Filling In Covariances

Trying to fill in missing covariances in modern evaluations

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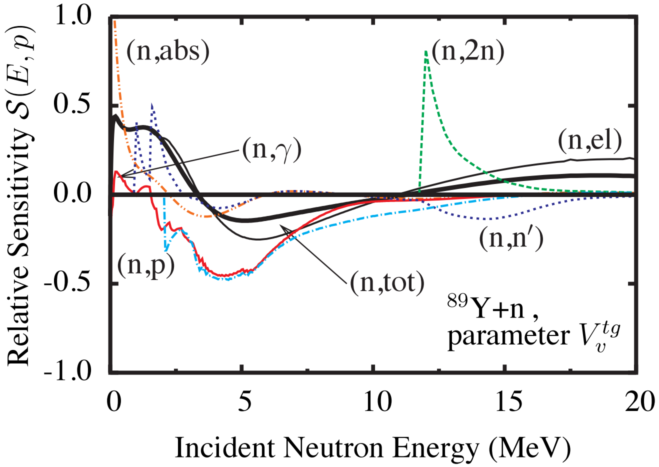
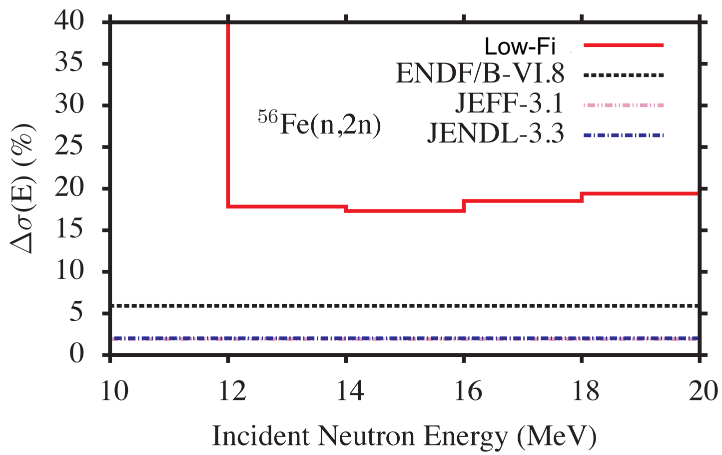
Filling In Inadequate Covariances

- Without a new full evaluation.
  - Construct simple “ad hoc” covariances based on
    - Differences between existing evaluation libraries.
    - Comparison of mean values with spreads of experimental data
    - Model-dependence between channels
      - Clone covariance pattern in library for neighbors in this nuclear region.
      - For example, elastic and inelastic are commonly anti-correlated.
  - Use low-fidelity (“Low-Fi”) covariances described by Little *et al* (2008):
    - Fills in gaps in ENDF/B-VII.0
  - Use “Machine learning” like approaches to make up covariances
- Eventually: new evaluations
  - Expensive without investments in automating the evaluation process.

The Low-Fi Approach (For Fast Region)

Little *et al* (2008):
M. T. Pigni *et al* (2009)





- Based purely on model variation.
  - Low-Fi's parameter variations built on intuition of Low-Fi collaboration
  - Extending to ENDF-VIII requires codification of that intuition.
- No cross correlations
- No direct connection back to measured data.
- Targeted quick approximate covariances to fill out library rather than

"Making Up" Missing Covariances

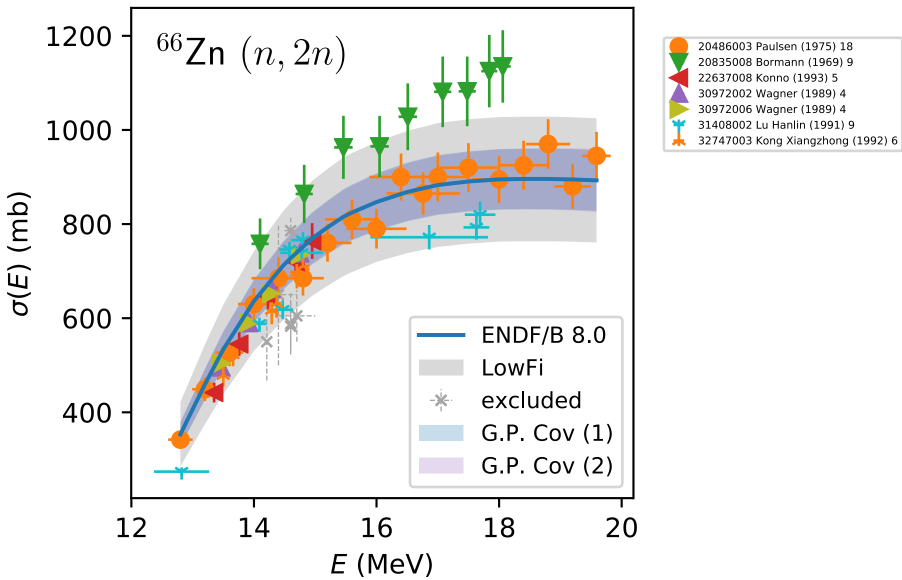
- We want a more generic needed tool to **generate** sensible **artificial** covariances for when no covariance data is available
  - We also want to generate sensible substitute covariances when application users have a reason to doubt available covariances.

