# Towards rigorous and reproducible uncertainty quantification in resonance evaluation

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#### Two primary efforts

- 1. Develop automated tool
  - Augment evaluators

- 2. Computational experiments
  - Benchmark tool
  - Improve tool
  - Learn new physics





### Methods

- SAMMY
- Robust, non-linear least squares algorithm
- Feature selection

## Results

- Accurate resonance I.D.
- No spin groups (yet)



#### Automated Tool

### Methods

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#### Computational Framework – ML approach

### Goal

- Benchmark at differential level
- Improve performance
- Test choices & assumptions

# ML Approach

- Synthetic data
- Transmission last year
- Capture yield this year















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#### **Computational Framework**







# Developing a generative model for the resonance experiments







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# Leveraging AI/ML to benchmark region of automation



# • Benchmarking the automation:

- 1. Quantitative assessment at differential level
- 2. Sensitivity to assumptions
  - Theoretical: parameter distributions
  - Experimental: unknown uncertainties









