Community Driven Repositories of Knowledge

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Introduction to ASCSN

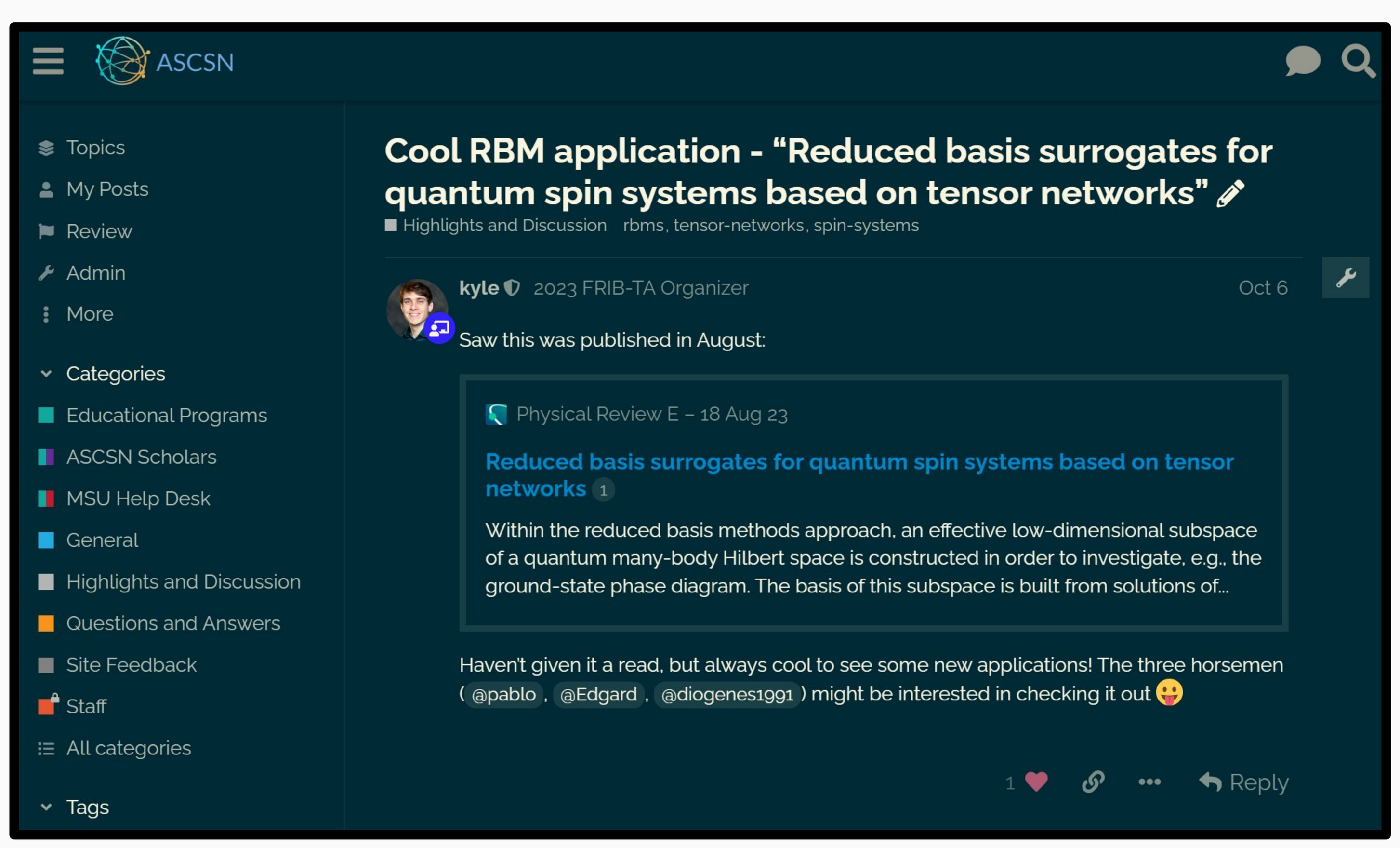
The Advanced Scientific Computing and Statistics Network's primary purpose is to foster collaborations and build connections between those that are pursuing technical developments in computational science, machine learning, statistics, and applied mathematics, and the various application domains that stand to benefit from that development.

