A toolkit, framework and application for automating DFT calculations

1 Overview

This package provides Python objects and functions for planning and carrying out VASP calculations, handling INCAR logic, and organizing VASP runs: ¹

It also provides a GUI (Figure 1).

What it doesn't do is heavy lifting. It doesn't generate adsorption structures or do machine learning. For those, specialized tools exist. Rather, it aims to facilitate a smooth, unobstructed VASP workflow, especially in places where existing solutions like ase or MedeA, in my experience, work awkwardly.

Its functionality is provided through 3 separate modules: the toolkit, the framework, and the application.

2 The toolkit

This module provides plain Python objects and functions for running VASP.

We provide a bare-bones poscar(unit_cell, positions), and rely on ase.io for IO. ase.Atoms would've been perfect if it were more straightforward and pickle-able.

We provide a getopt-style incar(opt, metal, cluster=nersc). Using python's exec built-in, the user can easily enforce custom rules on the incar:

```
if relaxation and metal:
    assert ismear == 1 or 2
```

To run VASP, simply call functions:

```
write_files(incar, poscar); submit(); if complete(): retrieve()
# alternatively, fluent interface
poscar.incar('opt, cluster=nersc').submit().retrieve()
```

No more Calculator classes with multiple inheritance. Also, ase somehow doesn't allow calculator.run('nersc'); we have submit() for that.

3 The framework

In software engineering, a toolkit provides tools, while a framework overarchingly modifies the working of the application.

¹It'll work with any DFT software, but "INCAR" is shorter than "input parameters including k-mesh", and "SLURM" shorter than "supercomputing cluster queueing systems".

Python is synchronous. Your first ase.calc.get_energy() command will block the session for however long it takes for the VASP computation to complete, before you can enter the second command. For everyday research, that's inconvenient. It's better to separate the planning stage from the execution stage:

Tensorflow 1.x does exactly this: define a computational graph first, then execute it. dask.delayed, a graph-parallel execution library, allows something similar. We borrow from their design pattern. Tensors hold values, and Operations link Tensors to form a computational graph.

To use the framework, wrap objects in Tensors, and functions in Operations. If desired, synchronous behavior can be restored similarly to tf.eager_execution in Tensorflow 2.x, or by using the toolkit stand-alone.

4 The application

The graph-parallel framework naturally introduces a data structure for managing VASP folders: nested directed graphs. Compared to ase's list of entries and Materials Studio's project folders, a graph database is both scalable and human friendly (method of loci).

Our web-based GUI (Figure 1) helps visualize the graph database, creating a persistent "look and feel" of a project, and provides access to common functionalities. Figure 2 explains its backend/frontend architecture.

The application is a work in progress. Linkurious JS has been deprecated, the backend API changed, and the ever-increasing database size highlights communication overhead issues.

In addition to the 3 main components, plugins provide additional extensible python API, currently including save/load, periodic table, electronic structure post-processing (past work), and MLqueue (past work).

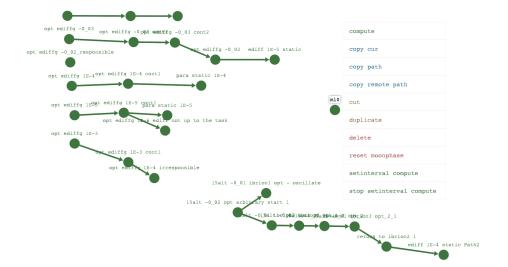


Figure 1: GUI, WIP, picture taken from 2019 version

$$\overline{\text{Framework}} \xrightarrow{\overline{\text{graph}}} \overline{\text{Flask}} \xrightarrow{\overline{\text{IJSON}}} \overline{\text{LinkuriousJS}} \xrightarrow{\overline{\text{Visualization}}} \overline{\text{User}}$$

Figure 2: Data flow between the database and the UI