Extended Abstract: Productive Parallel Programming with Parsl

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ABSTRACT

Parsl is a parallel programming library for Python that aims to make it easy to specify parallelism in programs and to realize that parallelism on arbitrary parallel and distributed computing systems. Parsl relies on developers annotating Python functions—wrapping either Python or external applications—to indicate that these functions may be executed concurrently. Developers can then link together functions via the exchange of data. Parsl establishes a dynamic dependency graph and sends tasks for execution on connected resources when dependencies are resolved. Parsl’s runtime system enables different compute resources to be used, from laptops to supercomputers, without modification to the Parsl program.

1 INTRODUCTION

As we approach the limitations of sequential processing power, computer architectures are becoming increasingly parallel and distributed. Unfortunately, parallel and distributed computing has a reputation for being complex, frail, and unsafe. To address the needs of a diverse developer community new programming languages, libraries, and tools are needed to better enable productive, safe, robust and portable parallel and distributed programming.

Python has established itself as one of the most productive programming languages as it is easy to use and has a thriving user community and ecosystem of libraries and tools. As a result, Python has been broadly adopted in industry and academia. However, one of the most well-known limitations of Python is its use of the Global Interpreter Lock (GIL) lock that limits concurrent execution of threads—and the resulting implications with respect to parallelization. Overcoming this limitation has been the focus of many Python libraries, for example, Python’s multiprocessing library allows applications to spawn new processes for execution before they are rejoined to the master process upon completion. While multiprocessing addresses the need for concurrent execution on a node, it does not support execution in a distributed setting.

Parsl is a Python library that augments Python to enable productive, safe, robust and portable parallel and distributed programming. Parsl’s productivity stems from its simple extensions to Python in which developers express opportunities for concurrent execution using function decorators. At runtime, Parsl establishes a dynamic dependency graph comprised of tasks (i.e., calls to Python functions) with edges representing shared input/output data between tasks. Parsl encodes this information as a Directed Acyclic Graph (DAG), which it uses to implement a safe concurrency model in which tasks are only executed when their dependencies (e.g., input data dependencies) are met. When the program executes, Parsl manages the execution of function invocations on various computing resources, from laptops to supercomputers. Parsl tracks task execution, detects exceptions, retries tasks when they fail, and is able to overcome various faults (e.g., node failure, task failure). Finally, to enable programs to be moved between different systems, Parsl separates program implementation from runtime configuration thereby enabling developers to load a system-specific Python configuration object at runtime.

In this extended abstract we highlight Parsl’s productive programming model. Further details of Parsl’s implementation and runtime model is available in prior publications [2–4].

2 PARSL PROGRAMMING MODEL

Parsl augments Python with constructs to enable specification of parallelism in Python programs. Parsl uses these constructs to establish a dynamic dependency graph via which it can determine a safe and portable execution plan.

2.1 Parsl Apps

At the core of the Parsl model are Parsl apps—decorated Python functions that wrap either pure Python code (python_app) or external applications that can be invoked via the shell (bash_app). Listing 1 shows how Parsl apps can be used to print “Hello world.”
Parsl apps are executed asynchronously and thus they must include all context needed for execution. For example, dependencies must be imported in the app and required data must be explicitly passed via arguments. The Parsl bash_app uses the return statement to specify the Bash command to be executed.

```python
@python_app
def hello():
    return 'Hello world'

@bash_app
def hello():
    return 'echo "Hello world"'
```

Listing 1: Hello world Python and Bash apps.

### 2.2 Futures

As Parsl apps are executed asynchronously, and perhaps on remote resources with variable delays, it would be inefficient for the Python program to wait for the app to complete execution. Instead, Parsl supports concurrent execution as follows. Whenever a Parsl program calls an app, Parsl will create a new task in its dependency graph and immediately return a future in lieu of that function’s result(s). The program will not block and can continue immediately through the program. At some point, for example when the task’s dependencies are met and there is available computing capacity, Parsl will execute the task. Upon completion, Parsl will set the value of the future to contain the task’s output. Listing 2 shows an example of the future being returned from the invocation of the hello app. Parsl’s futures also provide methods for inspecting the current status and accessing the result.

```
app_future = hello()

# Check if the app future is resolved
print('Done: {}'.format(app_future.done()))

# Wait for the future to resolve
print('Result: {}'.format(app_future.result()))
```

Listing 2: Invocation of a Parsl app will return a future to the calling program. The future can be used to retrieve the result when the app completes executing.

