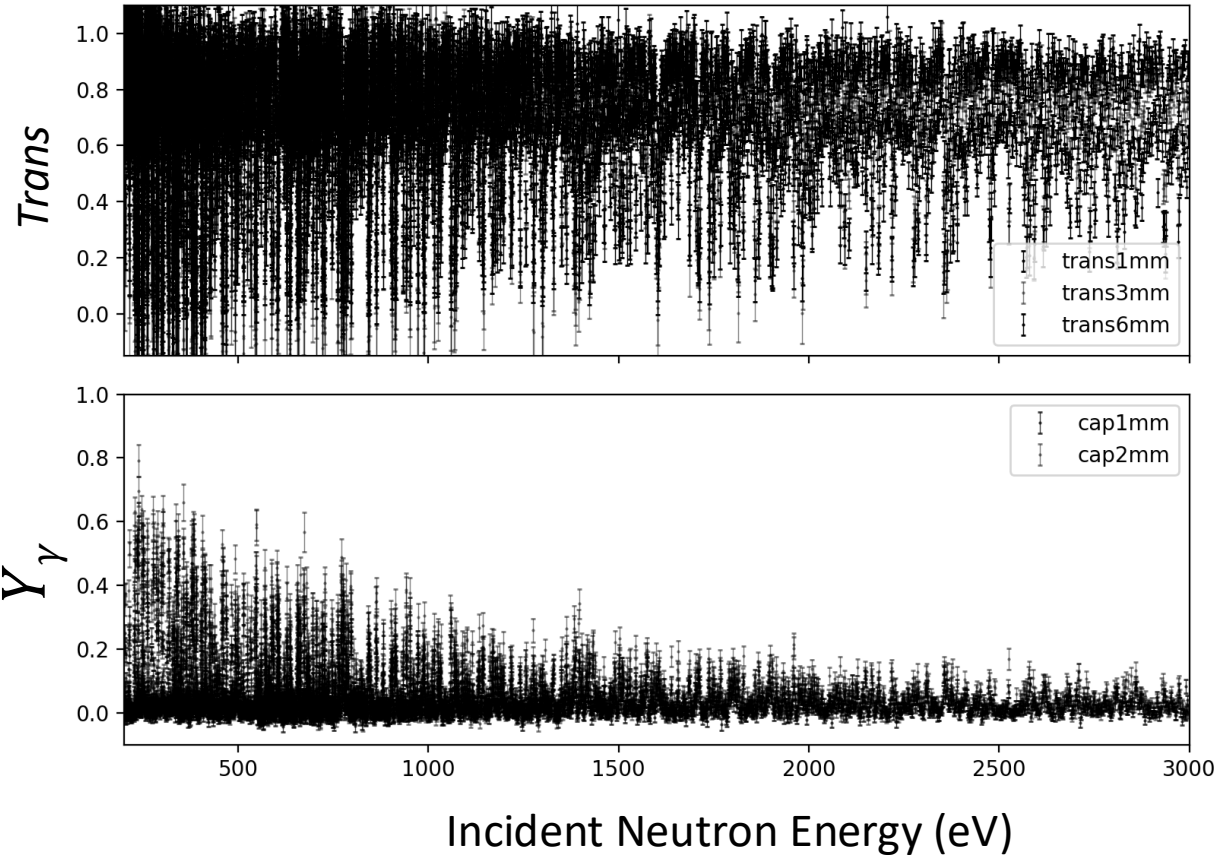
- Root Mean Squared Error (RMSE)

