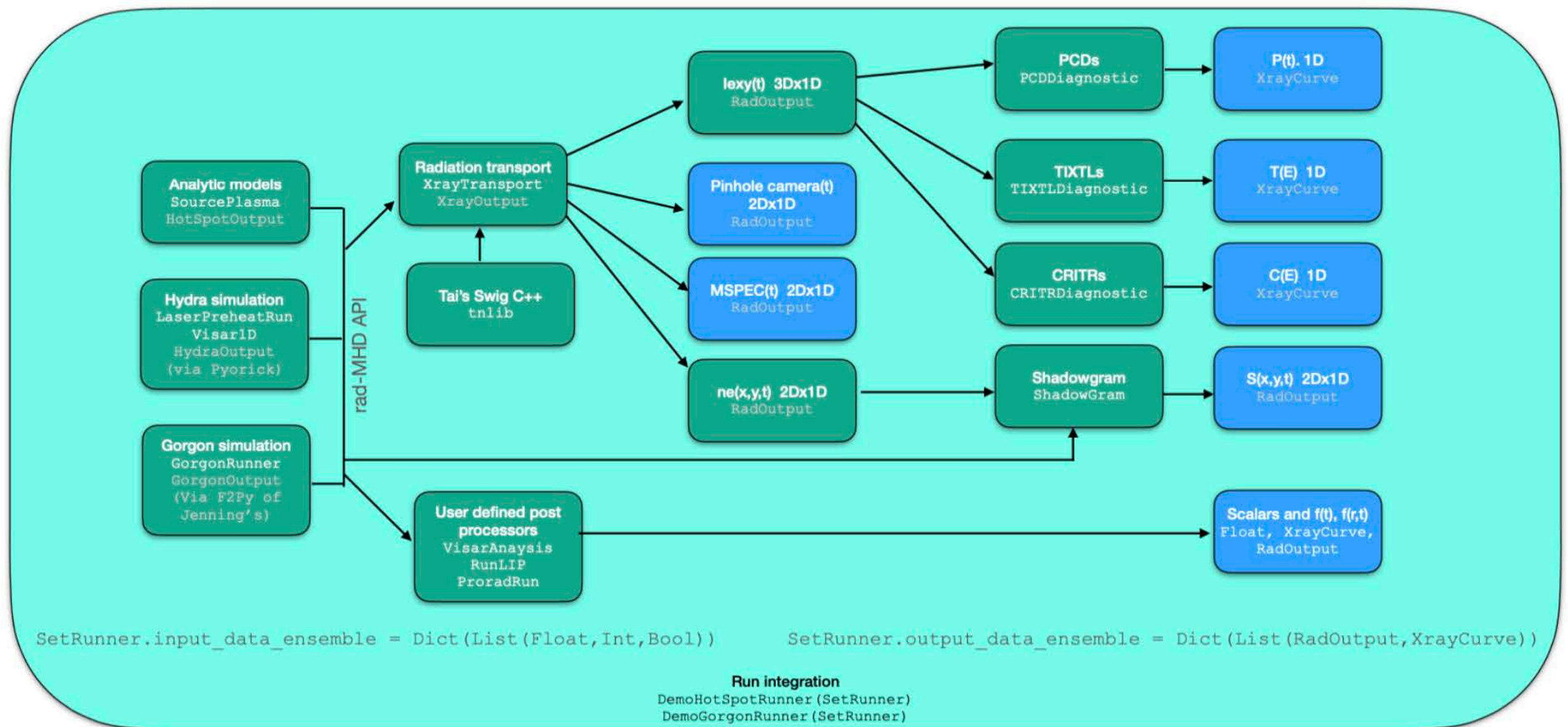


# The workflow



OUTPUTS

All classes inherit `AppRunner (HasTraits)` class giving:

- (1) Saved meta data state
- (2) GUI editor
- (3) CLI
- (4) `TraitsUI` (type checking, initial value, label, help)
- (5) `__str__()` method

This is the flow diagram of the workflow. Classes that implement the components of the workflow, and of the self described data (axis, labels, units, description, etc.). Put in links to Sphinx docs.

