



Development of Neural Thermal Scattering (NeTS) Modules For Data Representation and Applications

Ayman I. Hawari

**LEIP Laboratories
Department of Nuclear Engineering
North Carolina State University
Raleigh, North Carolina, USA**

International Conference on Physics of Reactors 2022 (PHYSOR 2022)
Making Virtual a Reality: Advancements in Reactor Physics to Leap Forward Reactor Operation and Deployment
May 15 – 20, 2022, Pittsburgh, PA, USA

Acknowledgement

- NNSA Nuclear Criticality Safety Program (NCSP)
 - collaboration with LLNL
- Naval Nuclear Propulsion Program (NNPP)
- DOE NE through the NEUP program
- The LEIP Team



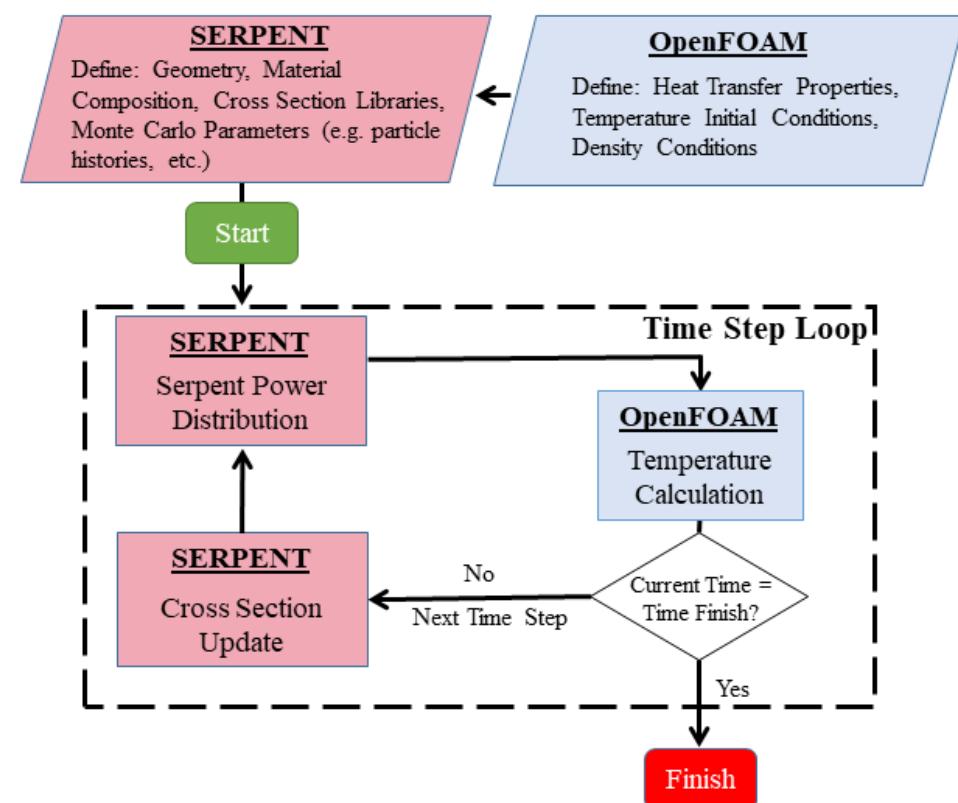
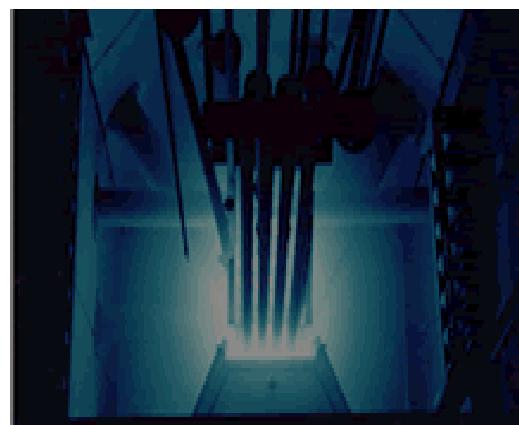
Outline

- **Motivation**
 - Advanced reactors
 - Multi-physics analysis
 - Neutron interactions
- **Introduction**
 - The thermal scattering law (TSL)
- **TSL Evaluation in *FLASCH***
 - Nuclear data ENDF/B files
- **Artificial Neural Networks**
 - NeTS development
- **Progress & Summary**

Motivation

- Develop a thermal neutron scattering, continuous and accurate, data representation that supports the needs of advanced modeling and simulations
- Multi-physics analysis
- Real time, on the fly, data generation

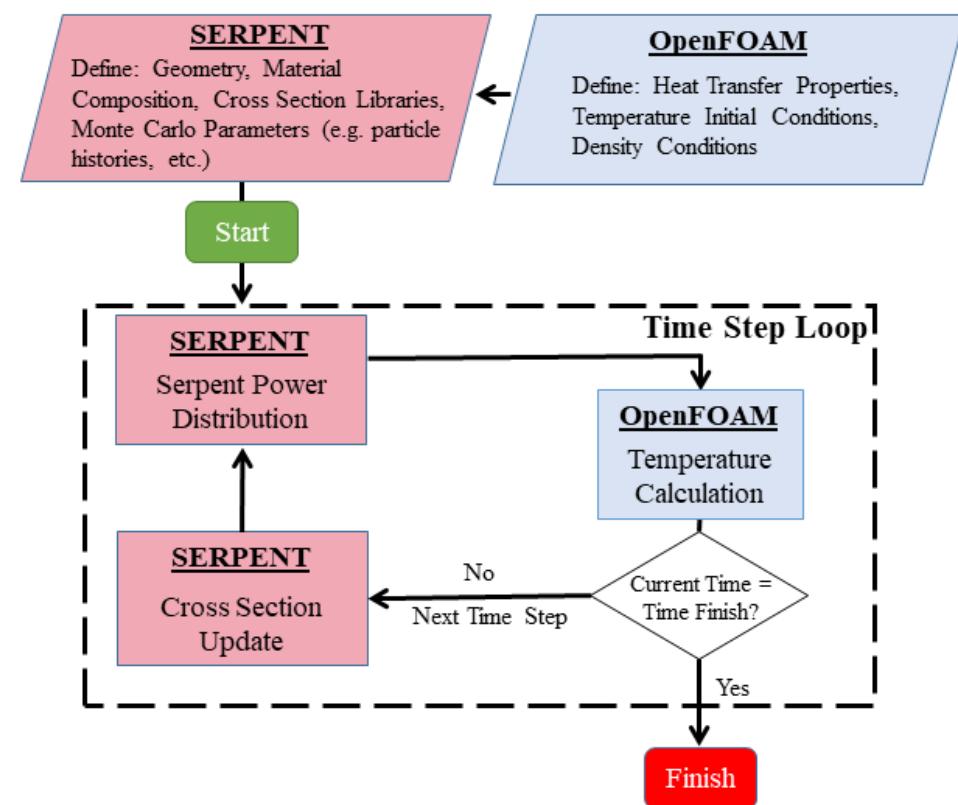
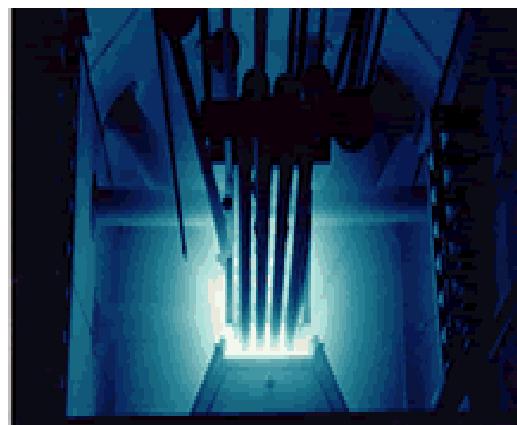
PULSTAR Reactor
NCSU



Motivation

- Develop a thermal neutron scattering, continuous and accurate, data representation that supports the needs of advanced modeling and simulations
- Multi-physics analysis
- Real time, on the fly, data generation

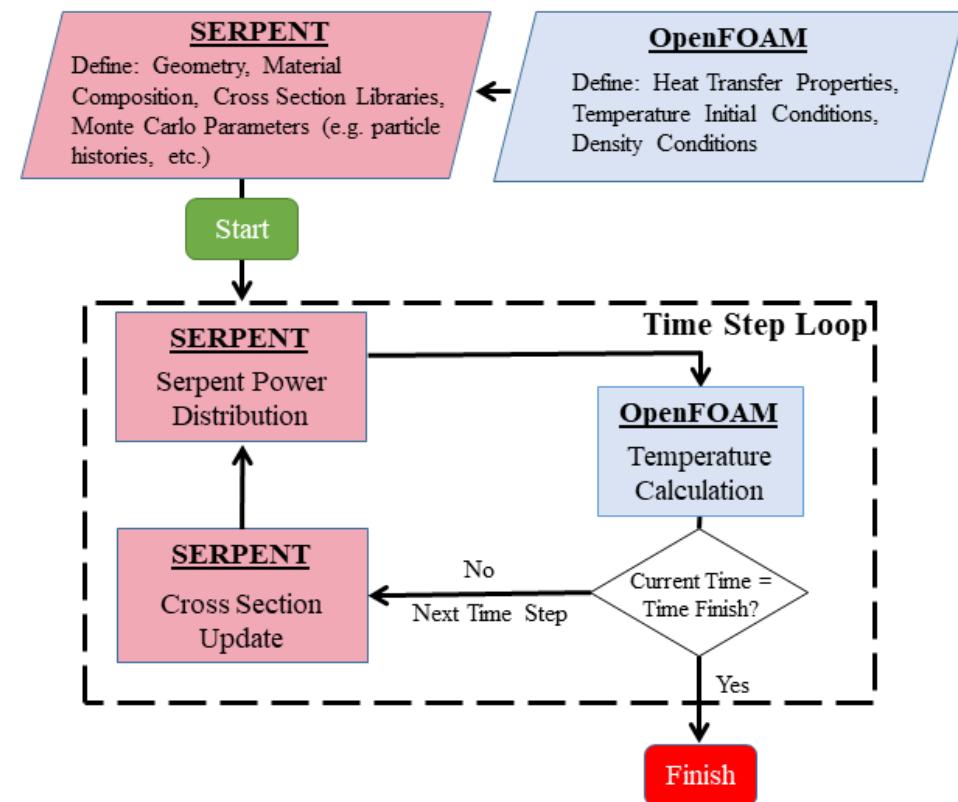
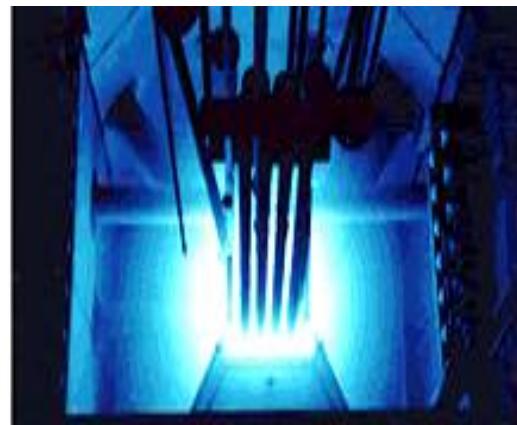
PULSTAR Reactor
NCSU