Doppler Broadened Reaction Cross Sections

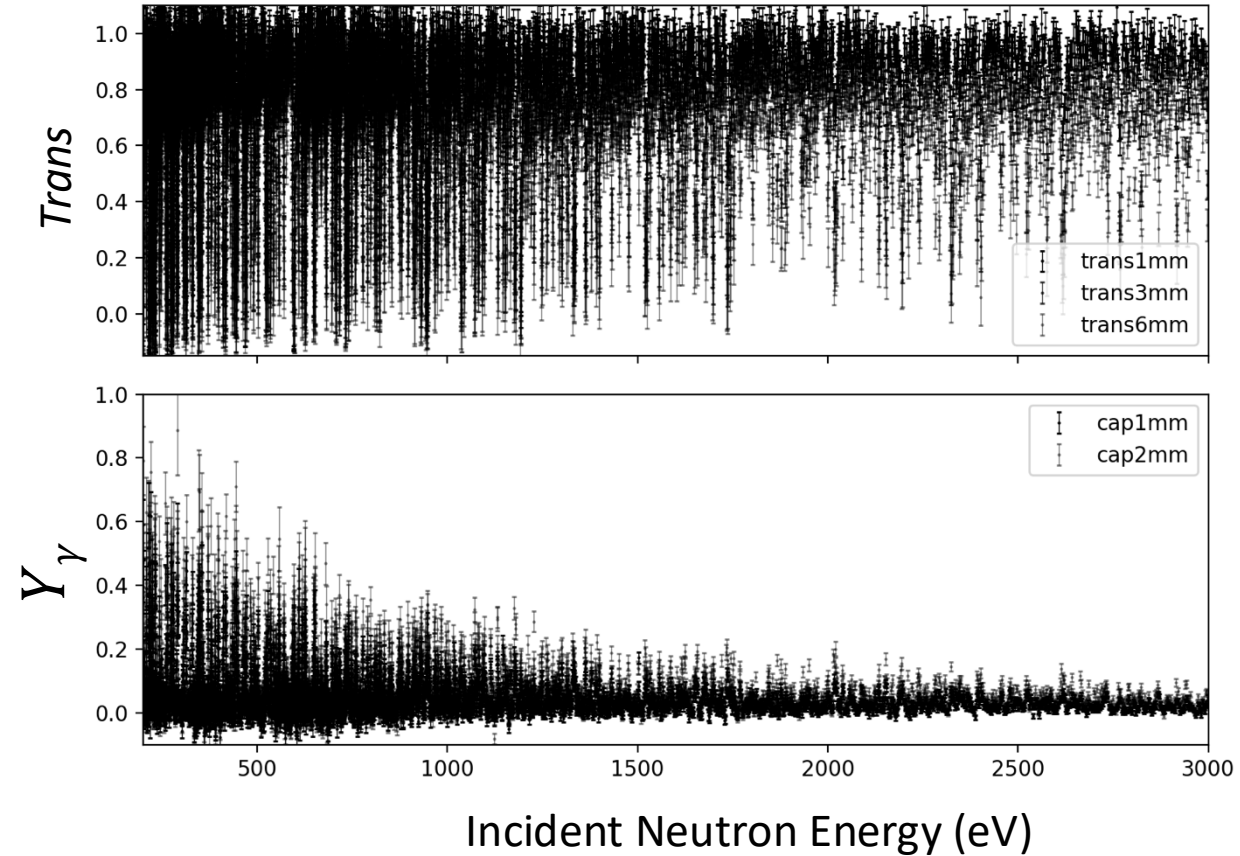


Generative Models Developed Mimicking Actual Measurements

5 Measurements Synthetically Generated



5 Measurements by Brown, et al.



What questions does this allow us to ask?

Different Regression Objectives

$$LS = (D - T)^T(D - T)$$

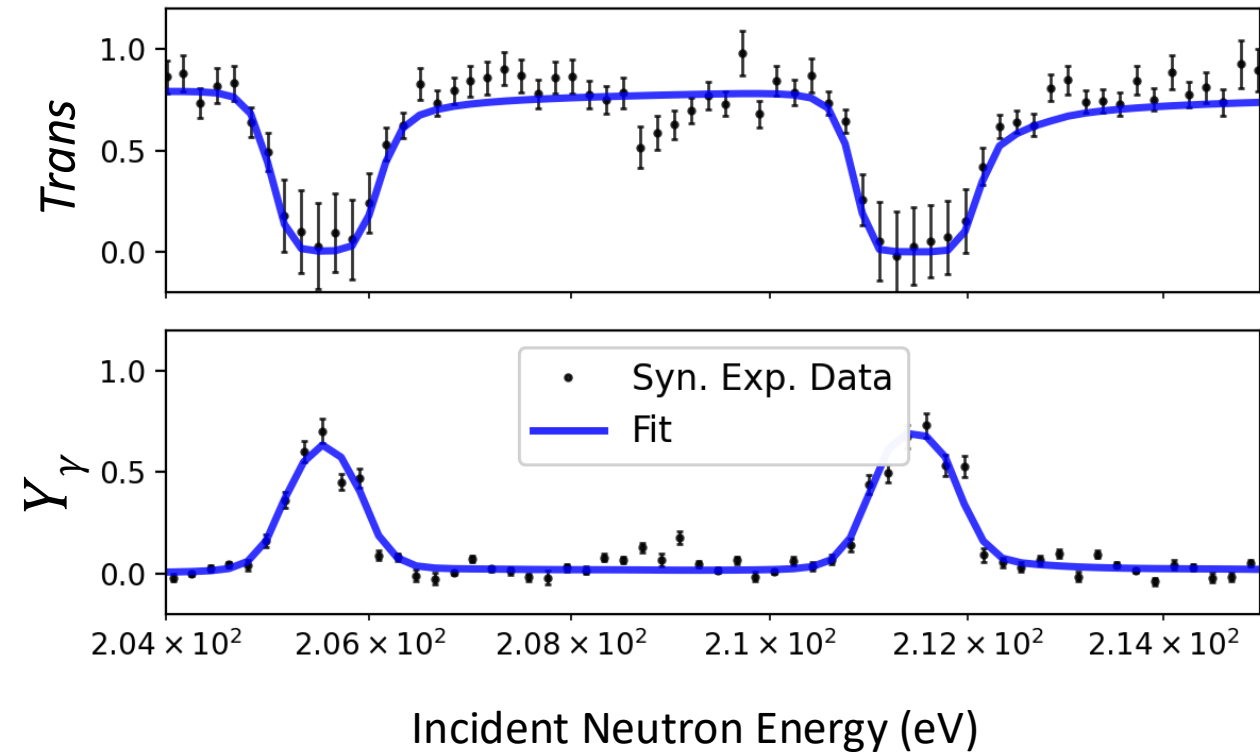