https://ascsn.net/

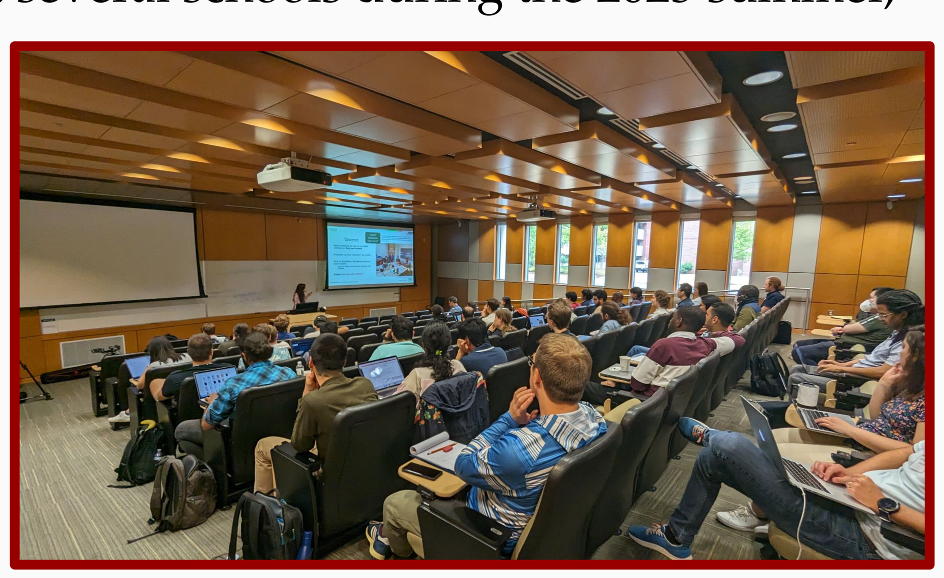
Advanced Scientific Computing and Statistics Network

Community driven forum

Interactive forum to foster discussions and collaborations on several topics, from machine learning and statistics applications to educational materials for **summer schools** and ongoing courses and lectures.



The ASCSN forum and github repository has been used extensively to support several schools during the 2023 summer, including the **FRIB Theory Alliance 2023 Summer School**[1] on Uncertainty Quantification and Emulator Development in Nuclear Physics.



https://github.com/ascsn/2023-FRIB-TA-Summer-School

Cloud Computing

Traditional use cases for cloud computing are those that can naturally leverage the **flexibility**, **scalability**, and **accessibility** provided by the paradigm.

Bayesian Mass Explorer Beta!

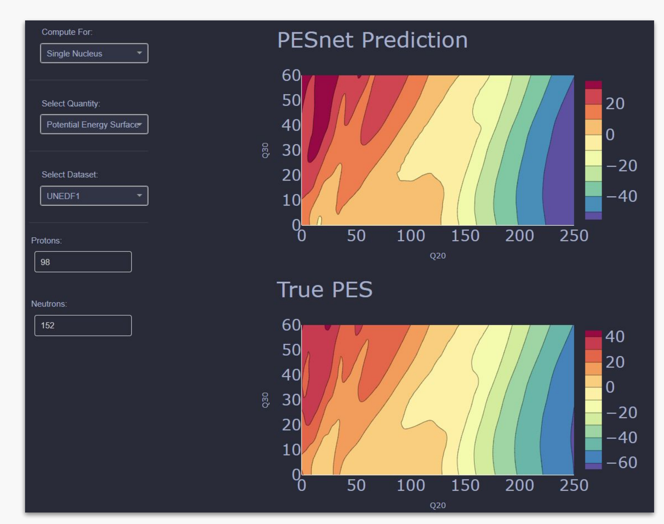
PROJECT SPOTLIGHT: BMEX[2] → https://bmex.dev

The BMEX (Bayesian Mass Explorer) web application is a one-stop-shop for theoretical nuclear data from microscopic physical models with a robust suite of plotting tools

An important opportunity with cloud software is to deploy machine learning models directly in a browser-accessible manner to end-users with minimal cost