Motivation

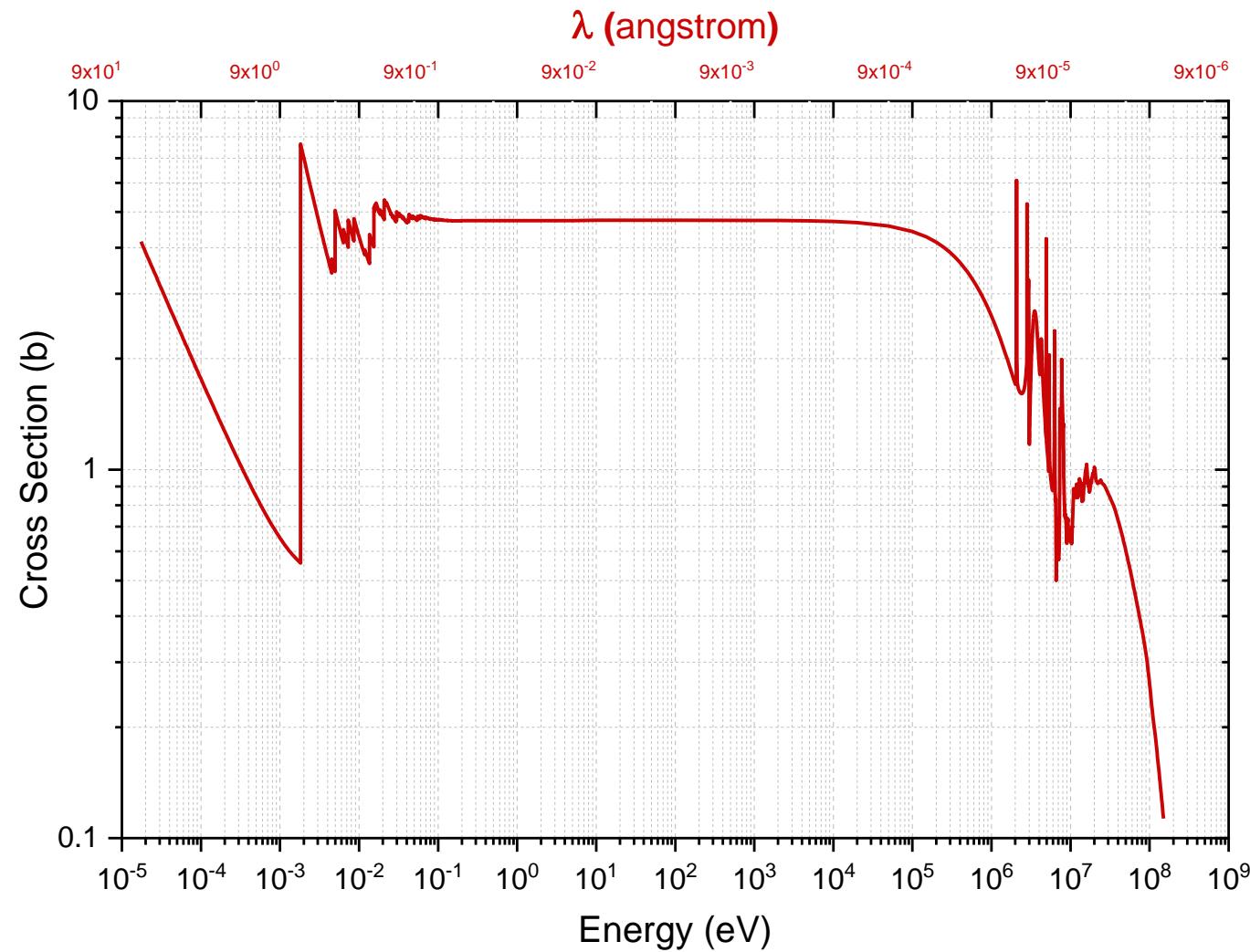
- Develop a thermal neutron scattering, continuous and accurate, data representation that supports the needs of advanced modeling and simulations
- Multi-physics analysis
- Real time, on the fly, data generation

PULSTAR Reactor
NCSU

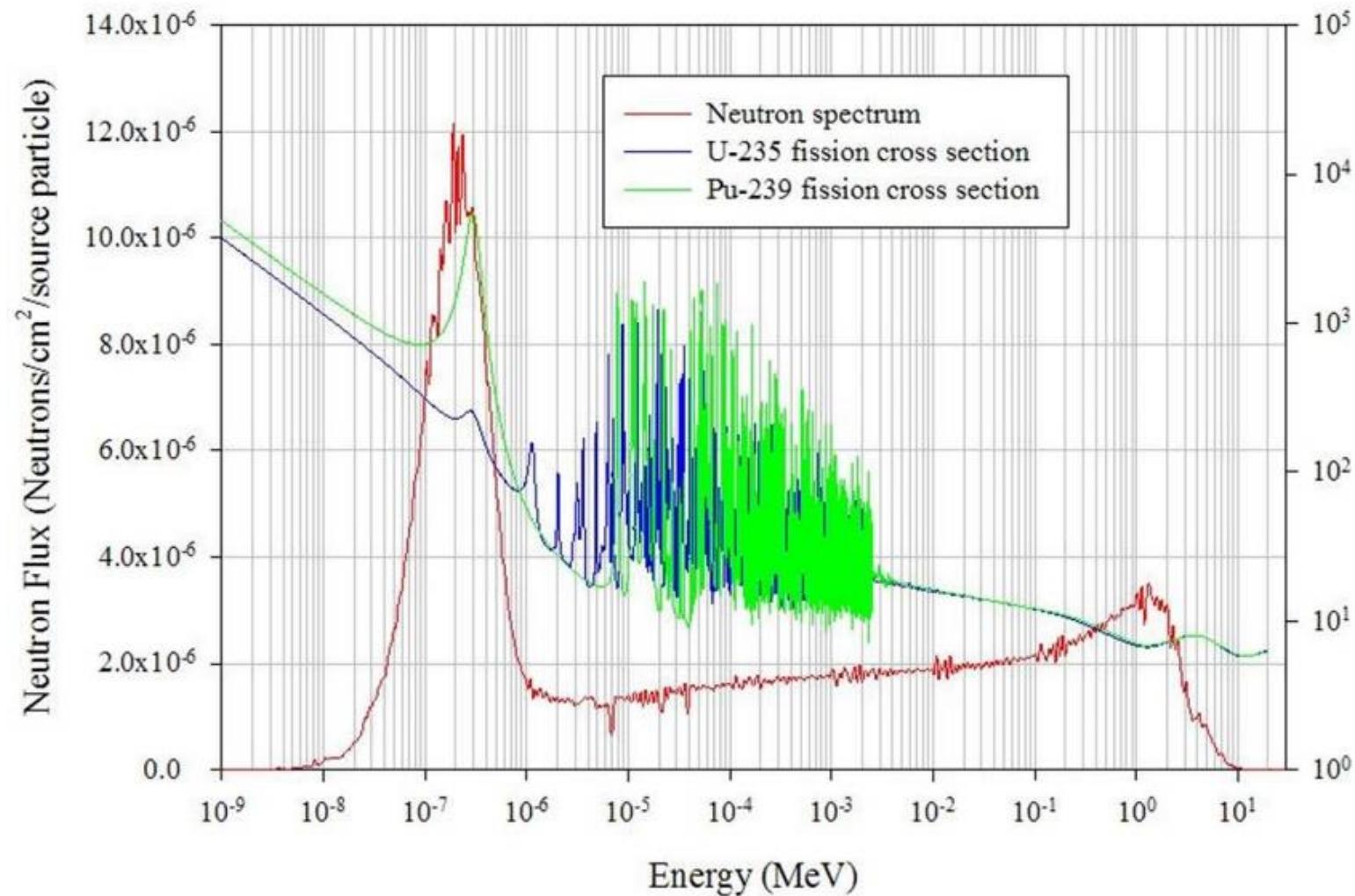


Neutron Interactions

Moderation & Thermalization



Neutron Interactions



Neutron Thermalization

Using first Born approximation combined with Fermi pseudopotential, it can be shown that the double differential scattering cross section has the form

$$\frac{d^2\sigma}{d\Omega dE'} = \frac{1}{4\pi} \sqrt{\frac{E'}{E}} \left\{ \sigma_{coh} S(\vec{k}, \omega) + \sigma_{incoh} S_s(\vec{k}, \omega) \right\}$$

The scattering law $S(\vec{k}, \omega)$ is composed of two parts

$$S(\vec{k}, \omega) = S_s(\vec{k}, \omega) + S_d(\vec{k}, \omega)$$

Van Hove's space-time formulation

$$I(\vec{k}, t) = \int G(\vec{r}, t) \exp(i\vec{k} \cdot \vec{r}) d\vec{r}$$

$$S(\vec{k}, \omega) = \frac{1}{2\pi\hbar} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} G(\vec{r}, t) e^{i(\vec{k} \cdot \vec{r} - \omega t)} d\vec{r} dt$$

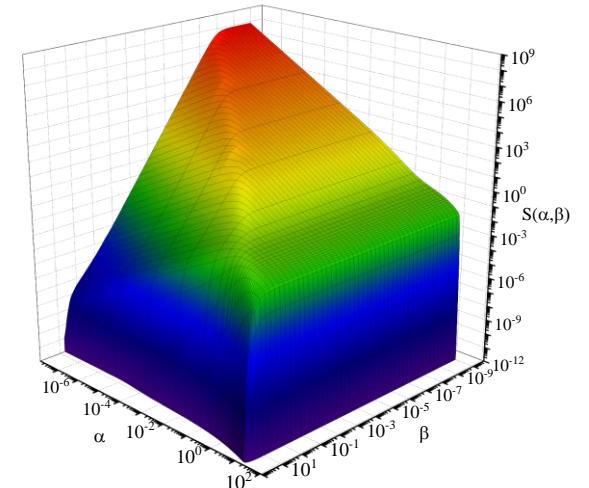
where $G(\vec{r}, t)$ is the *dynamic pair correlation function* and can be expressed in terms of time dependent atomic positions.

$$S_s(\alpha, \beta) = k_B T \cdot S_s(\vec{k}, \omega)$$

$$\left. \frac{d^2\sigma}{d\Omega dE'} \right|_{inelastic} = \frac{\sigma}{2k_B T} \sqrt{\frac{E'}{E}} S_s(\alpha, \beta)$$

$$\beta = \frac{E - E'}{k_B T} \quad \text{Energy transfer}$$

$$\alpha = \frac{(E + E' - 2\sqrt{EE'} \cos \theta)}{k_B T} \quad \text{Momentum transfer}$$



The scattering law (TSL) is the Fourier transform of a Gaussian correlation function

$$S_s(\alpha, \beta) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-i\beta t} e^{-\gamma(t)} dt$$

$$\gamma(t) = \frac{\alpha}{2} \int_{-\infty}^{\infty} \frac{\rho(\beta)}{\beta \sinh(\beta/2)} [1 - e^{-i\beta t}] e^{\beta/2} d\beta$$

$\rho(\beta)$ – density of states (e.g., phonon frequency distribution)

Nuclear Data - ENDF/B

□ Current format

- Dated
- Limited

□ Move to the Generalized Nuclear Database Structure (GNDS)

```

1.420000+2 6.955732+0      0      0      0      0 42 1451
0.000000+0 0.000000+0      0      0      0      6 42 1451
1.000000+0 5.000000+0      0      0     12      0 42 1451
0.000000+0 0.000000+0      0      0      31      3 42 1451
Li(FLiBe) LEIP LABS EVAL-MAR20 C.A. Manring, Y. Zha, A.I. Hawari 42 1451
DIST-          42 1451
MATERIAL 42   42 1451
-----THERMAL NEUTRON SCATTERING DATA
-----ENDF-6 FORMAT
Temperatures = 773 873 923 973 1073 1173 1273 1473 1673 K
BACKGROUND      42 1451
The inelastic thermal scattering law data for FLiBe was
developed by the Low Energy Interaction Physics (LEIP) group at
NC State University using molecular dynamics methods [1,2].
This material is a liquid salt mixture, such that the diffusive
contribution to the TSL is expected to be consequential. The
FLASH3 (Beta 3) code was used with a Schofield diffusion model
to produce File 7 for Li in FLiBe.
REFERENCES      42 1451
1. A.I. Hawari, "Modern Techniques in Inelastic Thermal Neutron
Scattering Analysis," Nuclear Data Sheets 119 (2014) 172.
2. Y. Zha, A.I. Hawari, "Thermal Neutron Scattering Cross
Section of Liquid LiBe," Progress in Nuclear Energy 101
(2017) 468.
-----
```

Open TSL (File 7) of choice

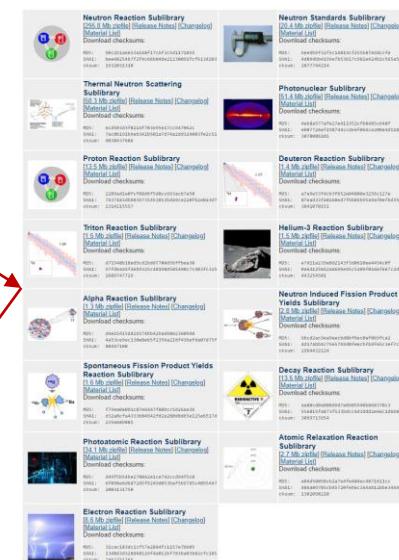
No.	NNDC Sublibrary	Short name	V8.0	V8.1	V8.1b	V8.5
1	Photoneutron		163	163	163	-
2	Photo-electric	photo	100	100	100	100
3	Radioactive decay	3621	3017	3838	3797	-
4	Spontaneous fission	sf	100	100	100	100
5	Atomic relaxation	atom_relax	100	100	100	100
6	Neutron	n	567	423	363	326
7	Thermal neutron flux yields	tnf	100	100	100	100
8	Thermal scattering fd	tsf	34	21	20	15
9	Standards	s	10	6	6	6
10	Energy-dependent	ed	100	100	100	100
11	Proton	p	49	48	48	35
12	D moderation	d	5	5	5	2
13	Tritium	t	5	5	5	1
14	20230 Ne	ne20230	3	2	2	1
15	20240 Ne	ne20240	a	-	-	-

Thermal Neutron Scattering Sublibrary
[\[58.3 Mb zipfile\]](#) [\[Release Notes\]](#) [\[Changelog\]](#)
[\[Material List\]](#)
Download checksums:

MD5: ecd503d3f8214f703e95e17cc947062c
SHA1: 7ac0b191b9eb342b501a7d74a2dd324003fe
cksum: 4038437686