$$WLS = (D - T)^T V^{-1}(D - T)$$

where : $V_{i \neq j} = 0$

$$\chi_D^2 = (D - T)^T V^{-1}(D - T)$$

$$\chi_T^2 = (D - T)^T V(T)^{-1}(D - T)$$

Accessible



Start From True Parameters

$$LS = (D - T)^T(D - T)$$

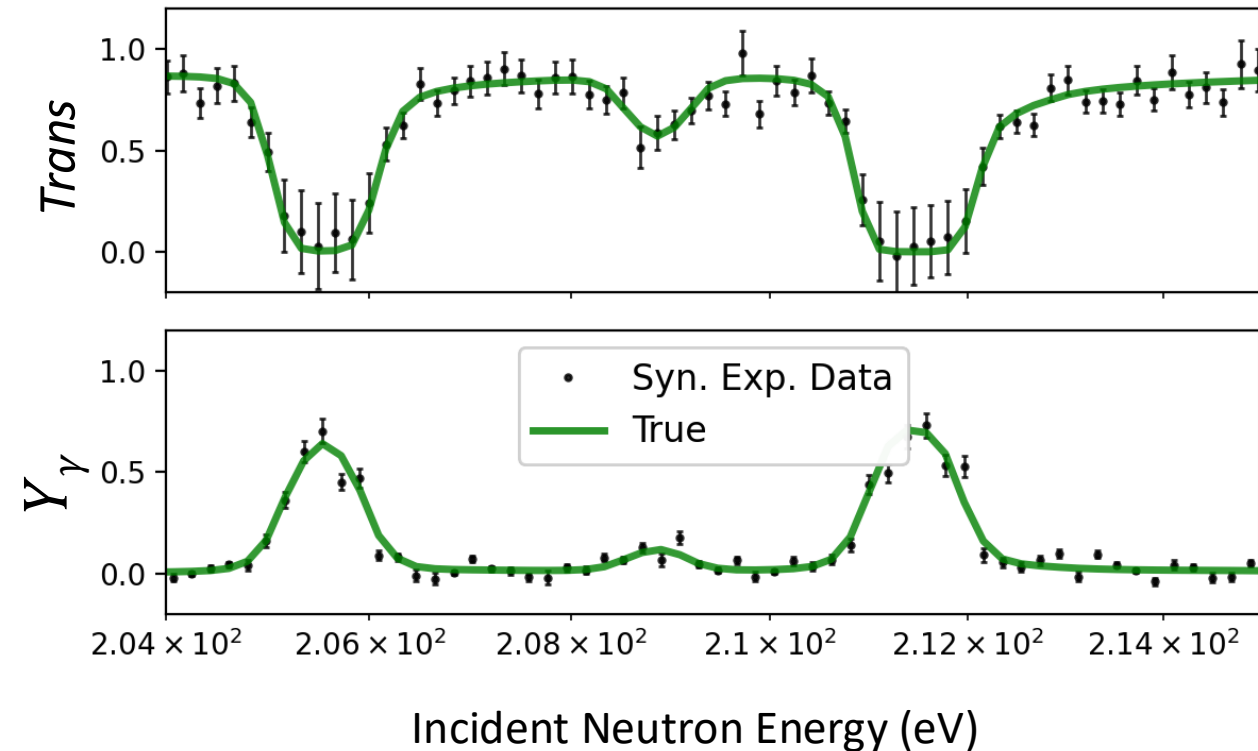
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Start From True Parameters