- Abstractly, an evaluation with a covariance matrix represents a way to sample a set of (nearly) continuous functions that are distributed pointwise as a multivariate Gaussian
  - **i.e. A Gaussian Process**

$$F(x) \sim GP\big(\mu(x), K(x', x)\big)$$

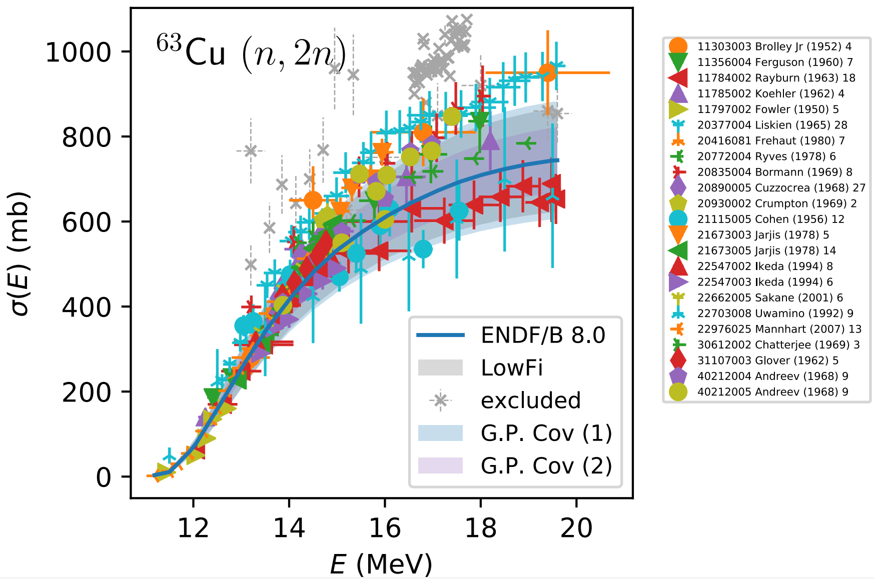
    - $\mu(x)$ is the average or mean function
    - $K(x', x)$ is the covariance kernel of the functions
    - $\mu(x), K(x', x)$ are often parameterized

Gaussian Processes to Make Up Covariances



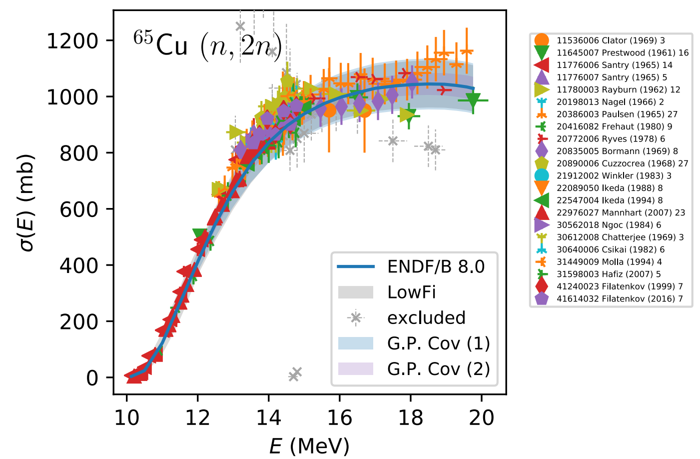
- Use Gaussian Process formalism to relate a parameterized covariance kernel to an evaluation + EXFOR data.
- Provides alternative to 'Low Fi'.
  - Few cases studied thus far are competitive.

- Purely data driven,
  - No evaluation code is used, extremely fast to run
  - Dangerous, no physics model backing up the covariance!
- Still codifying how to pick kernels and avoiding pitfalls
  - How to avoid collapsing length scales
- Extend to coupled channels, angular distributions, etc.



Conclusions

- Modern nuclear data libraries have many inadequate or incorrect covariances
  - Limits uncertainty analysis of applications that consume nuclear data.
- Present solutions to supplement covariances
  - Ad hoc mix and match from nearby evaluations.
  - Low-fidelity “fill-in” covariances capture model variations
- Potential future solutions
  - Gaussian processes provide a formalism to extract “data driven” covariances for fast region of cross sections.
  - More general machine learning can replace concept of covariances completely.
    - But this would require “new” evaluations.



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