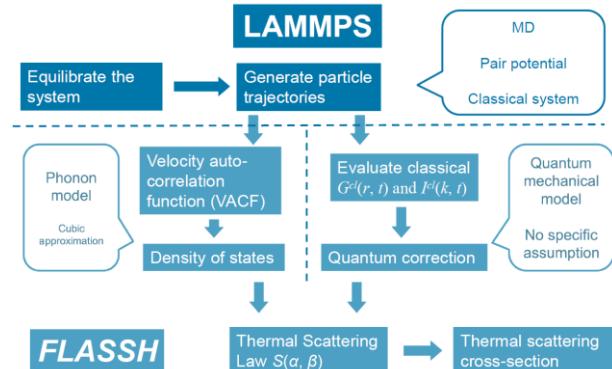
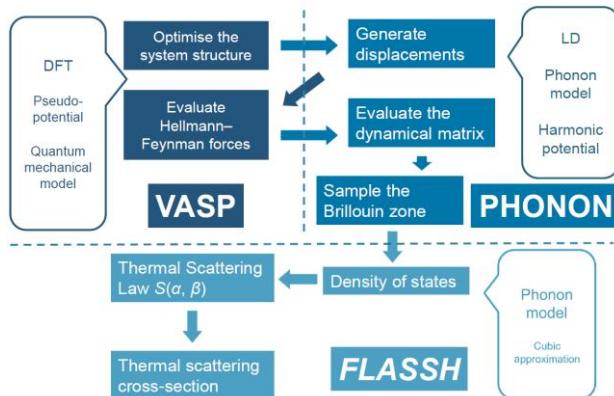
Select thermal neutron scattering

Navigate to NNDC website

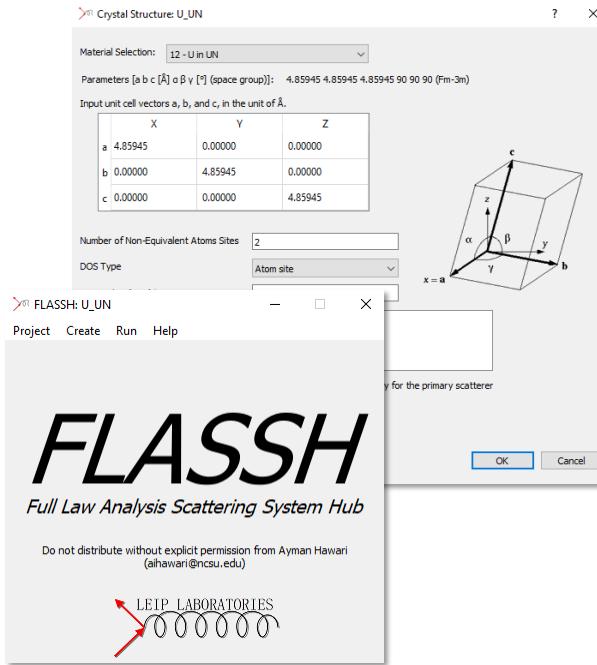
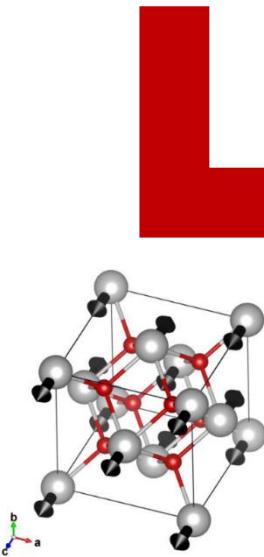


Open list of reactions

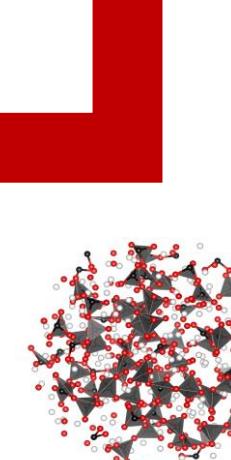
Methodology



DFT/LD approach



MD approach



TSL Implementation

□ General task

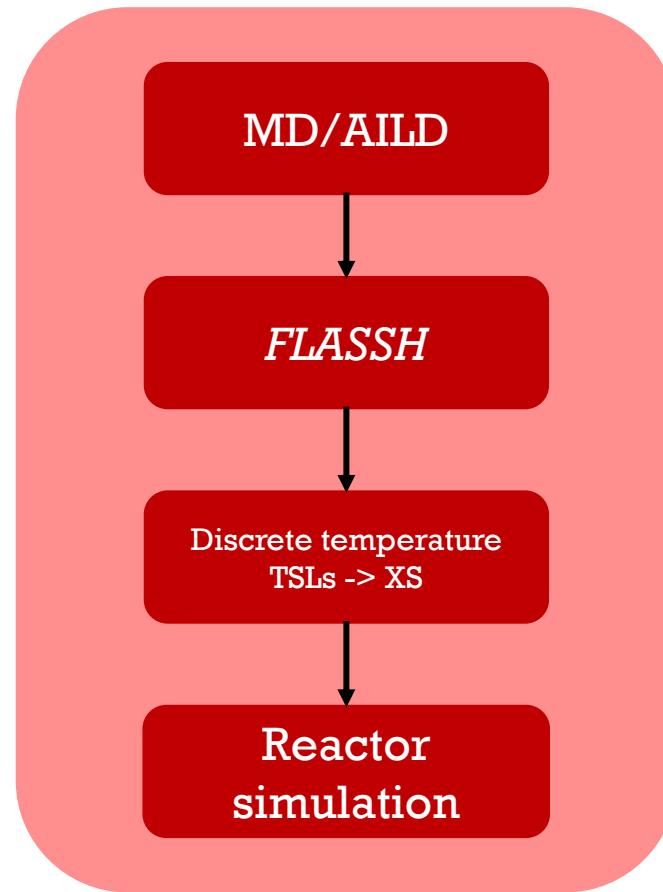
- Provide the most accurate multivariate TSL representation

□ Current capabilities

- Discrete temperature grids
- Interpolation
- Basis functions
- Higher max percent deviations
- Higher memory consumption

□ What is missing?

- Continuous temperature (interpolation free)
- Improve memory footprint
- Improve accuracy
- Maintain or Improve computation speed
 - Context dependent



TSL Implementation

□ General task

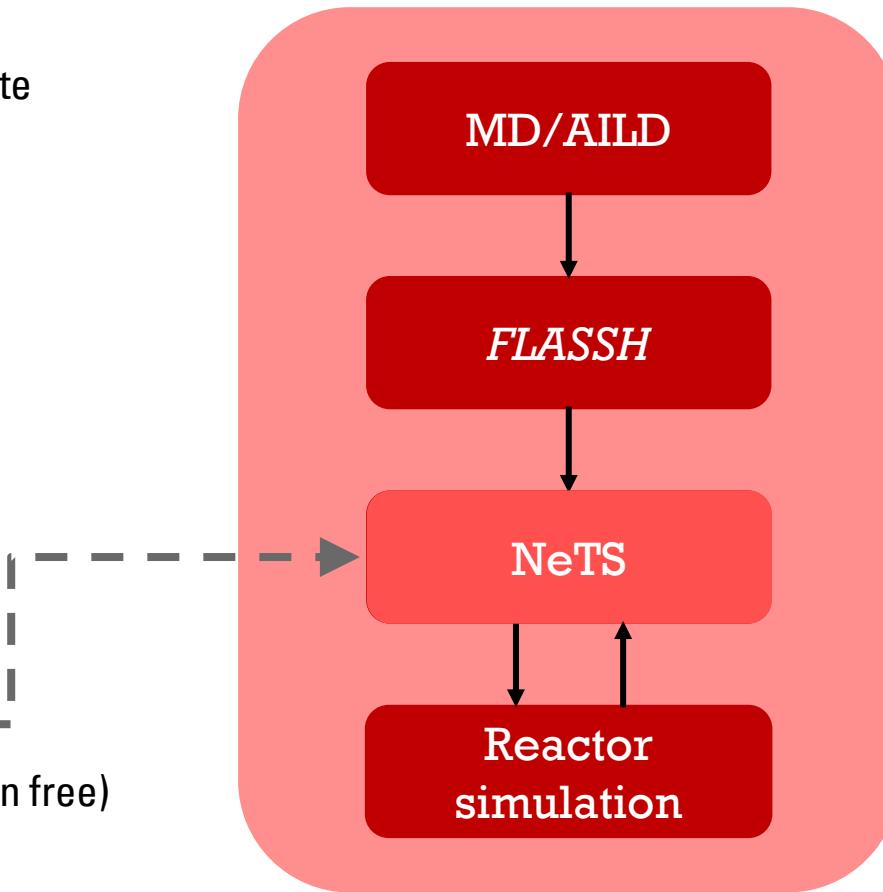
- Provide the most accurate multivariate TSL representation

□ Current capabilities

- Discrete temperature grids
- Interpolation
- Basis functions
- Higher max percent deviations
- Higher memory consumption

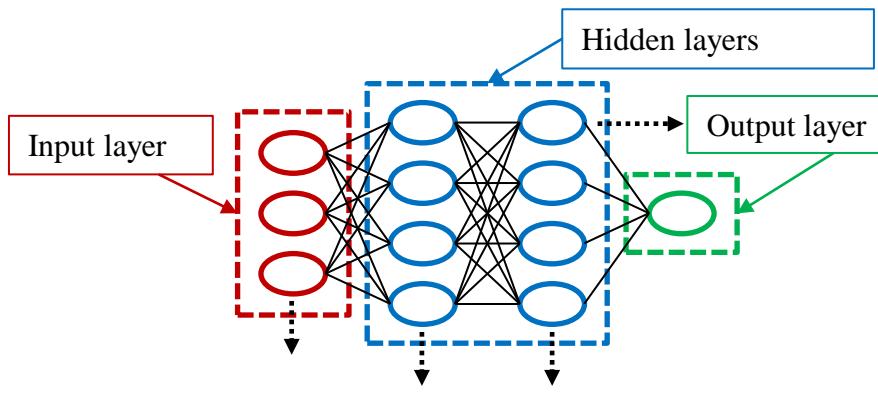
□ What is missing?

- Continuous temperature (interpolation free)
- Improve memory footprint
- Improve accuracy
- Maintain or Improve computation speed
 - Context dependent



Artificial Neural Networks

A data representation originally inspired by the abstraction of biological neurons



Input

$$\begin{array}{c} x_1 \\ x_2 \\ x_3 \end{array} \xrightarrow{\text{Weights}} \begin{array}{c} g_1 \\ g_2 \\ g_3 \\ g_4 \end{array}$$

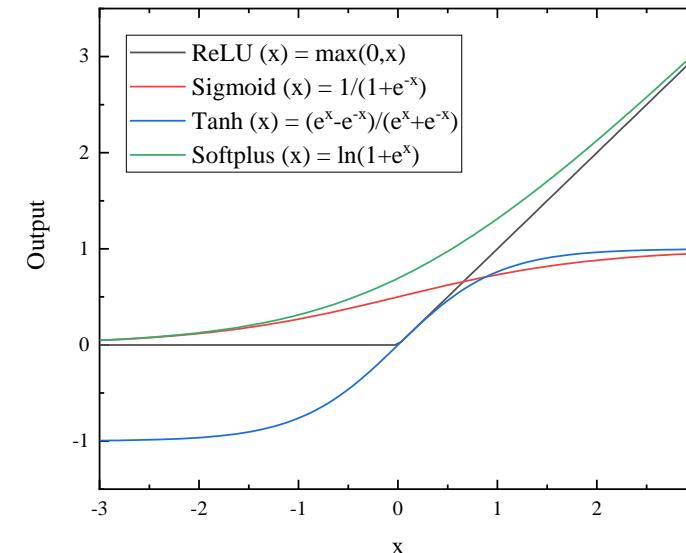
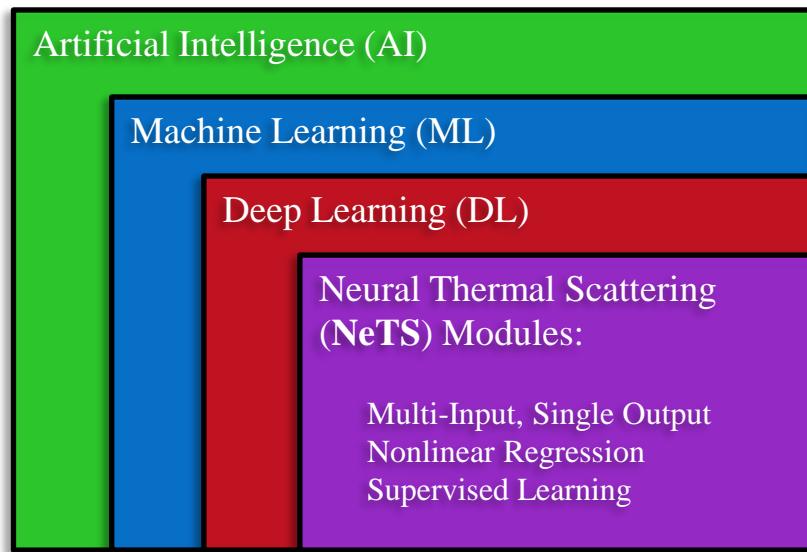
Output

$$\begin{bmatrix} w_{1,1} & w_{2,1} & w_{3,1} \\ w_{1,2} & w_{2,2} & w_{3,2} \\ w_{1,3} & w_{2,3} & w_{3,3} \\ w_{1,4} & w_{2,4} & w_{3,4} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} = \begin{bmatrix} w_{1,1}x_1 + w_{2,1}x_2 + w_{3,1}x_3 + b_1 \\ w_{1,2}x_1 + w_{2,2}x_2 + w_{3,2}x_3 + b_2 \\ w_{1,3}x_1 + w_{2,3}x_2 + w_{3,3}x_3 + b_3 \\ w_{1,4}x_1 + w_{2,4}x_2 + w_{3,4}x_3 + b_4 \end{bmatrix}$$

