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GLUE Code: A framework handling communication and interfaces between scales

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Summary

Many scientific applications are inherently multiscale in nature. Such complex physical phenomena often require simultaneous execution and coordination of simulations spanning multiple time and length scales. This is possible by combining expensive small-scale simulations (such as molecular dynamics simulations) with larger scale simulations (such continuum limit/hydro solvers) to allow for considerably larger systems using task and data parallelism. However, the granularity of the tasks can be very large and often leads to load imbalance. Traditionally, we use approximations to streamline the computation of the more costly interactions and this introduces trade-offs between simulation cost and accuracy. In recent years, the available computational power and the advances in machine learning have made computing these scale-bridging interactions and multiscale simulations more feasible.

One driving application has been plasma modeling in inertial confinement fusion (ICF) which is fundamentally multiscale in nature. This requires deep understanding of how to extrapolate microscopic information into macroscopically relevant scales. For example, in ICF one needs an accurate understanding of the connection between experimental observables and the underlying microphysics. The properties of the larger scales are often affected by the microscale behavior incorporated usually into the equations of state and ionic and electronic transport coefficients (Liboff, 1959; Rinderknecht et al., 2014; Rosenberg et al., 2015; Ross et al., 2017). Instead of incorporating this information using reliable molecular dynamics (MD) simulations, one often needs to use theoretical models, due to the inability of MD to reach engineering scales (Glosli et al., 2007; Marinak et al., 1998). One approach to resolve this issue is by coupling two MD simulations of different scales via force interpolation, e.g. the AdResS method (Krekeler et al., 2018; Nagarajan et al., 2013). Another approach, which we will pursue in the scope of this work, is by enabling scale bridging between MD simulations and meso/macro-scale models.

State of the art

Traditionally, multiscale simulations combine multiple simulation methods that need to be simultaneously executed and coordinated. To achieve this, we use asynchronous task-based runtime systems that include load balancers. Such load balancers can schedule and migrate tasks to maintain throughput; however, the issue of fault tolerance remains (Cappello, 2009).

To avoid this, checkpointing is often used (Koo & Toueg, 1987), but it could be prohibitively expensive when its output frequency is high. Other works such as the `mystic` framework (Michael McKerns & Aivazis, 2019) is more geared towards large-scale machine learning techniques (McKerns et al., 2011). Such codes are not designed toward coupling multiscale simulations but have been demonstrated to be highly effective at solving hard optimization problems.

In this work, we propose the Generic Learning User Enablement (GLUE) Code to facilitate the coupling between scales. The GLUE Code builds upon previous work on multiscale coupling (Haack et al., 2021; Karra et al., 2022; Lubbers et al., 2020; R. Pavel et al., 2017; R. S. Pavel et al., 2015). At its simplest, we determine what physical properties must be exchanged between the various scales and derive application programming interfaces (APIs) from these.

To take advantage of modern supercomputing and exascale platforms and we couple our framework directly with high-performance-computing-friendly job schedulers. This allows us to use one framework to generate training data with a minimal footprint (task scheduler can fire off all jobs) and perform "hero-runs" of multiscale simulations. At every point, we perform a fine grain simulation or utilize an upscaled result from the active learning model. The GLUE Code uses active learning to evaluate the level of uncertainty and executes fine grain simulations when more training data is required.

Statement of need

The GLUE Code is a modular framework designed to couple different scientific applications to support use cases, including multiscale methods and various forms of machine learning. The workflow was initially designed around supporting active learning as an alternative to coupled applications to support multiscale methods but has been written in a sufficiently modular way that different machine learning methods can be utilized. Application programming interfaces (API) are available for C, C++, Fortran, and Python with support for various storage formats. The code also provides direct coupling with high performance computing job schedulers such as SLURM (Yoo et al., 2003) and Flux (Ahn et al., 2018). An overview of the GLUE Code implementation is shown in Fig. 1, where the meso/macro-scale solvers BGK, CFDNS, and LBM are also defined.

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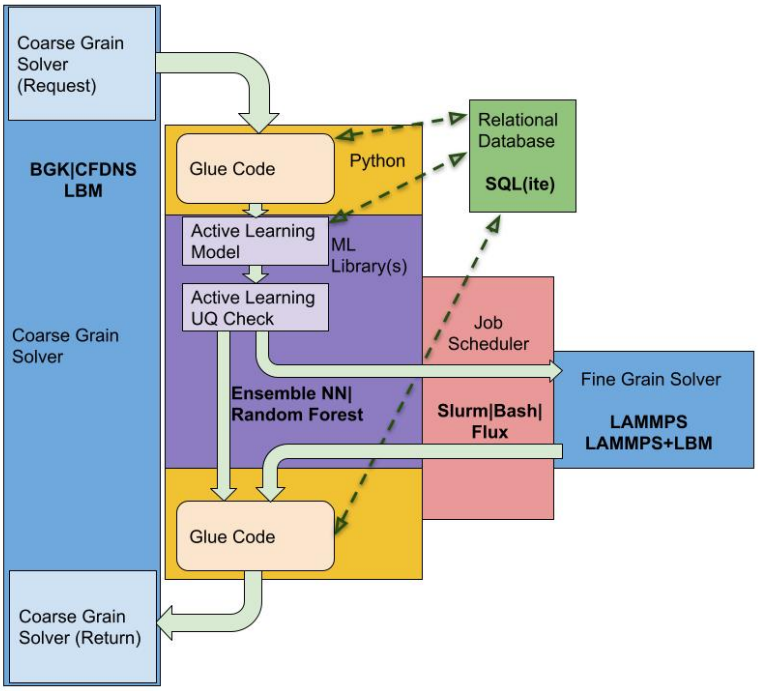