Fit Regression Objective

$$LS = (D - T)^T(D - T)$$

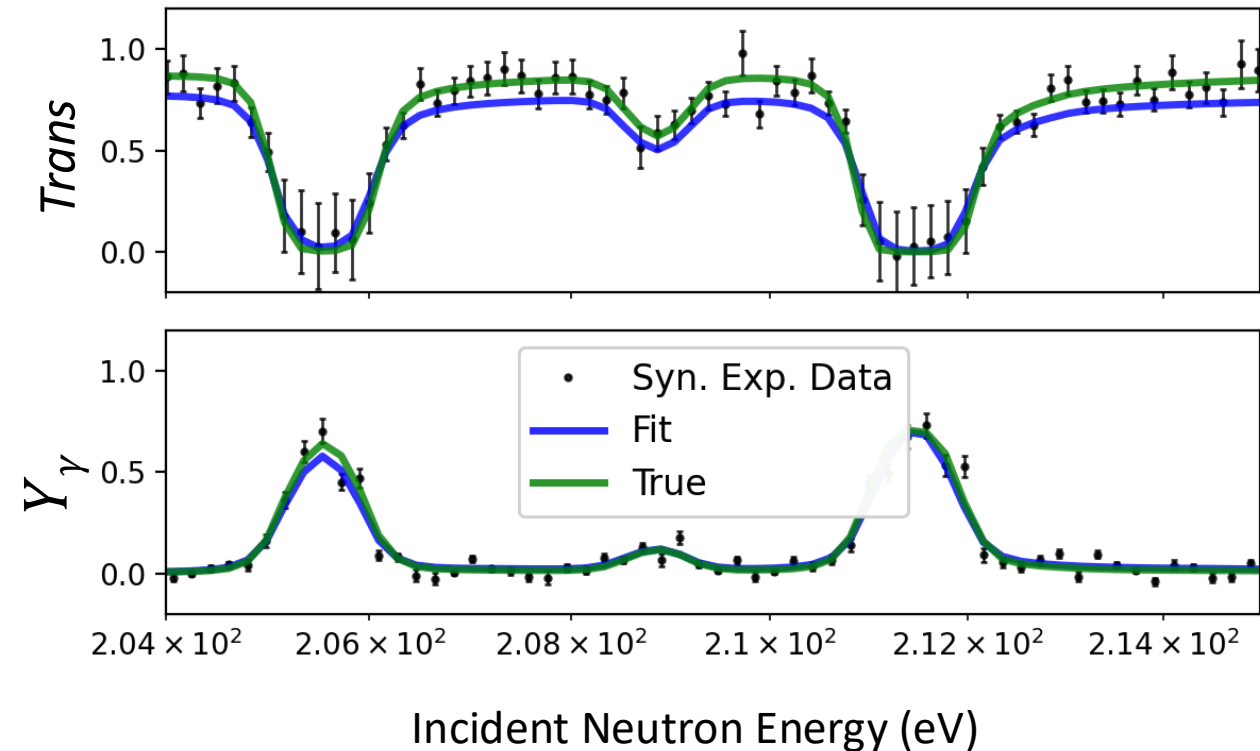
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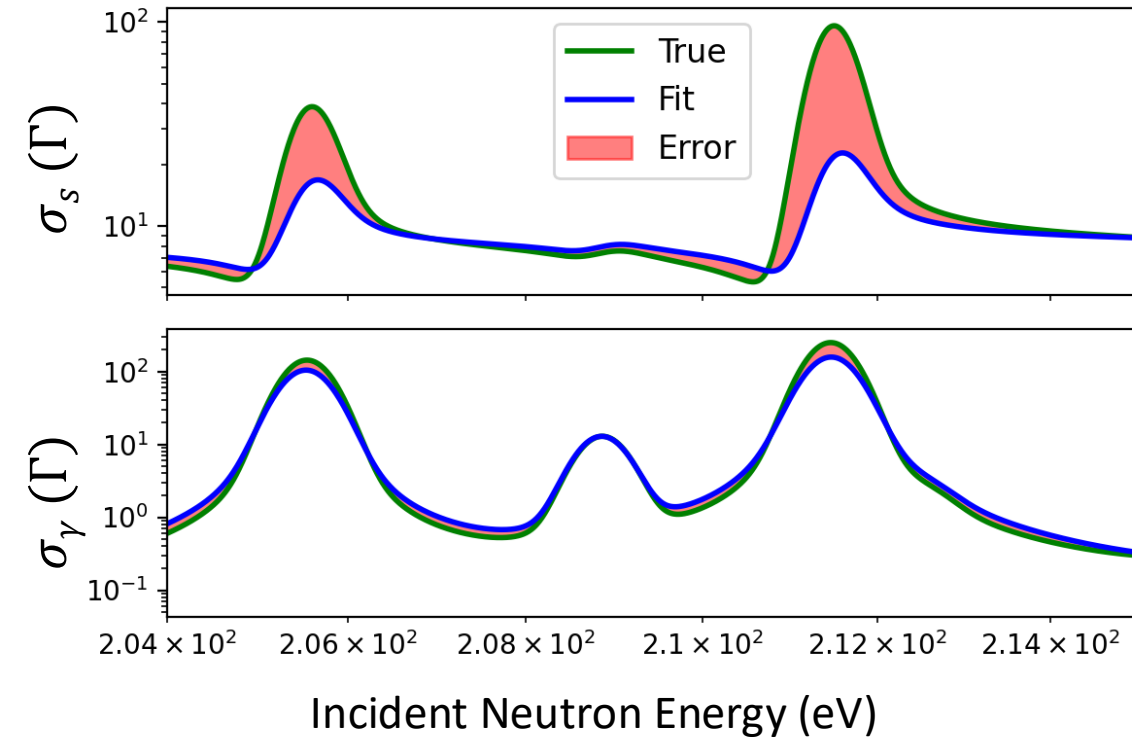
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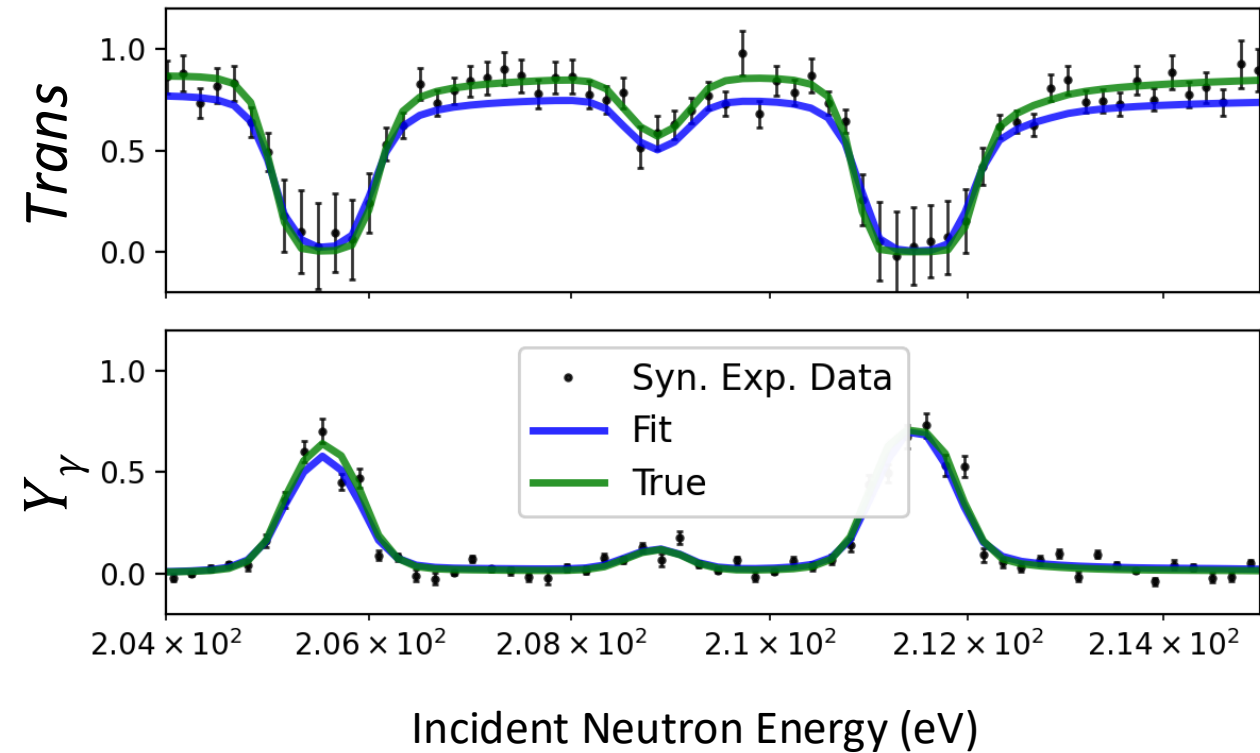
Fit Regression Objective