Activation

$$h\left(\begin{bmatrix} w_{1,1}x_1 + w_{2,1}x_2 + w_{3,1}x_3 + b_1 \\ w_{1,2}x_1 + w_{2,2}x_2 + w_{3,2}x_3 + b_2 \\ w_{1,3}x_1 + w_{2,3}x_2 + w_{3,3}x_3 + b_3 \\ w_{1,4}x_1 + w_{2,4}x_2 + w_{3,4}x_3 + b_4 \end{bmatrix}\right) \rightarrow \begin{bmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \end{bmatrix}$$

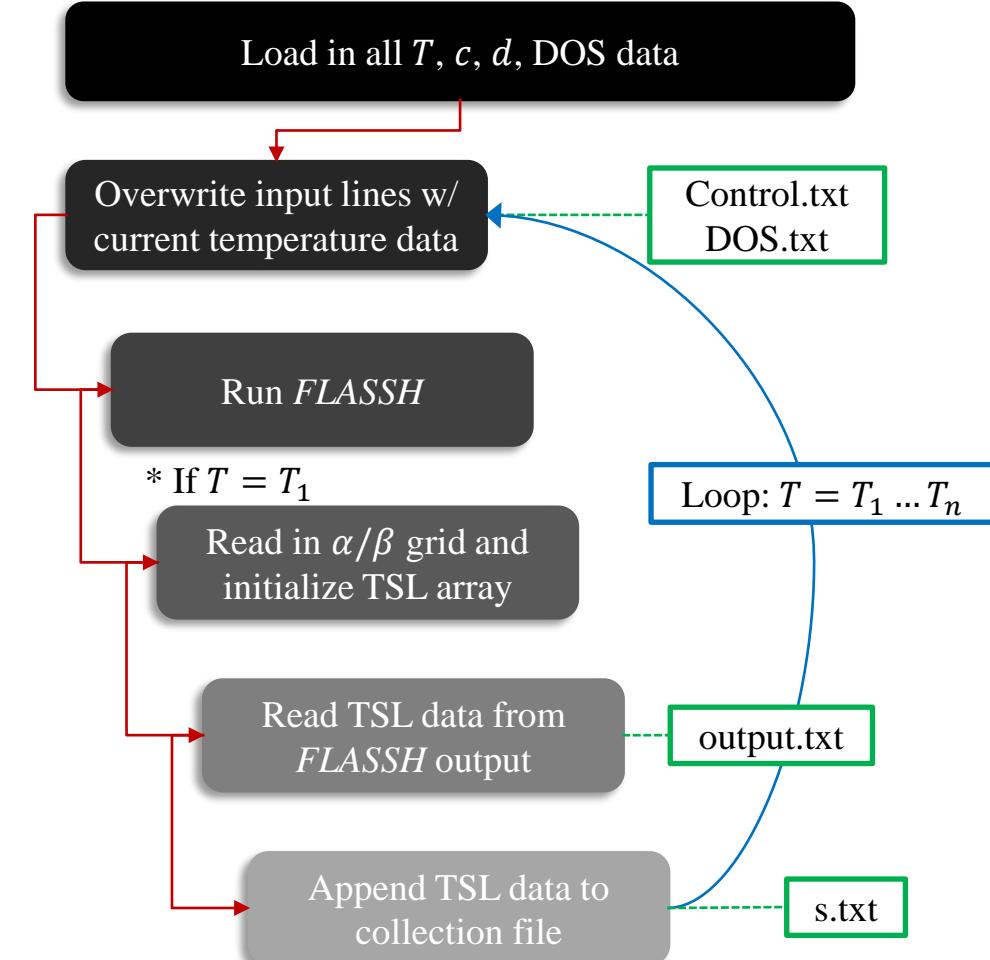
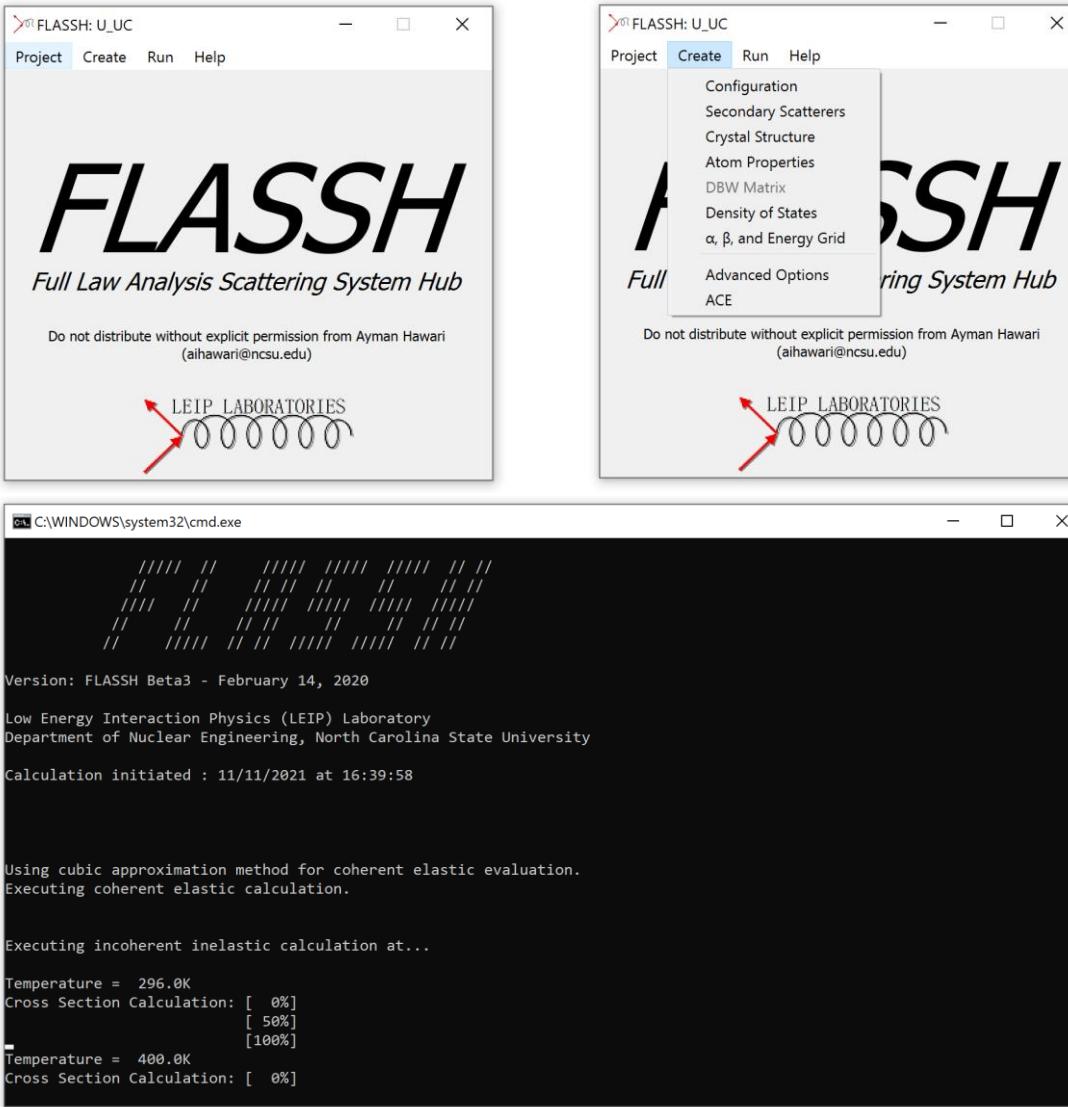
$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$



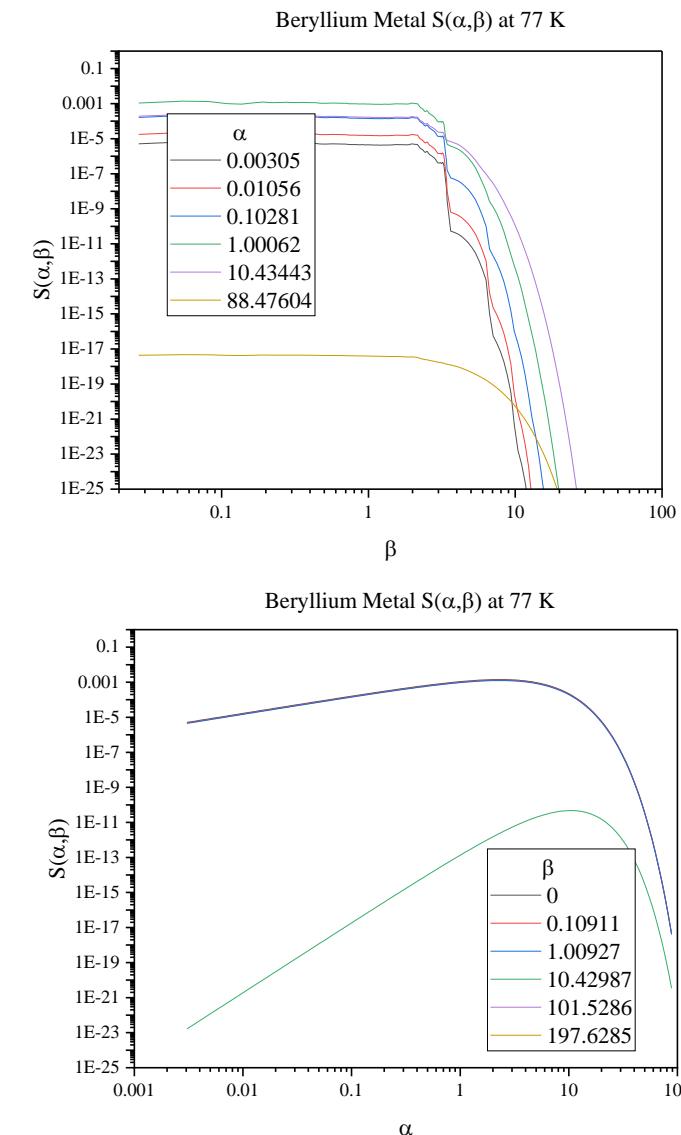
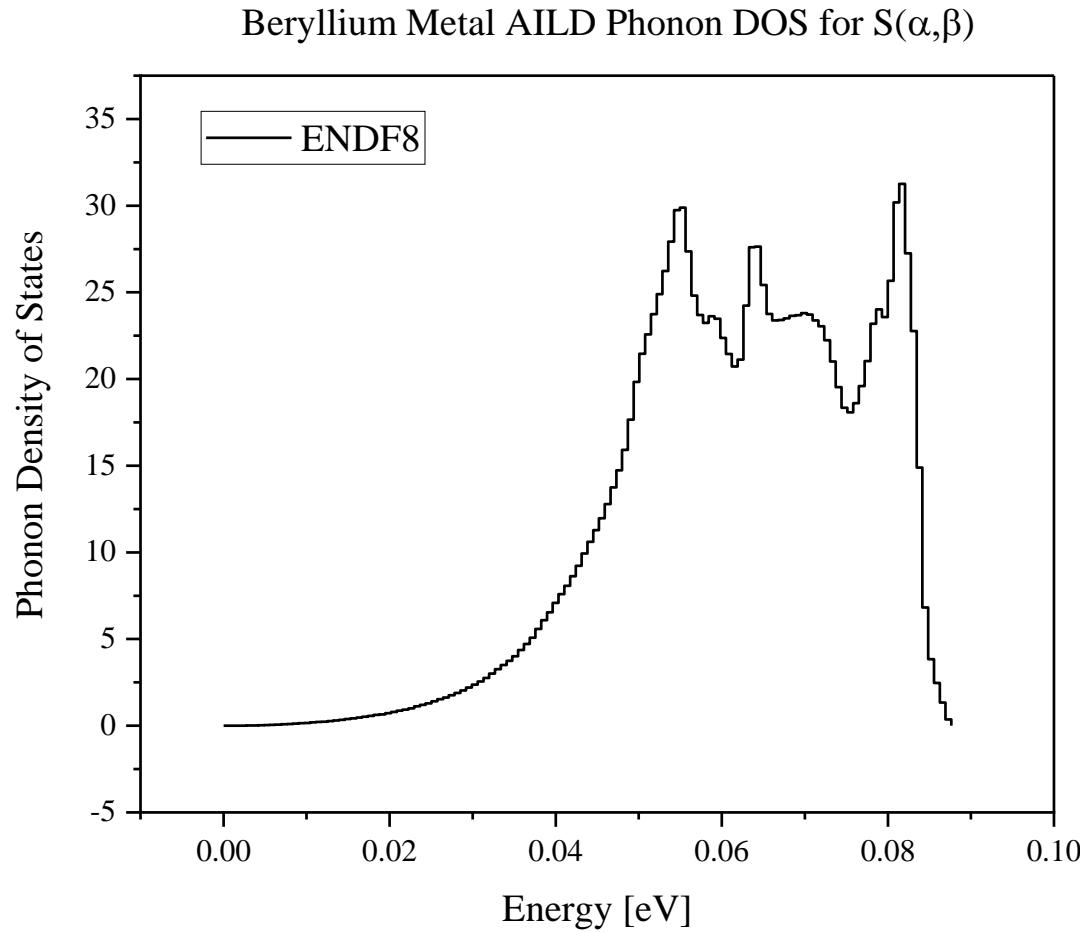
Neural Thermal Scattering (NeTS) Flow Chart