## General description of the software architecture

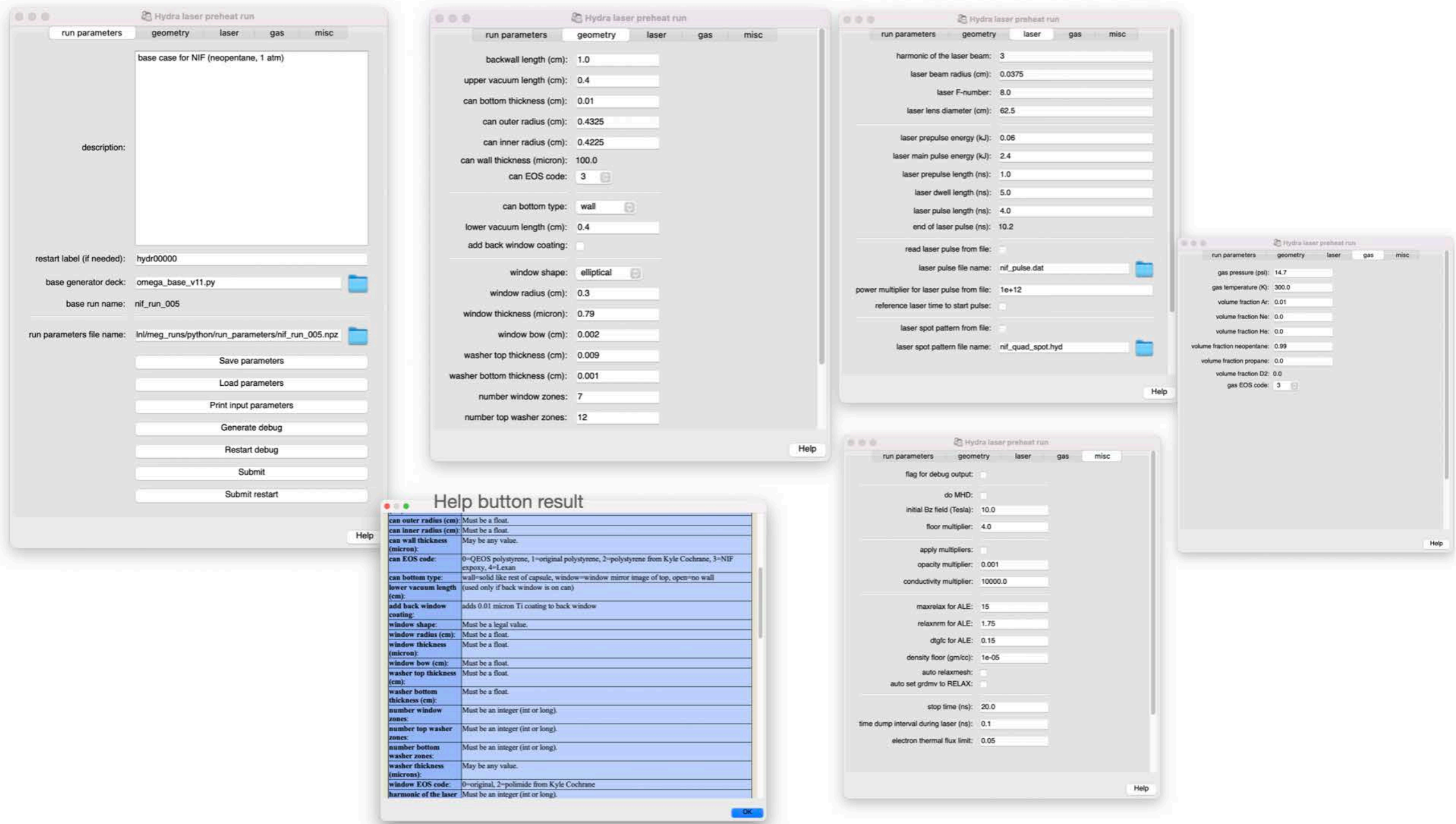
What has systematically been constructed over since I arrived at Sandia in 2016 is realization of a software architecture (maintained from the start) in Git and documented using the Sphinx documentation system (<http://s1008570.srn.sandia.gov:8080>, using Markdown syntax in the source code to facilitate this). It was developed using concepts of object oriented design in Python. Classes were most times, subclasses of `HasTraits`. This allowed for strict variable typing & error checking (dramatically reducing parameter input errors), initial value, variables labels, and variable help. In addition to setting the variables and objects from a CLI with error checking, `TraitsUI` provides an interactive GUI editor view of the object. This was enhanced by the creation of the `AppRunner` class that supplemented `Traits` and `TraitsUI` to give:

1. saved and restored meta data state, so that data formats would be self descriptive and templates of application parameters can be retained
2. app type and app version with a version conversion facility to maintain backward version compatibility
3. provision of variables such as `run_name`, `input_directory`, and `output_directory` that are almost always needed, along with methods such as `run()`, `save()`, `load()`, `save_results()`, `load_results()`, `plot()`, `default_output_file()`, and `save_figs()`.
4. a better default GUI editor view, with fine grain control of Traited parameters that are displayed and common methods displayed as buttons.
5. a better default `__str__()` method with more fine grain control of what is printed.



The `AppRunner` class is not only used for applications but also for data objects. It is used to run Hydra and Gorgon in the following way. A generic Hydra run deck is constructed that is controlled by a set of variables. A set of parameters is imported into this run deck, first thing, from the saved state of an `AppRunner` class constructed with these parameters as edited properties (from both the CLI and GUI editor). In fact there is a template class `HydraRun` that supplements the `AppRunner` class with common methods such as `srun()`, `submit()`, `archive()`, and `restore()`, along with the infrastructure to inject the parameters into the Hydra deck. A similar method can now be implemented to run Gorgon since Chris Jennings has refactored the code to give it an input deck.

A general API was constructed for rad-hydro simulation results (for Gorgon, Hydra, and a more general implementation for analytic construction). The interface grid format is based off of `tvtk`, a Traitd form of `VTK`. A class was constructed, `XrayTransport`, that uses this API for its input, then performs the radiation transport using the methods developed by Tai in C++ and made available using `Swig` to `Python`. This code also directly calculates MSPEC and Pinhole imaging diagnostics. The output also has been piped into subsequent applications that calculate PCD, TIXTL, and CRITR synthetic diagnostics. Many other diagnostics are anticipated to be developed in the near future. Where appropriate `C`, `C++`, and `FORTRAN`, such as for the re-gridder of block structured grids (which was done in `C`). An example of the GUI editor for the Hydra laser preheat run follows:



Many of the applications are parallelized asynchronously, through MPI or Posix subprocess forks, using the `bsync` package developed by John Field for the LLNL data science effort.

The data classes have many common mathematical and utility methods defined such as: `plot()`, `convolve()`, `integrate()`, `__mult__()`, `__add__()`, and `__str__()`.

The ultimate goal of this infrastructure is embodied in the `SetRunner` class. This class captures the complete workflow. It also has the ensemble construct, `Distribution` objects, where distributions can be given for a set of input parameters. Ensembles can then be generated from these distributions, and the workflow executed for each member of the ensemble. The synthetic diagnostics for each member of the ensemble are then available for analysis using statistical and MLDL methods.

This infrastructure has already been used to generate movies of GXD and MSPEC images for MagLIF preheat Hydra simulations, and to generate stochastic ensembles of 1D VISAR measurements for statistical and MLDL applications. It is also an integral part of critical deliverables for a REHEDS LDRD on applications of MLDL for Z, and a CIS LDRD on the same subject.

The instructions on how to set up the environment can be found in `pysnl/docs/build_soe.txt`. It is highly recommended that this infrastructure be executed via a Jupyter notebook served from a Docker image set up using `build_soe.txt`.