Compare Theoretical Objective



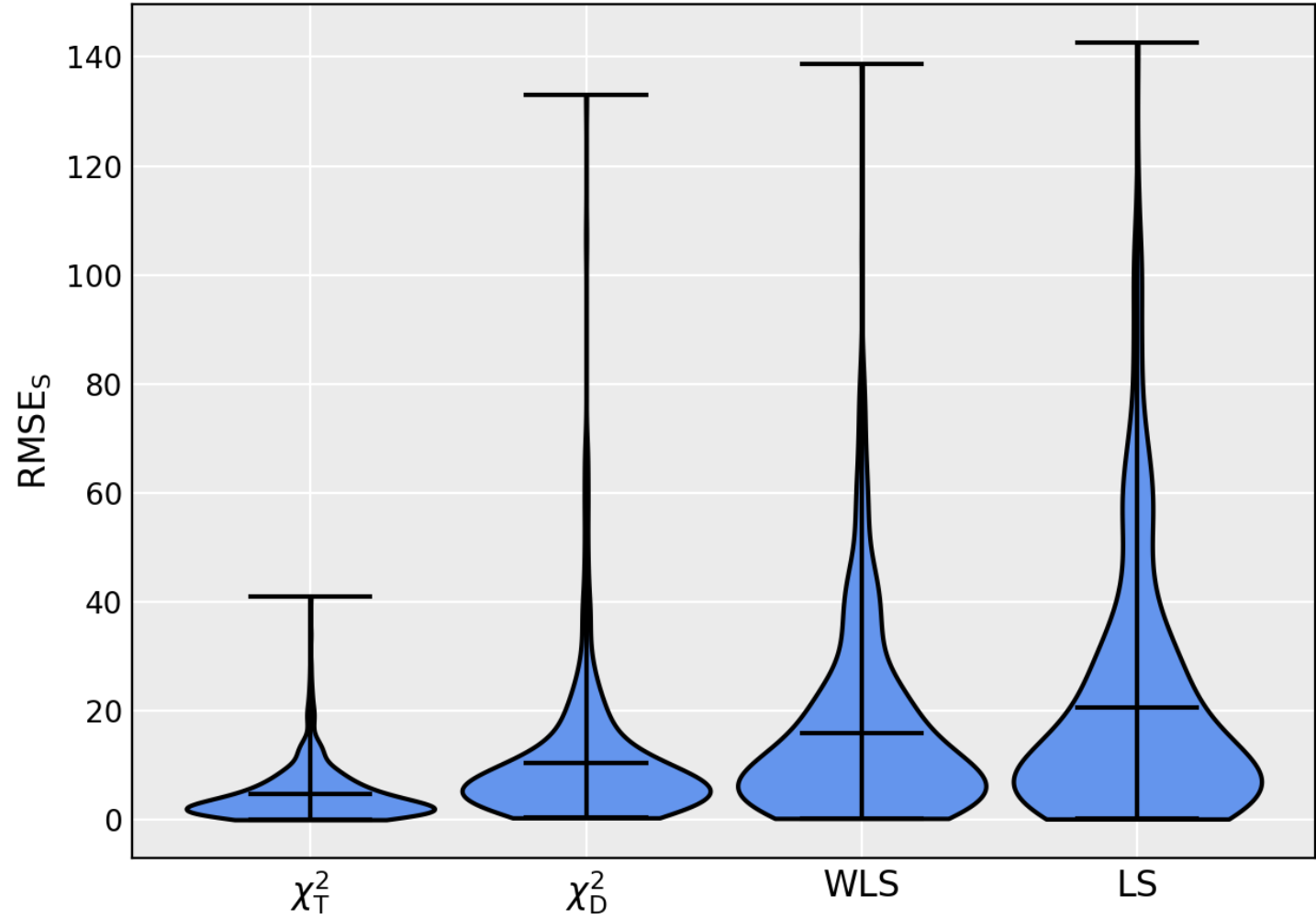
Fit Regression Objective



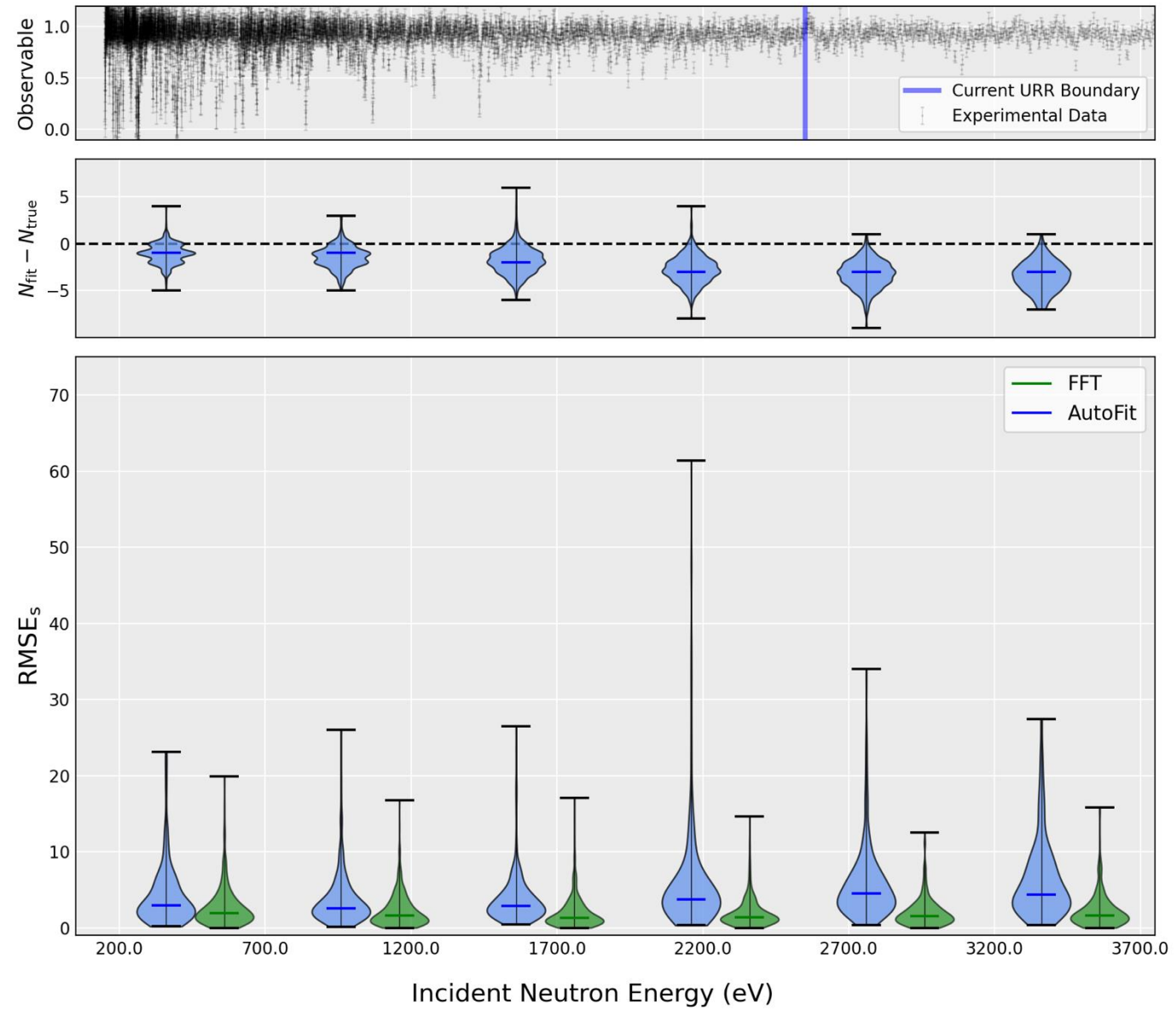
Repeated over 500 Samples

Surrogate Objective	RMSE (bn)	MAE (bn)
χ_T^2	6.68	1.40
χ_D^2	16.37	3.22
WLS	23.40	4.97
LS	30.88	6.74