0. DOS: Calculate/verify *ab initio* phonon density of states
1. *FLASSH*: Produce training data and aggregate $S(\alpha, \beta)$
2. Data-preprocess: Scale alpha, beta, temperature, $S(\alpha, \beta)$ data and split between training/validation/test datasets
3. Network training: Train Artificial Neural Network (ANN)
4. Evaluate network: Produce deviation metrics for train, validation, test datasets
5. Produce $S(\alpha, \beta)$ data: Use optimized network weights with neural architecture

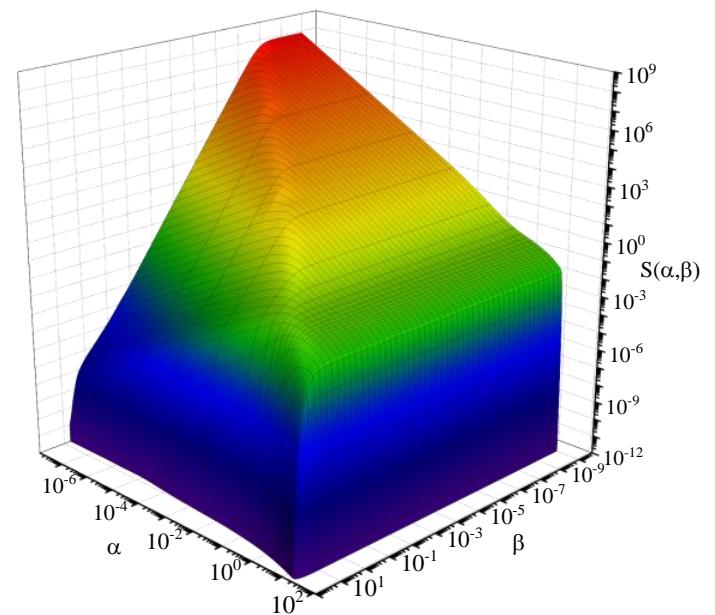
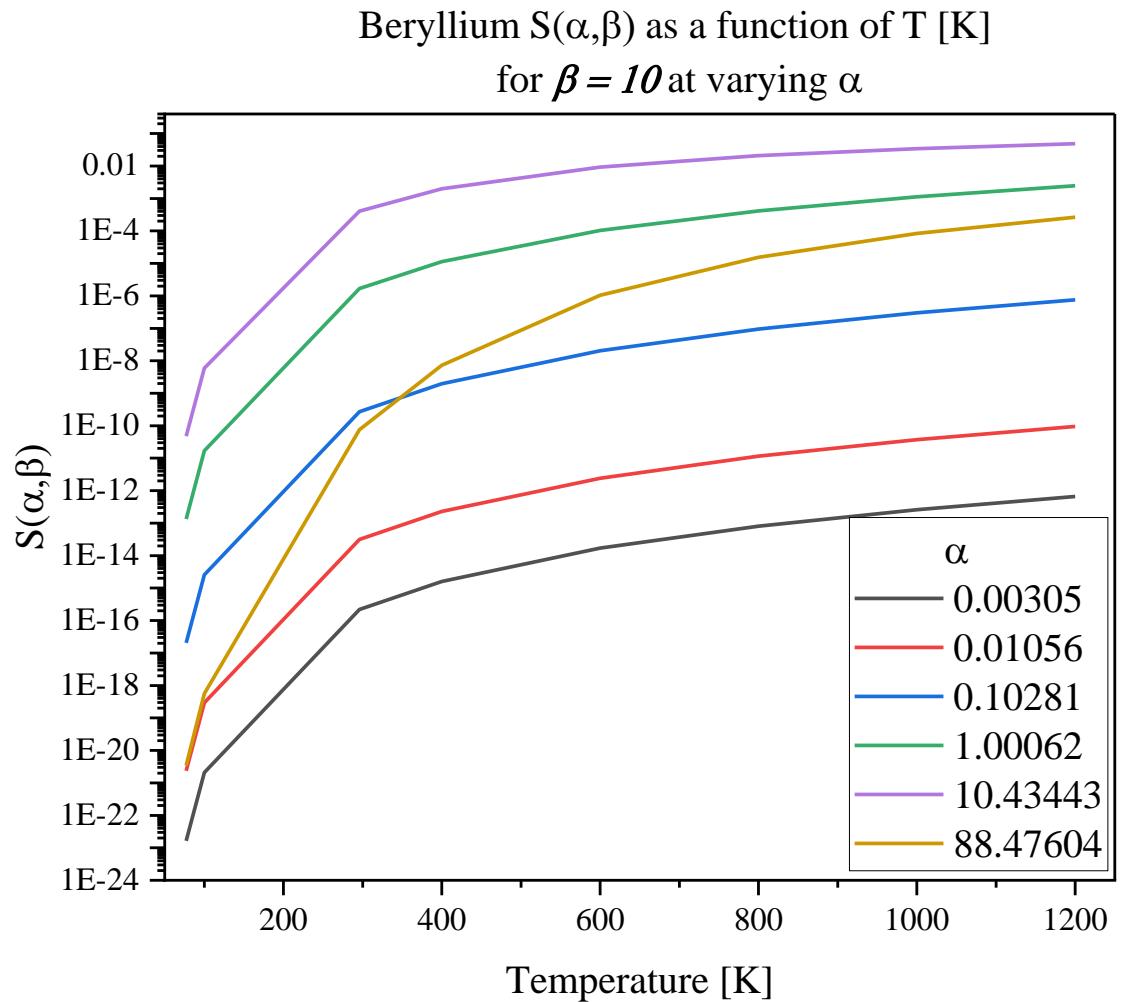
1. Training Data: *FLASSH* Loop



1. Beryllium Metal Evaluation at 77 K



1. Beryllium Metal Temperature Dependence

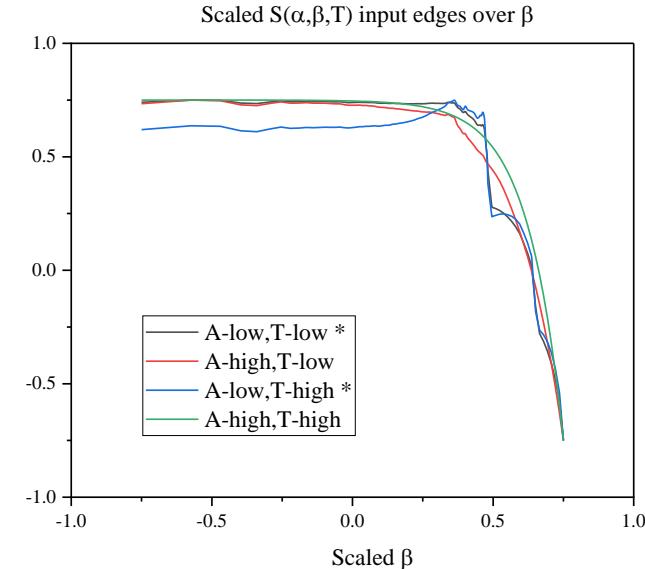
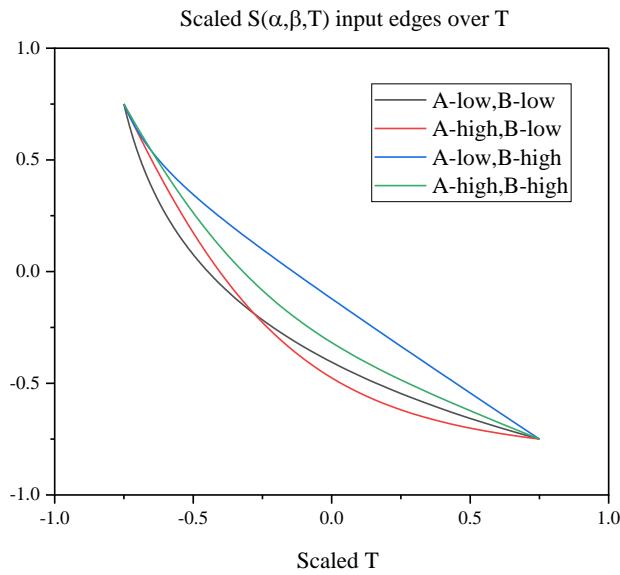
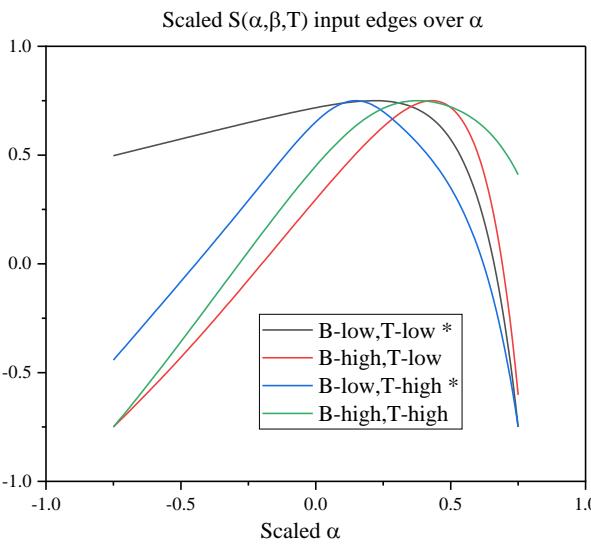
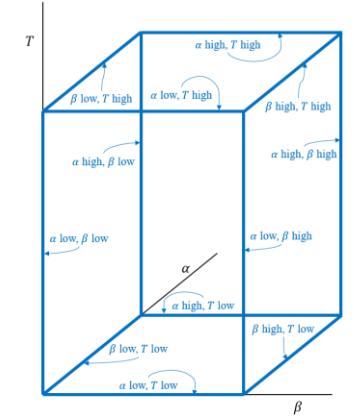


2. FLASCH Data Preprocessing

1. Linearize alpha (log10), beta (log10) , temperature grids (1/T) to [-.75 , .75]

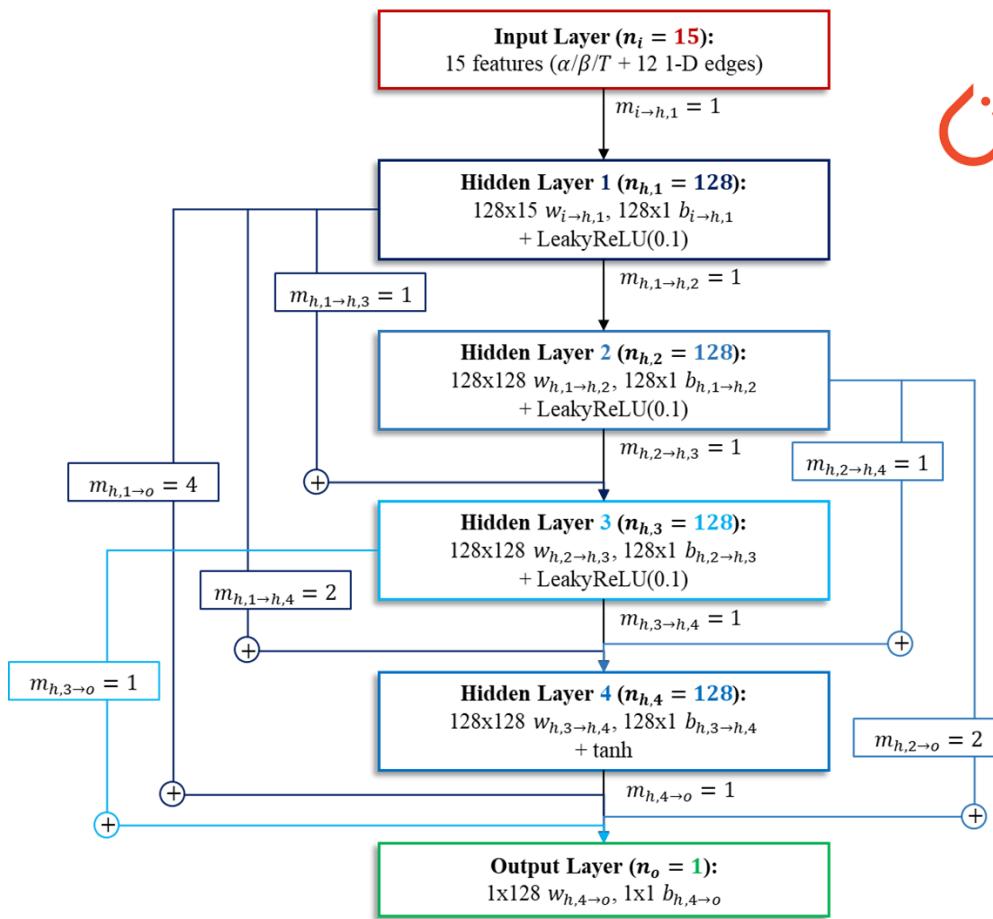
2. Transform Thermal Scattering Law Data (log10)