Figure 1

Figure 1: Sample of the GLUE Code implementation of our microscale-macroscale coupling. On the macroscale simulation (left) sending a request, the GLUE Code (center) uses the active learning algorithms (center purple) to determine if the model's uncertainty quantification is such that a new fine grain simulation (right) needs to be called. Then either the result of the fine grain simulation or the model's prediction is returned to the macroscale simulation. This figure is adapted from Fig. 2 in Diaw et al. (Diaw et al., 2020).

The aim of the GLUE Code is to efficiently handle the communication and interfaces between the computing platform, surrogate model, coarse-scale code, and fine-scale code (Diaw et al., 2020). At its core, the GLUE Code determines what physical properties need to be exchanged between the scales of interest and spawns APIs using this information. The GLUE Code ensures that these physical properties are communicated between the various scientific codes needed for the given multiscale problem. The GLUE Code uses active learning algorithms to evaluate if the model has a high level of uncertainty, and thus, a fine grain simulation needs to be executed. At the end of each cycle, the framework returns either the result of the fine grain simulation or the model's prediction of the macroscopic simulation.

Characteristics of the GLUE code:

- The GLUE Code has a modular lightweight structure, where each component can be swapped out for a different implementation. This is possible due to the APIs structure of the framework.
- The modularity of the GLUE code allows us to replace a scientific solver with a machine learning solution. The scale bridging structures are explicitly defined, which allows us to switch between a fine grain MD simulation and an ML solution. If a neural network is capable of reproducing the same outputs as an MD simulation from the same inputs, then they would be functionally identical.
- As shown in Fig. 1, the main components of the GLUE Code are a Coarse Grain Solver, an active learning backend, a relational database, a job scheduler, and the coupling and coordination logic.

- The GLUE Code is written with a collection of commodity software as the backend to most of these components. Currently, the relational database is supported via SQL(ite), while the job scheduler has support for SLURM (Yoo et al., 2003), Lawrence Livermore National Laboratory's Flux scheduler (Ahn et al., 2018), and a rudimentary serialization model for debugging. Active learning is provided through PyTorch (Paszke et al., 2019) and Scikit-Learn (Pedregosa et al., 2011).
- This approach relies on SQL(ite) for the communication as it is a guaranteed atomic read and write that simplifies a lot of our efforts at the cost of performance.
- For coarse grain simulations, we currently couple with the Multi-BGK (Los Alamos National Laboratory, n.d.) as well as additional ICF codes. Preliminary studies have been made of coupling with more general Lattice Boltzmann simulations for other fields of study.
- For fine scale simulations, we use a mixture of LAMMPS (Plimpton, 1995) and proven analytic solutions; however, one could easily switch to another MD solution as long as they have similar capabilities.
- Since the effectiveness of machine learning methods varies depending on the available training data and problem, an additional check for any machine learning solution is added to the framework. In the GLUE Code, we query the models provided by the machine learning solution for the output associated with our inputs. The surrogate model then provides both the expected outputs and the uncertainty quantification to indicate its confidence that this specific model gave a valid answer. If the confidence is too low, the code falls back to calling the actual MD simulation and providing the data for the machine learning solution to retrain and generate a new surrogate model for future use.

Code structure

The GLUE code is organized as follows:

- `GLUECode_Library` contains the C++ library that is meant to be linked to the coarse grain solver. This allows existing applications to couple to the `GLUECode_Service` with minimal code alterations.
- `GLUECode_Service` contains the python scripts that the library communicates with and uses a combination of active learning and spawning of fine grain simulation jobs to enable and accelerate multiscale scientific applications.
- `docs` contains documentation for the Flux scheduler.
- `examples` contains sniff tests for the serial and the MPI versions of the code, and utility scripts, such as `pullICFData.py` that demonstrate how the GLUE Code framework can be used to access training data to perform deeper analysis.
- `jsonFiles` contains example input decks for the GLUE Code service.
- `lammpsFiles` contains LAMMPS example scripts (`in.Argon_Deuterium_masses` and `in.Argon_Deuterium_plasma`) that compute the mutual diffusion for a plasma composed of argon and deuterium at different concentrations and temperatures. More information about the test cases can be found within the files.
- `training` contains training data required for active learning.

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