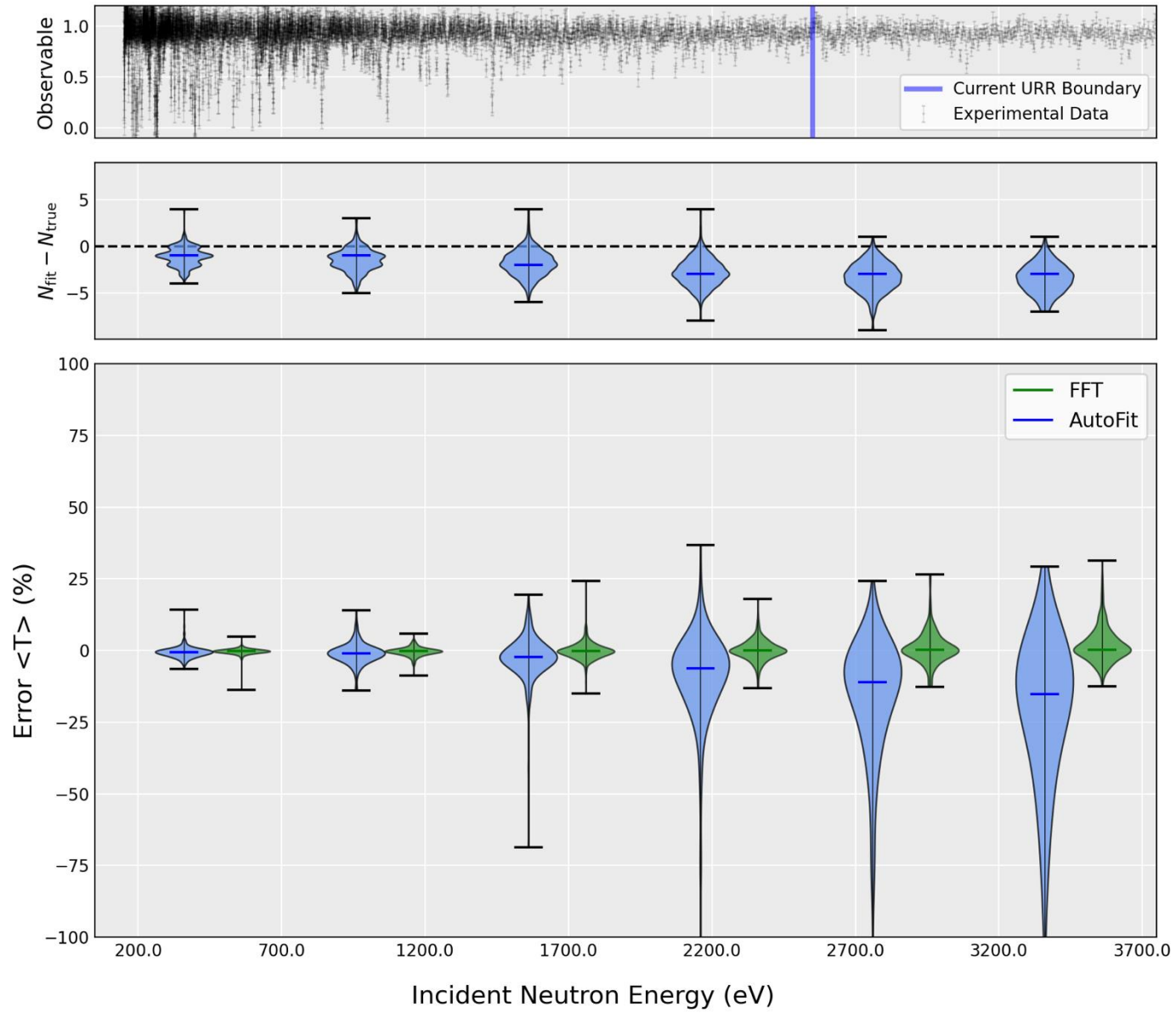
Error Metric Across 500 Samples for Different Regression Objectives



Performance Across a Wide Energy Domain



Performance Across a Wide Energy Domain





ATARI

AI/ML Tool for Automated Resonance Inference

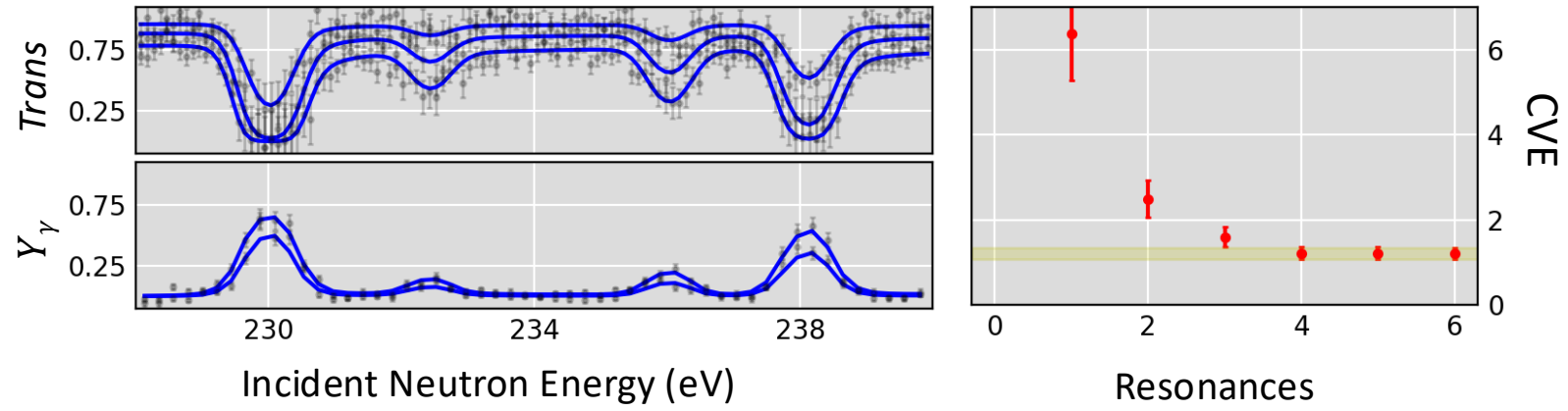
Computational framework: ATARI

- Automated resonance inference is **reproducible** and **fast**
- Performance can be **tested** and **benchmarked**
- Constant PPP bias even if correlations are small
- Future work: resonance parameter statistics, uncertainty quantification