3. Generate input “edges” to assist training (feature engineering)



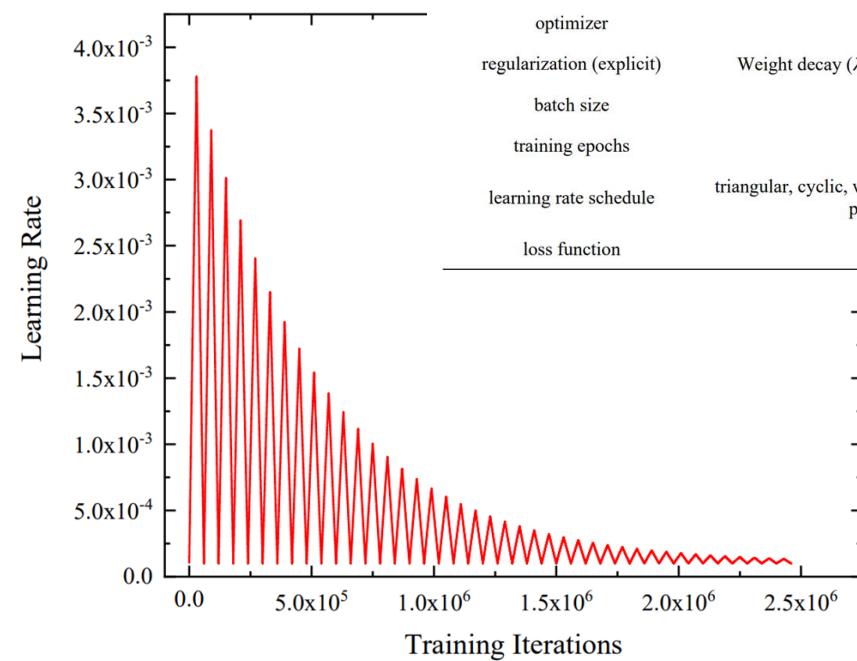
4. Divide dataset into training (99%), validation (.5%), and test (.5%)

3. Network Architecture and Hyperparameters



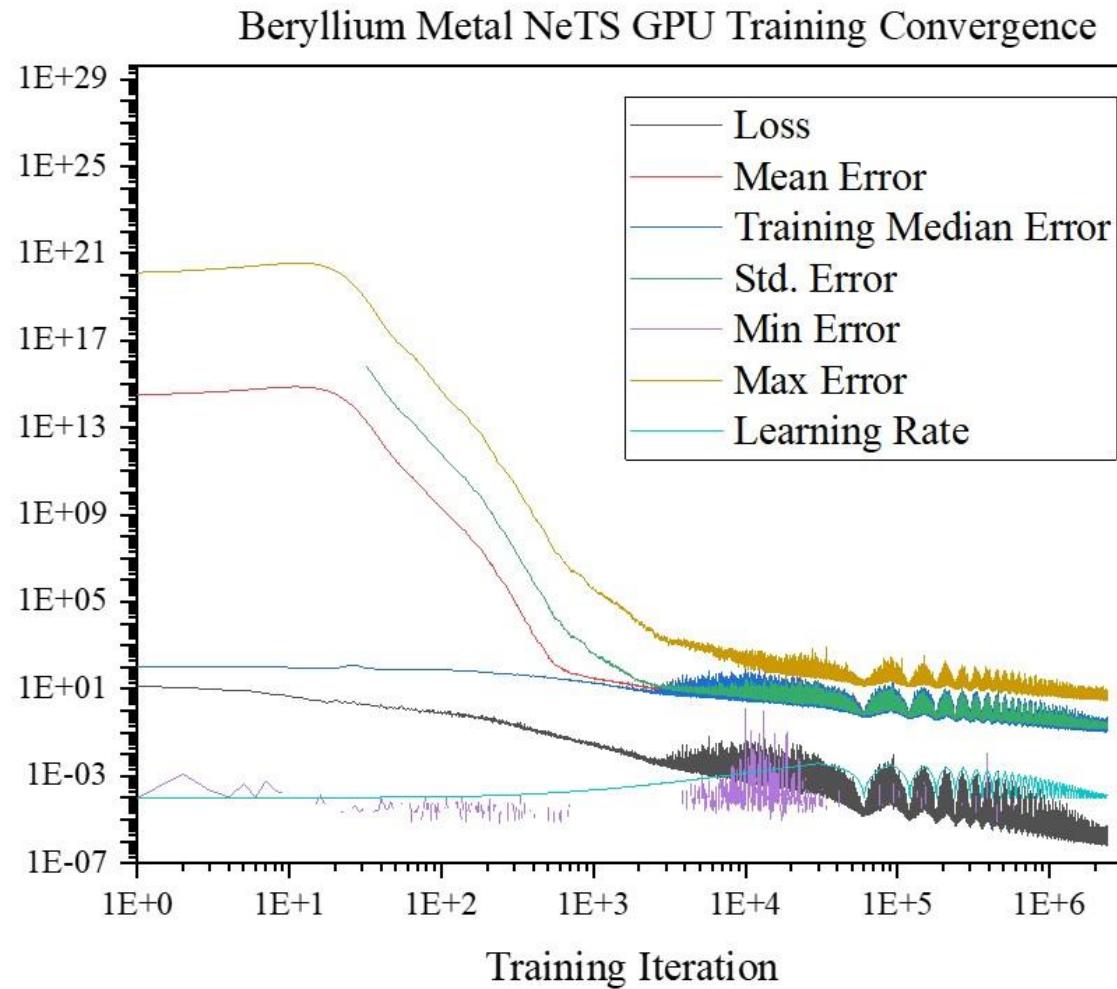
PyTorch

Setting	Selection
$n_{\text{hidden_layers}}$	4
n_h	128
cascading	none
skip connections	dense, weighted
skip weight scheme	multiplicative, 1:2:4
activation function	LeakyReLU(0.1) in hidden layers 1-3, tanh in hidden layer 4
weight initialization	Xavier uniform
optimizer	AdamW
regularization (explicit)	Weight decay ($\lambda \rightarrow 1e-6$, as implemented in AdamW)
batch size	1024
training epochs	400
learning rate schedule	triangular, cyclic, w/ exponentially decaying amplitude (see parameters in Table 4.3)
loss function	MSE



3 LEIP Cluster NVIDIA V100 GPUs, 32 GB onboard memory each
Intel Xeon E5-2690v4 CPUs (sharing 128 GB RAM)

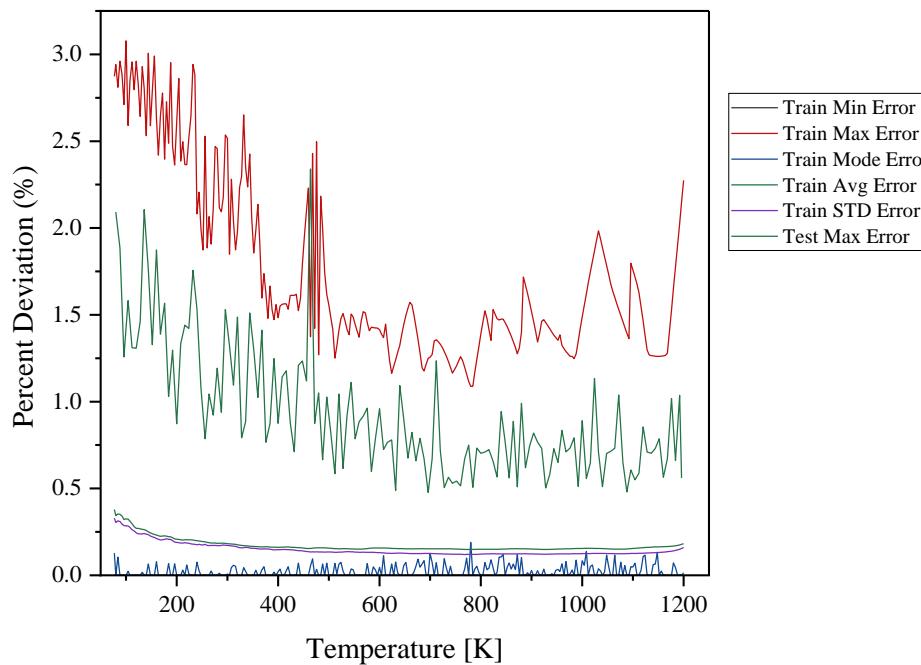
3. ANN convergence



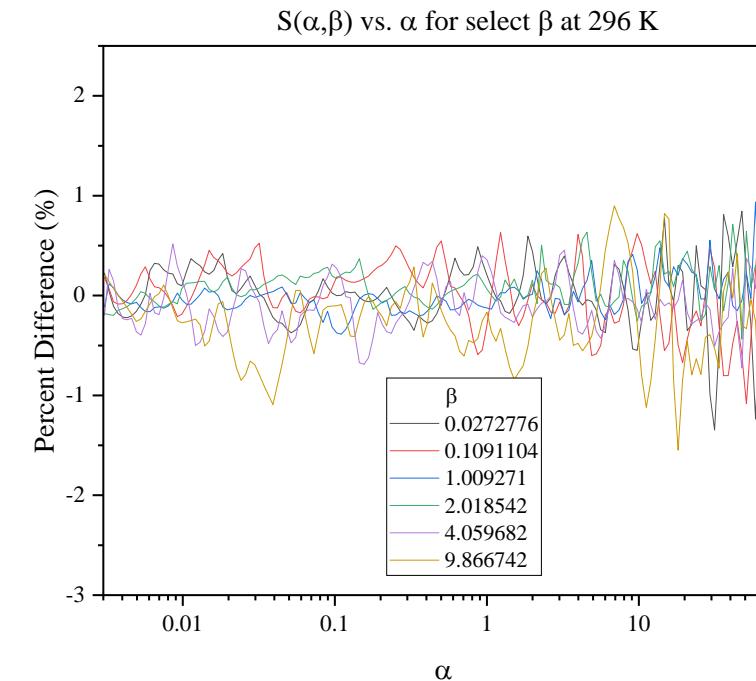
$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

4. Network Evaluation (Train/Valid/Test)

Beryllium NeTS Accuracy Metrics as a Function of Temperature [K]