SOFTWARE SPOTLIGHT: PESNET

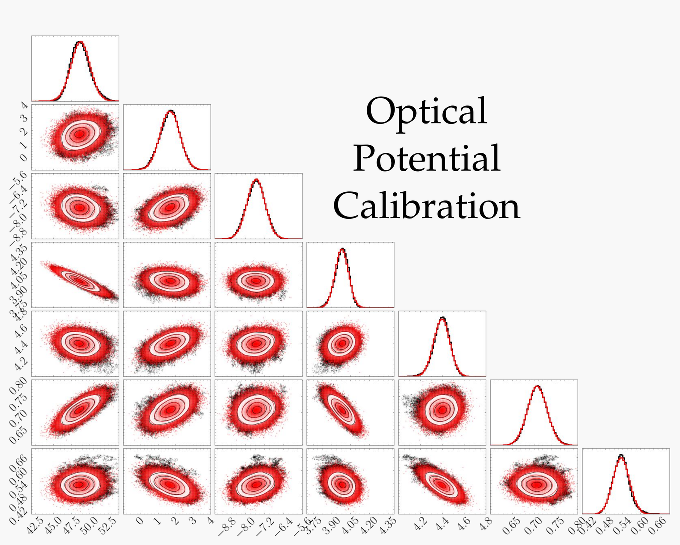
PESNET is a potential energy surface surrogate model that enables fast emulation of nuclear fission surfaces with minimal required resources



CLOUD PERSPECTIVES: DEVELOPMENT WORKFLOWS

One other key benefit provided by cloud environments is that of an easily repeatable workflow. This includes research activities like training machine learning models as well as the automated setup of cloud development environments

PROJECT SPOTLIGHT: Normalizing Flows



Optical Potential Calibration

Black: Monte Carlo Samples
Red: Normalizing Flow Samples

One project merging AI/ML and statistics is utilizing normalizing flows to learn Bayesian posterior distributions for theoretical models. Once learned, samples can be drawn as needed in cloud environments and posteriors can be tagged and frozen to certain data sets. Furthermore, this framework will enable the continuous calibration of theoretical models as new experimental data becomes available.

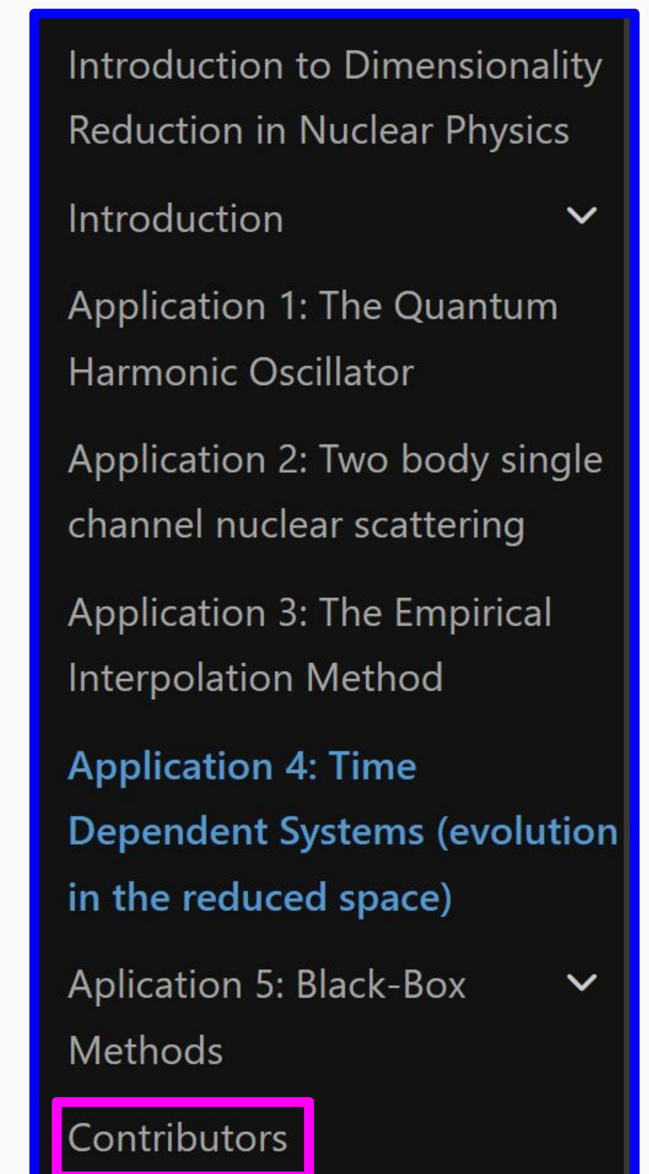
References and links

[1] FRIB TA 2023 Summer School. https://indico.frib.msu.edu/event/65/overview
[2] Bayesian Mass Explorer, https://bmex.dev
[3] Y. Yamauchi, et al "Normalizing Flows for Bayesian Posteriors: Reproducibility and Deployment" pre-print(2023)
[4] Dimensionality Reduction in Nuclear Physics, https://dr.ascsn.net
[5] Quantum Computing Applications in Nuclear Physics, https://qc.ascsn.net