### 2.3 Data

Parsl supports the exchange of both Python objects and external files between Parsl apps. To enable portability, and simplify use, Parsl aims to abstract execution location by ensuring that apps may access the same input arguments and files irrespective of where the app is executed.

Listing 3 illustrates how apps can communicate using standard Python parameter passing and return statements. Parsl enables passing of primitive types, files, and other complex types that can be serialized (e.g., numpy array, scikit-learn model).

```
from parsl.data_provider.files import File

@python_app
def communicate(name):
    return 'hello {}'.format(name)

r = communicate('bob')
print(r.result())
```

Listing 3: App communication via Python arguments.

```
@python_app
def sort_numbers(in_file):
    with open(in_file.filepath, 'r') as f:
        strs = [n.strip() for n in f.readlines()]
        strs.sort()
    return strs

unsorted_file = File('https://raw.githubusercontent.com/Parsl/parsl-tutorial/master/input/unsorted.txt')

f = sort_numbers(unsorted_file)
print (f.result())
```

Listing 4: App communication via files. In this case a remote file is passed to an app that sorts the contents of that file.
2.4 Configuration

Parsl separates program logic from execution configuration, enabling programs to be developed in a way that is agnostic of execution environment. Configuration is expressed in a Python object (Listing 5) which is loaded at runtime. The configuration object enables developers to introspect permissible options, validate configurations, and dynamically modify configurations during execution. The configuration specifies details of the provider, executors, connection channel, allocation size, and data management options.

3 RELATED WORK

Considerable prior work has explored methods for supporting parallelism in applications. We briefly review methods that are offered as domain specific languages, as libraries in an existing language, and as language-independent frameworks.

There are a number of domain specific languages and workflow systems that support the orchestrated execution of tasks in dependency graphs. Systems, such as Pegasus [9] implement a static DAG model in which developers define the structure of the program in a custom representation and then they execute it via the workflow system. Python-based workflow systems such as FireWorks [11], Apache Airflow [1], and Luigi [12] provide similar capabilities within Python. Swift [13] and NextFlow [10] implement their own DSL which is evaluated to generate a DAG.

Most well-known programming languages offer a range of libraries designed to support parallel and distributed execution. In Python, Dask [8] supports parallel data analytics via custom implementation of common Python libraries (e.g., Pandas) and a general distributed runtime for execution on clusters. FaaS systems, such as funcX [6], often use similar methods for distributed execution. Other systems take a language-independent approach to developing parallel and distributed applications. Concurrent Collections [5] implements a language-independent way of encoding parallelism in different host languages. Developers identify data and control dependencies, and encode these dependencies in a graph. The graph is executed by translating the specification to code for a specific runtime system (e.g., in C++, Java, and .NET). OpenMP [7] provides a set of language- and platform-independent directives for augmenting an application and parallelizing execution on nodes. It is often combined with MPI for distributed execution.

4 SUMMARY

Parsl offers a productive way of implementing portable parallel and distributed programs in Python. The benefit of extending Python with simple extensions has enabled a diverse range of developers to leverage Parsl in various domains and use cases. The modular configuration and execution model allows Parsl programs to be moved between different parallel and distributed computing environments. In prior work we have shown that Parsl can execute millions of tasks, scale to more than 250,000 workers across more than 8000 nodes, and process upward of 1200 tasks per second [3].

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from parsl.config import Config
from parsl.channels import LocalChannel
from parsl.providers import SlurmProvider
from parsl.executors import HighThroughputExecutor
from parsl.launchers import SrunLauncher
from parsl.addresses import address_by_hostname

config = Config(
    executors=[
        HighThroughputExecutor(
            label="frontera_htex",
            address=address_by_hostname(),
            max_workers=56,
            provider=SlurmProvider(
                channel=LocalChannel(),
                nodes_per_block=128,
                init_blocks=1,
                partition='normal',
                launcher=SrunLauncher(),
            ),
        ),
    ]
)

Listing 5: Parsl configuration for running on TACC’s Frontera supercomputer.

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