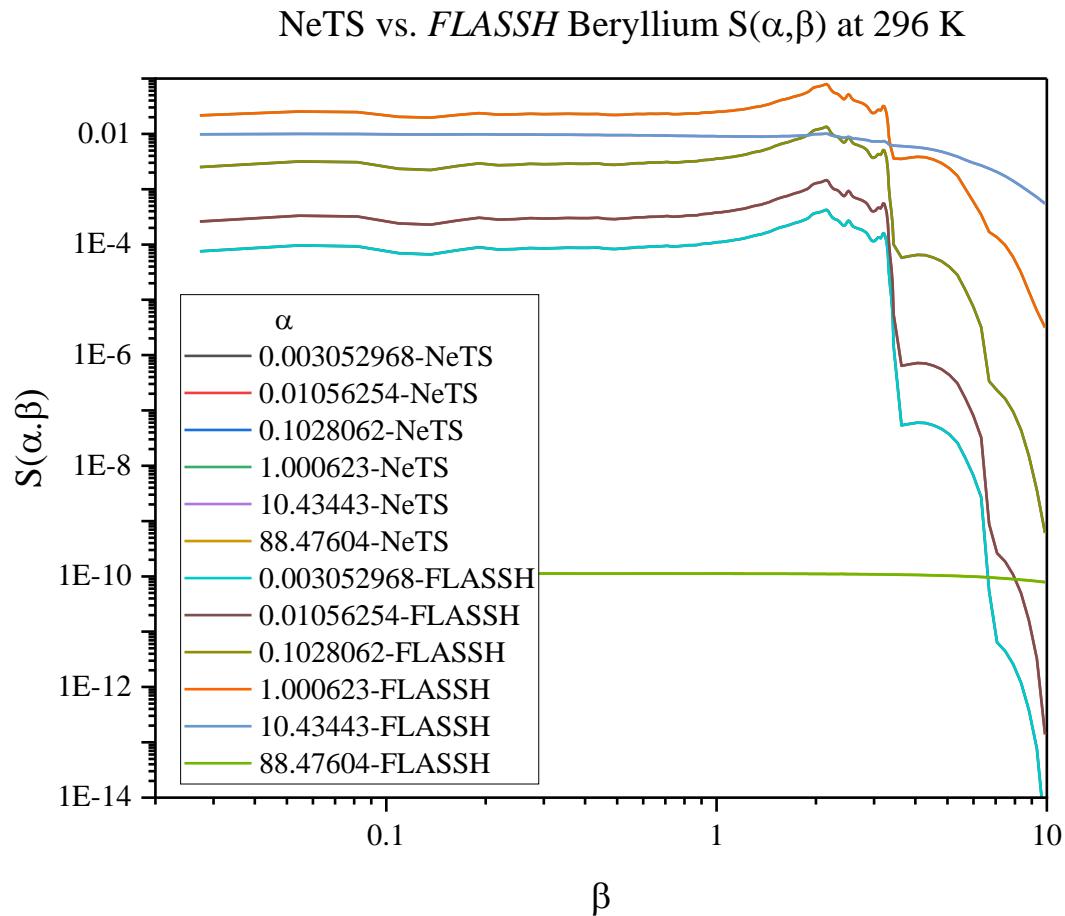
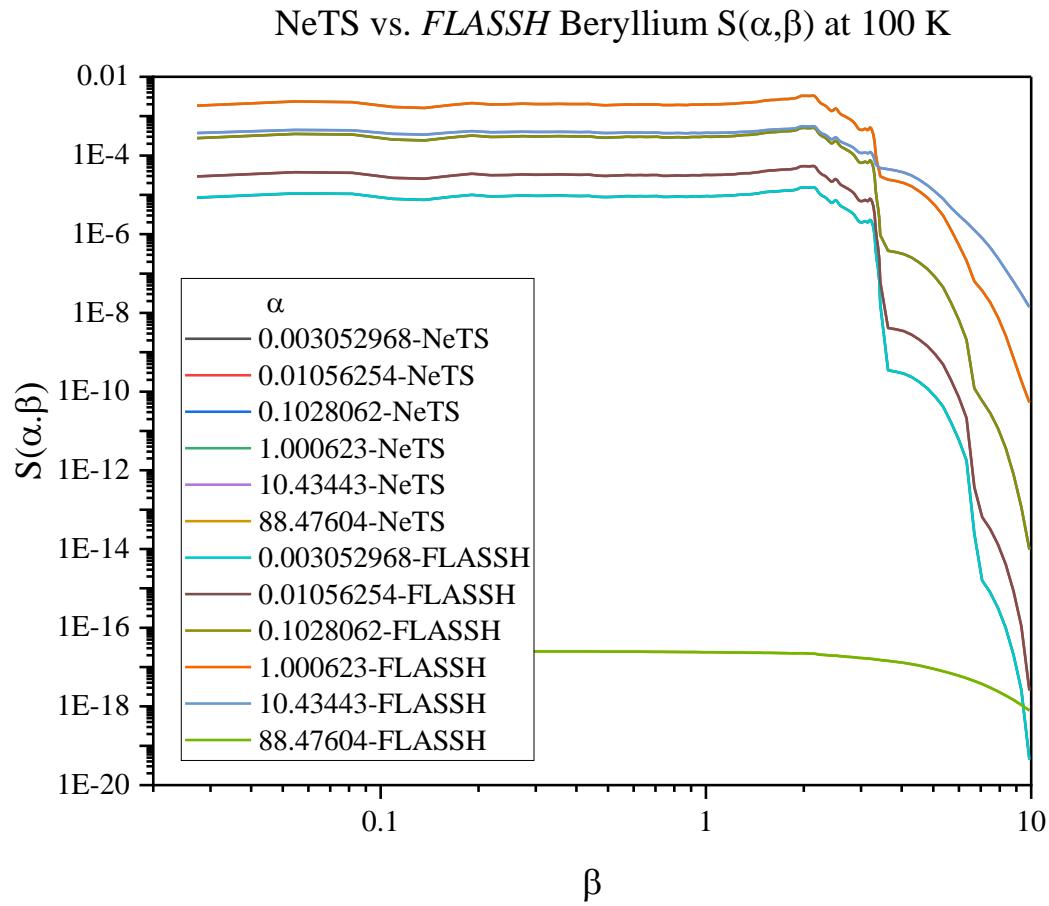
Beryllium NeTS vs. FLASSH Percent Difference [100*(N-F)/F]



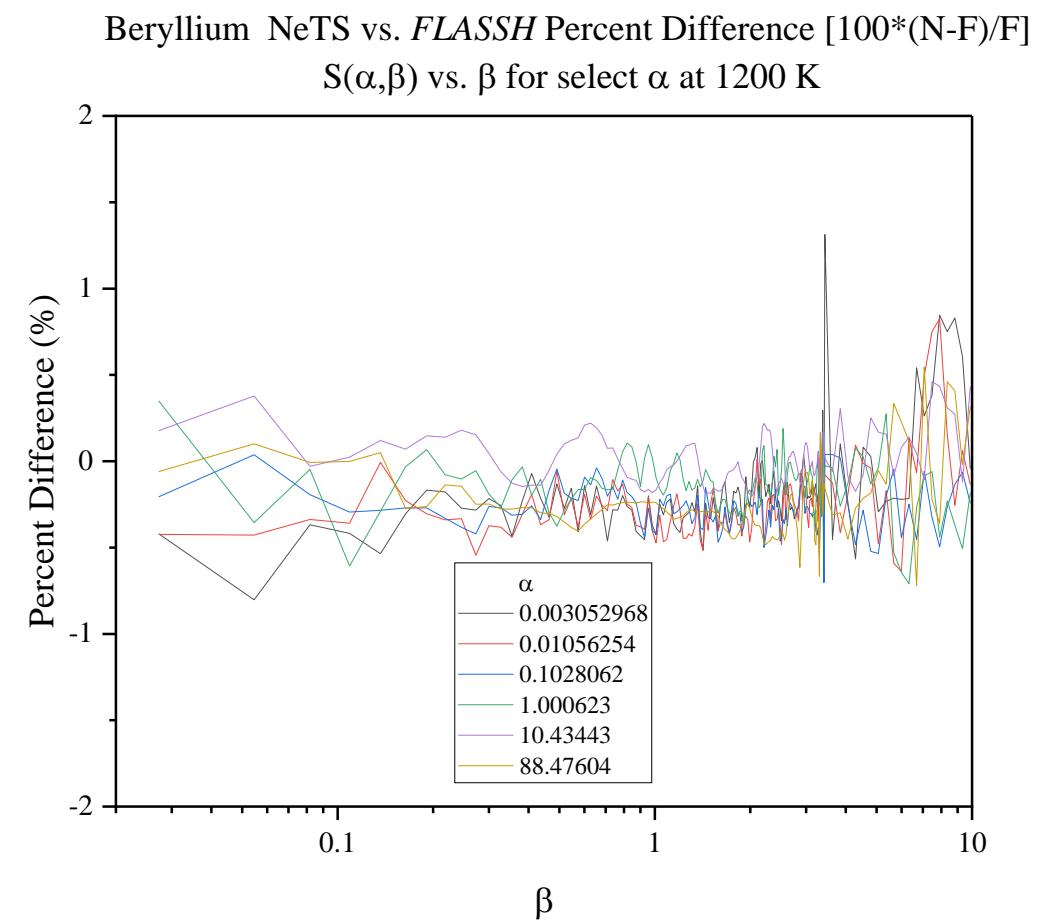
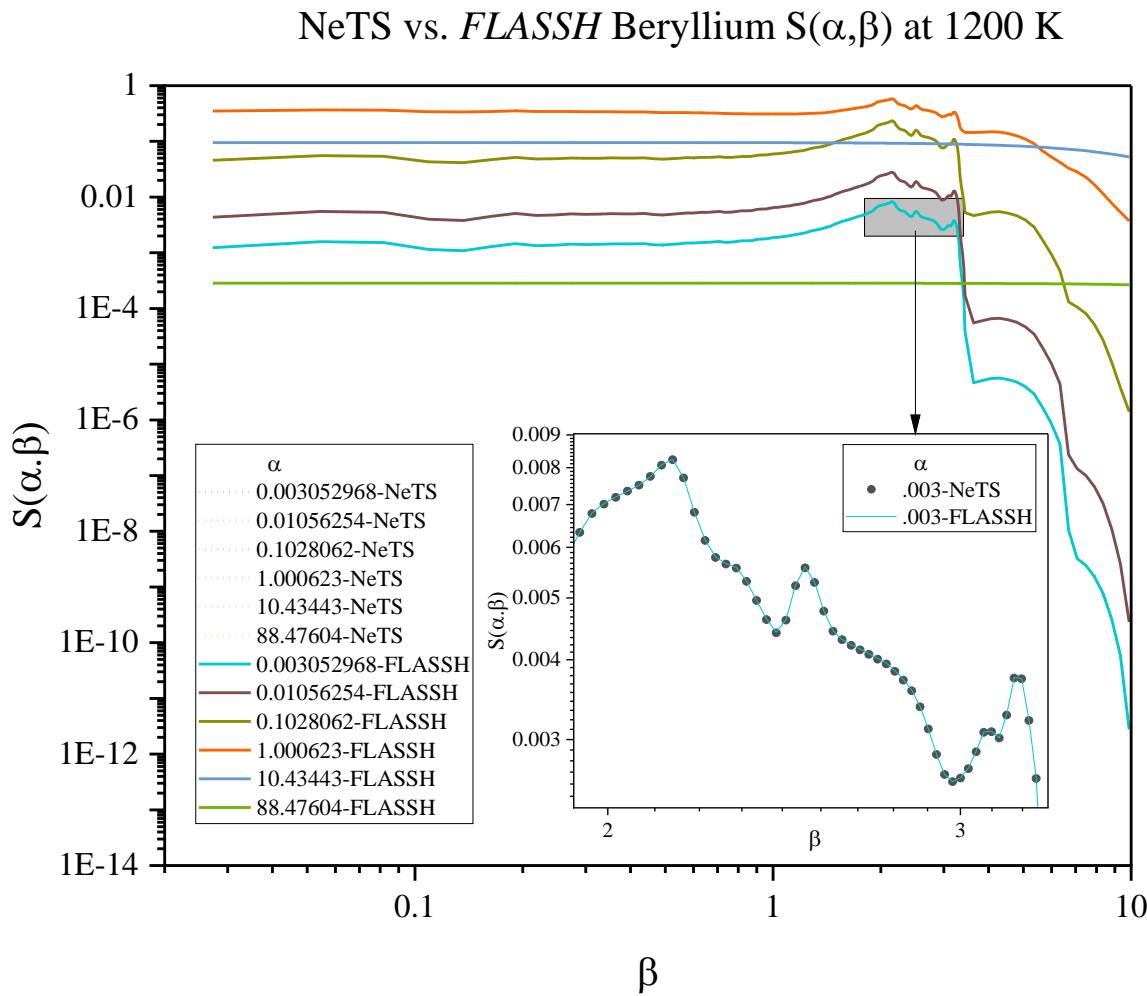
$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

Dataset	Mean APD [%]	Med. APD [%]	Max APD [%]	< 2% [%]	< 1% [%]
Train	0.1755	0.1574	3.0190	99.9959	99.8477
Validation	0.1775	0.1579	2.7552	99.9955	99.8139
Test	0.1770	0.1574	1.6474	100.000	99.7913

5. ANN $S(\alpha, \beta, T)$ Prediction at 100 K , 296 K



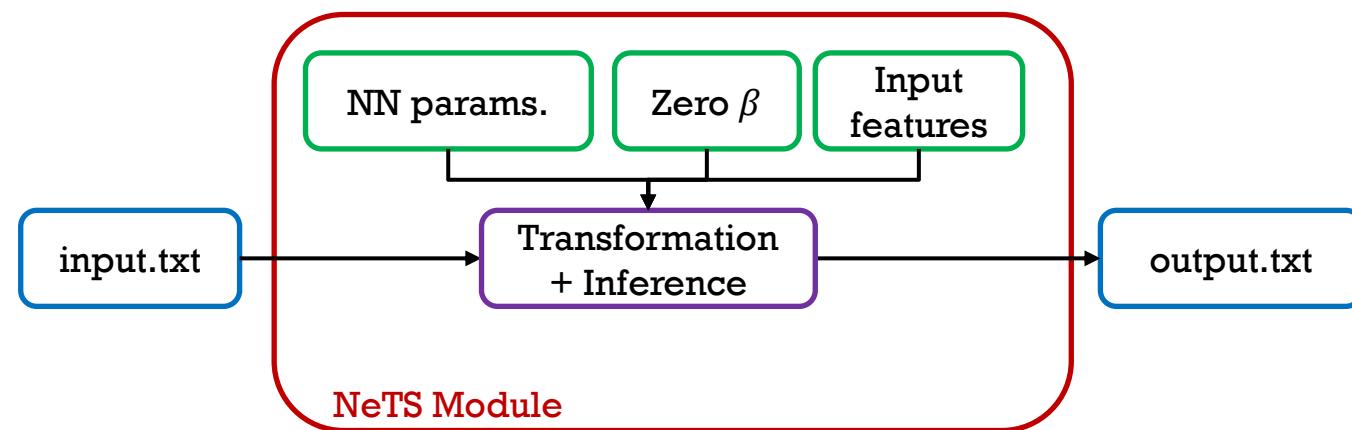
5. ANN $S(\alpha,\beta,T)$ Prediction at 1200 K



Finally ... What's a NeTS Module

- Compact, accurate functional representations of TSL data for a specific material over a given range of input conditions

- α/β
- Temperature
- Porosity
- Burnup
- Alloy %
- Pressure



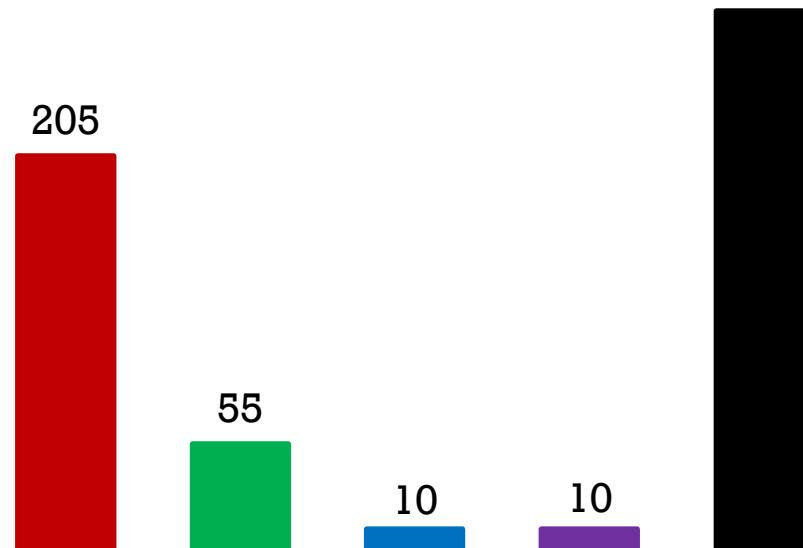
- Functional
- Continuous
- Highly accurate
- Memory efficient
 - Explicit vs. representative storage

Memory & Speed

□ Adding it all up...