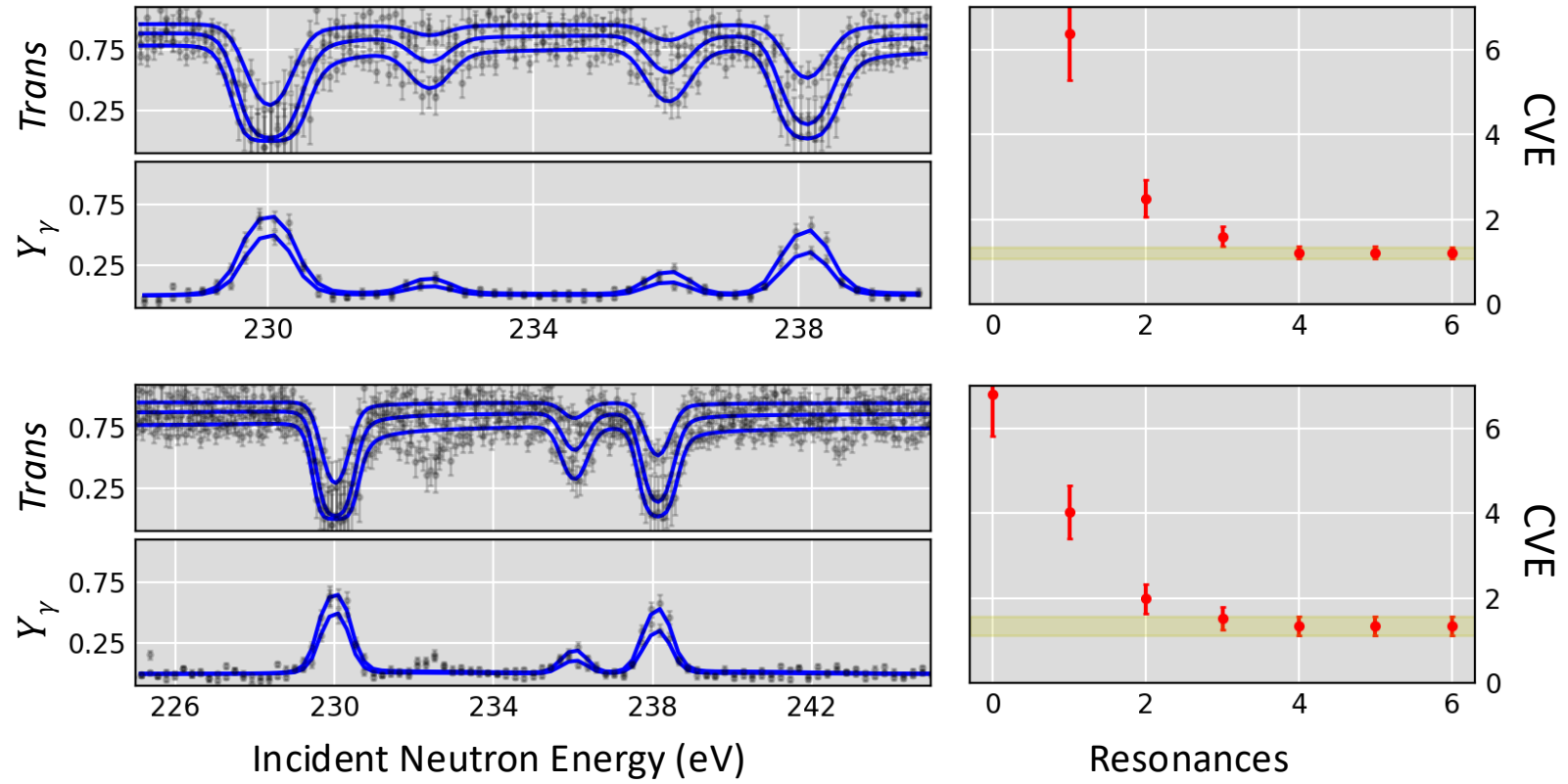
Ta-181 Analysis

- Minimal deterioration of **theoretical objective** approaching URR
- **Regression objective** is as-good-or-better than ENDF/B-VIII.1 evaluation
- Differential data has **some** spin information