Online ML living resources

The cloud also affords an opportunity to develop high quality tutorials and examples of advanced technology being used to tackle problems in nuclear physics[4,5]

Dimensionality Reduction in Nuclear Physics
Presented by ASCSN



$$\frac{d}{dt}a_j(t) - i\hat{H}\boldsymbol{a}(t) = 0, \quad (30)$$

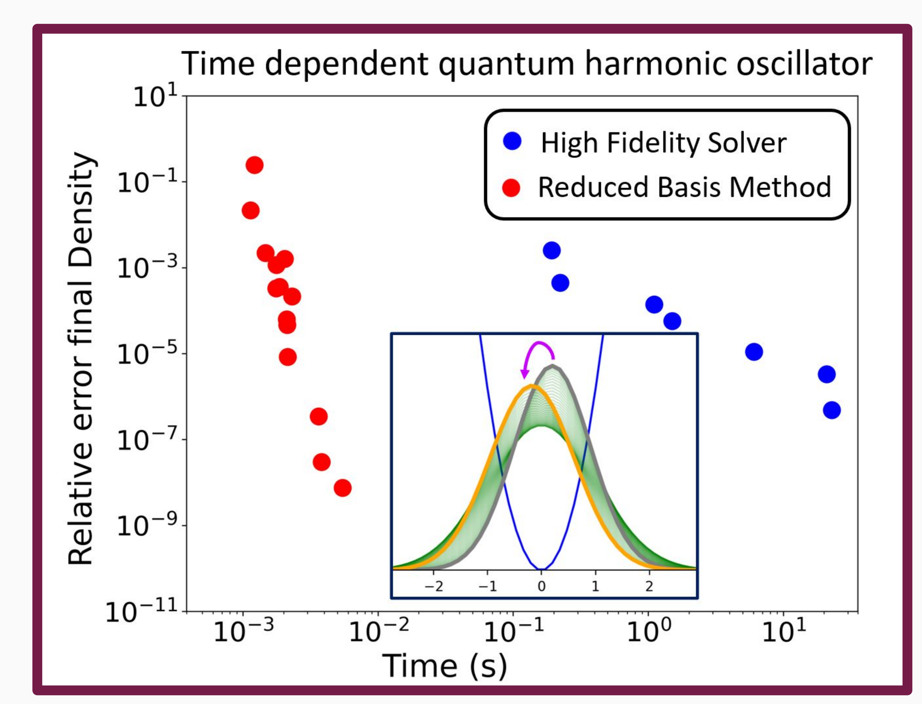
where $\boldsymbol{a}(t) = \{a_1(t), \dots a_n(t)\}$ and the reduced Hamiltonian is computed as:

$$\hat{H}_{j,k} = \langle \phi_j | H | \phi_k \rangle$$

Next one could be you!

```python
#Funciton that makes the RB and the equations
def Galerkin_Helper(wf_list,total_basis,N_grid):
    x = np.linspace(-x_max, x_max, N_grid)
    dx = x[1] - x[0]
    D2 = generate_second_derivative_matrix(N_grid, dx)
    U, S, Vt = np.linalg.svd(wf_list, full_matrices=False)
```

Interactive Jupyter book with **pedagogical descriptions**, **runnable adaptable code**, and **physics applications and results**



Future Prospects

Given the versatility of machine learning to be applied in almost any discipline, building pedagogical resources for the community -by the community- will help to lower the entry barrier for scientists across a wide institutional spectrum, backgrounds, and career stages to contribute to scientific discovery. Establishing a network of internal collaboration at MSU with the wide groups already involved in this research will propel the Spartan community into this new age of science, ultimately adding another push for creating a more diverse and inclusive scientific community.