- Big improvements
- Relative to 10+MB

Total: 280



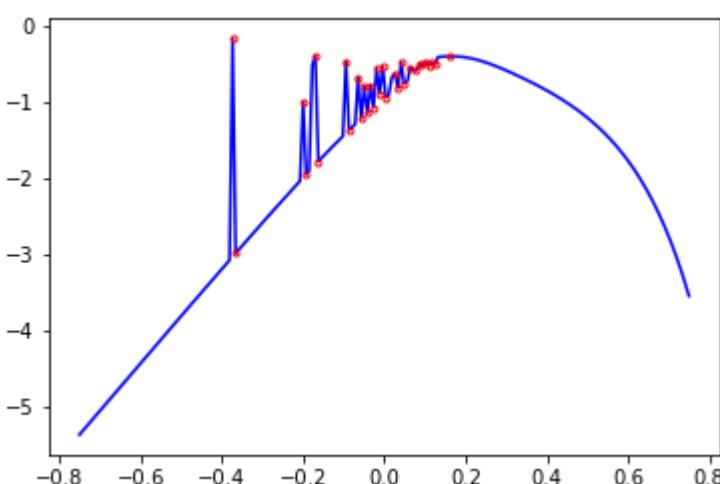
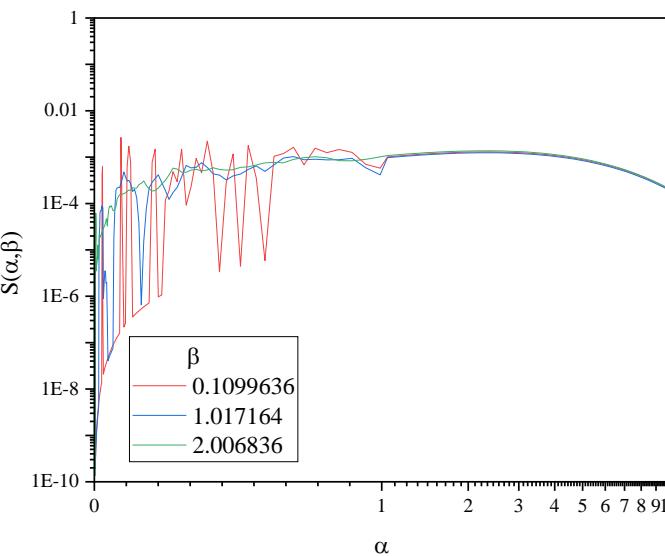
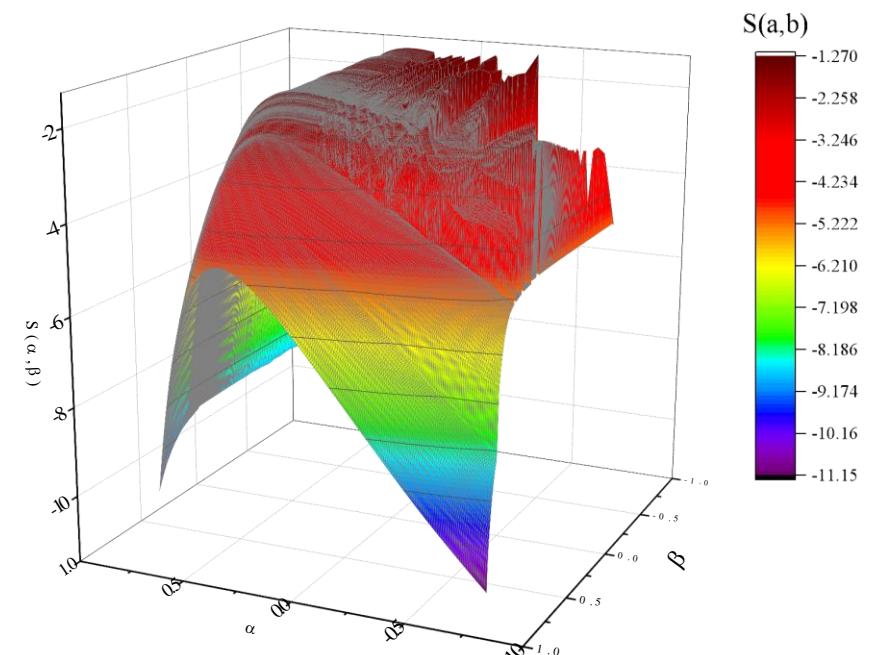
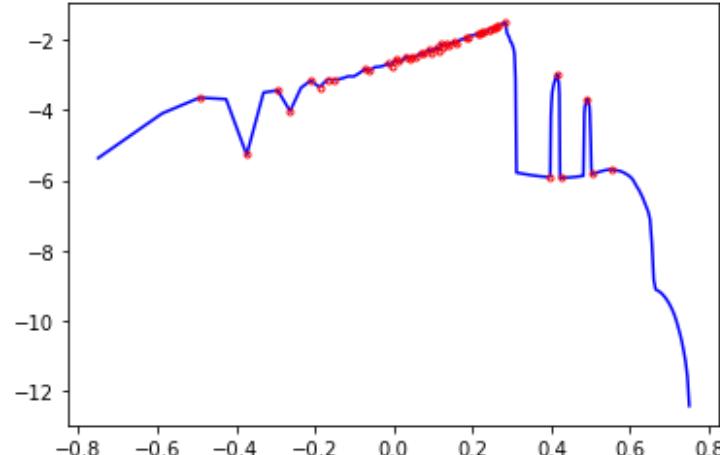
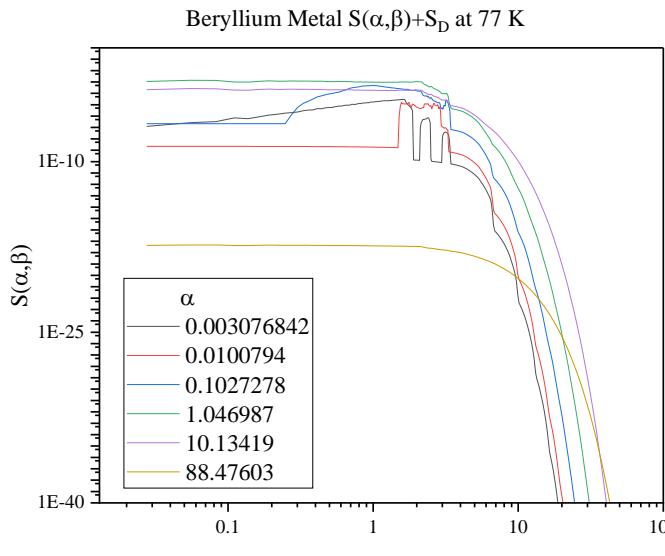
□ Components

- NN parameters
- Zero β
- Input features
- Inference Engine

□ Cache memory utilization

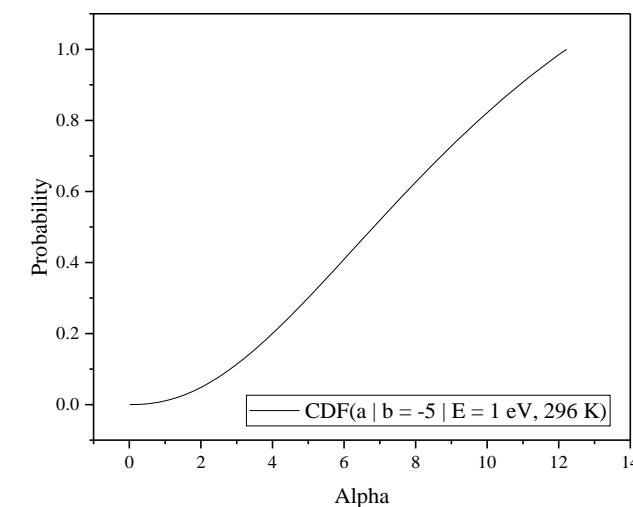
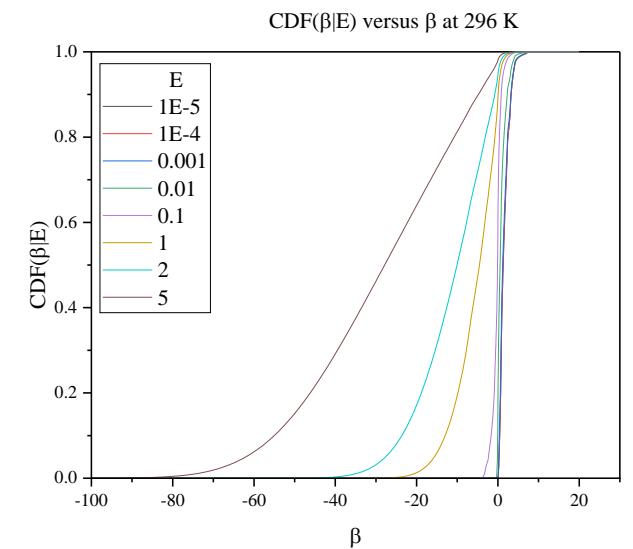
- L1, L2

NeTS- Beryllium One-Phonon Correction, $S_d(\alpha, \beta, T)$



Areas for Development and Application

1. Transfer Learning : Warm-start network training from a similar NeTS run (implemented)
2. Optimal Brain Damage : Reduce final network size, increase network prediction speed by selectively pruning neurons that don't contribute to neural structure (implemented)
3. Include one-phonon correction and train highly structure $S(\alpha, \beta, T)$ surface (in-progress)
4. Extend dimensionality : additional material properties (i.e., porosity, burnup, pressure), and new materials
5. Couple NeTS to reactor physics framework (in-progress)



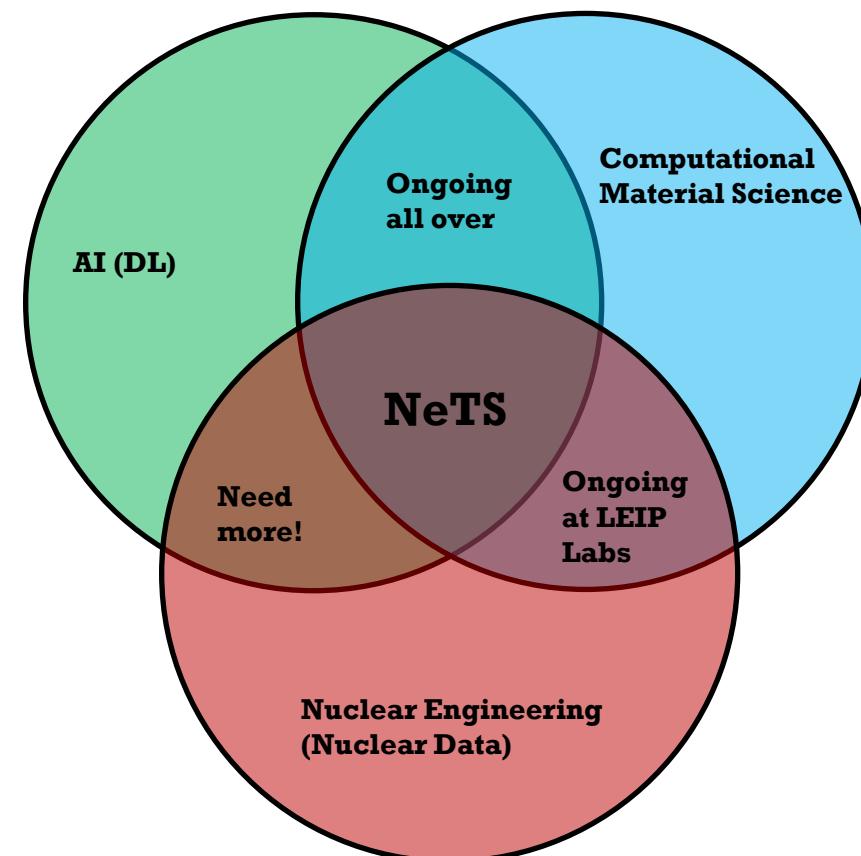
Summary

- Producing first-of-a-kind NN representations of trivariate TSL data (NeTS)

- Improvements

- Accuracy
- Memory consumption
- Speed implications

- Many new possibilities



Thank You