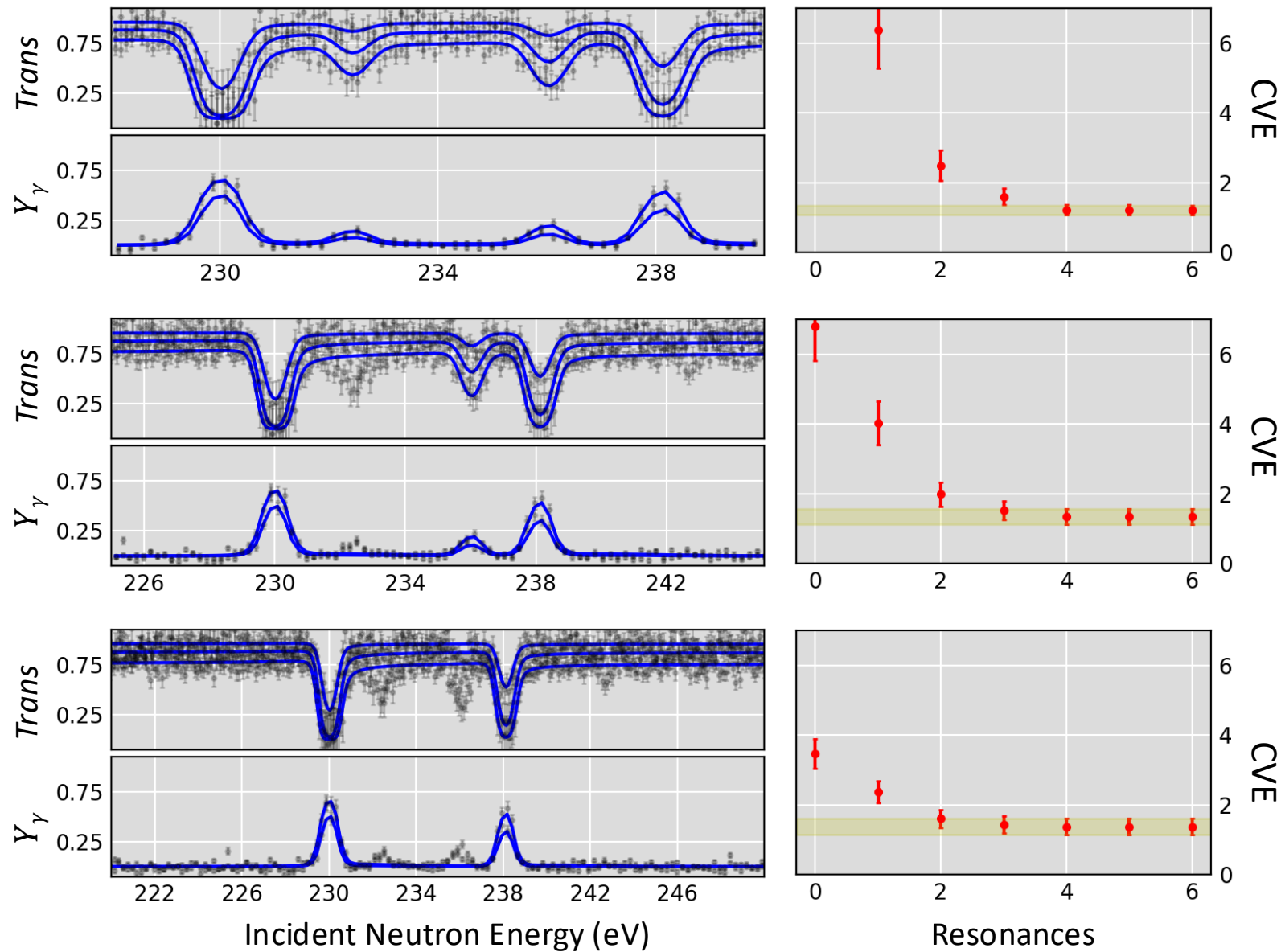
Impact of Window Size on CV-model selection



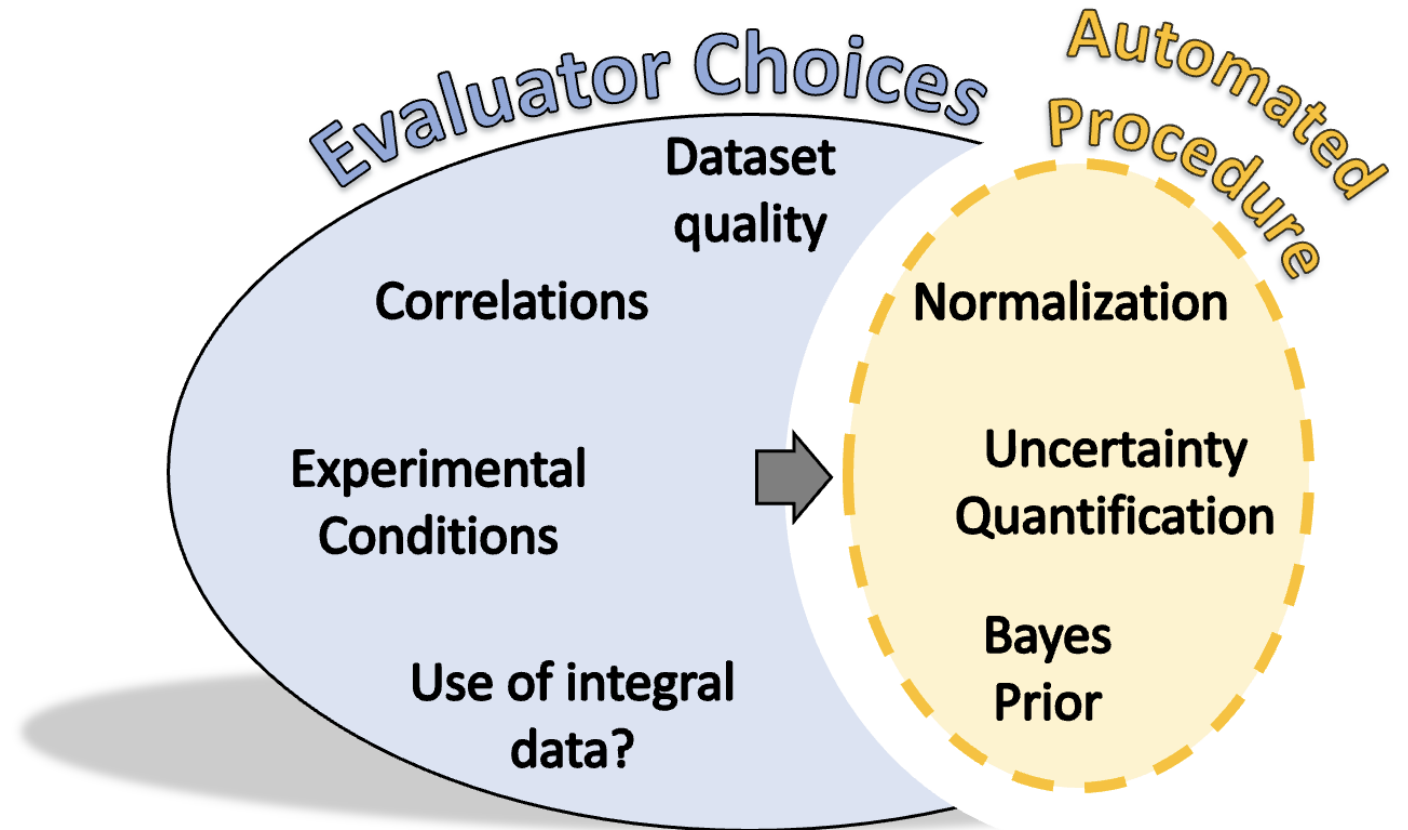
Impact of Window Size on CV-model selection



Impact of Window Size on CV-model selection



1. Develop automated tool
 - Augment evaluators
2. Computational experiments
 - Benchmark tool
 - Improve tool
 - Learn new physics



Computational Framework

