

Parsl: A Parallel Programming Library for Python

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On behalf of the Parsl community (including Yadu Babuji, Ben Clifford, Ian Foster, Dan Katz, Zhuozhao Li, Mike Wilde, Anna Woodard)

http://parsl-project.org







Example workload: simulating images from the Vera C. Rubin Observatory



Example workload: Applying extreme-scale AI to screen billions of druglike molecules against COVID-19 proteins



COMPUTING RESOURCES



Hidden Layer

Output Lave





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CHEMICAL

LIBRARY DATABASE

Distribution, parallelism, and composition

Parallel and distributed computing is ubiquitous

- Increasing data sizes combined with plateauing sequential processing power

Software is increasingly assembled rather than written

- High-level language to integrate and wrap components from many sources

Python (and the SciPy ecosystem) has established itself as one of the most productive and popular environments for research

- Thriving ecosystem of libraries, tools, Jupyter, etc.



Parsl: parallel programming in Python

Apps define opportunities for parallelism

- Python apps call Python functions
- Bash apps call external applications

Apps return "futures": a proxy for a result that might not yet be available

Apps run concurrently respecting dataflow dependencies. Natural parallel programming!

Parsl scripts are independent of where they run. Write once run anywhere!

🖉 parsl

pip install parsl





Parsl's dataflow programming model delivers intuitive parallel

- Programming paradigm in which program is assembled as a directed graph of data flowing between tasks
- Intuitive way to think about parallelism (tasks run independently when data slice ready)
- Parsl's dataflow model allows data to be passed between Apps
 - Python types and objects
 - Files (local or via HTTP, FTP, or Globus)





Data-driven example: parallel geospatial analysis



Land-use Image processing pipeline for the MODIS remote sensor



Expressing parallelism using Parsl

```
1) Wrap the science applications as Parsl Apps:
@bash_app
def landuse(img, outputs=[]):
   return `./landuse_sim.sh {} {}'.format(img, outputs[0])
```

```
@python_app
def colorize(img, num_chunks):
    return color_package(img, num_chunks)
```

```
@python_app
def analyze(land_chunks, color_chunks):
    return combine(land_chunks, color_chunks)
```



Expressing a many task workflow in Parsl

2) Execute the parallel workflow by calling Apps: lchunks = []

```
for i in range (nchunks):
    lchunks.append(landuse(img, outputs=[File(`l%s.txt' % i)]))
colored = colorize(img, num_chunks=5)
results = analyze(lchunks, colored)
```



Decomposing parallelism into a dynamic task-dependency graph for distributed execution

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Monte Carlo workflow	
Many scientific applications use the monte-carlo method to compute results.	Darcl
If a circle with radius r is inscribed inside a square with side length $2r$ then the area of the circle is πr^2 and the area of the square is $(2r)^2$. Thus, if N uniformly distributed random points are dropped within the sugare then approximately $N \pi/4$ will be inside the circle.	
Each call to the function pi() is executed independently and in parallel. The avg_three() app is used to compute the average of the futures that were returned from the pi() calls.	
The dependency chain looks like this:	
App Calls pi() pi() pi()	
Futures a b c	
\ / App Call avg_points()	
 Future avg_pi	
<pre>In []: # App that estimates pi by placing points in a box @python_app</pre>	
<pre>def pi(total): import random</pre>	
# Set the size of the box (edge length) in which we drop random points	
center = edge_length / 2	
count = 0	
for in range(total):	
<pre># Drop a random point in the box. xy = random.randint(1, edge_length),random.randint(1, edge_length)</pre>	
# Count points within the circle	
count += 1	
<pre>return (count*4/total)</pre>	
# App that computes the average of the values	
epychol_app def avg_points(a, b, c):	
return $(a + b + c)/3$	
# Estimate three values for pi	
a, b, c = p1(10**b), p1(10**6), p1(10**6)	Wich corvigoo
<pre># Compute the average of the three estimates avg_pi = avg_points(a, b, c)</pre>	WED SET VICES
# Print the results	
<pre>print("A: (0:.5f) B: (1:.5f) C: (2:.5f)".format(a.result(), b.result(), c.result())) print("Average: (0:.5f)".format(avg p1.result()))</pre>	

nd Engineering

Enabling portable Parsl programs: providers

The same Parsl program can be run locally, on grids, clouds, or supercomputers

Growing support for various schedulers and cloud vendors



Configuration How-to Configure Comet (SDSC)

Cori (NERSC)

Stampede2 (TACC)

Theta (ALCF)

Cooley (ALCF)

Swan (Cray)

CC-IN2P3

Midway (RCC, UChicago)

Open Science Grid

Amazon Web Services

Ad-Hoc Clusters

Further help

Separation of code and execution





Parsl implements a Python's Concurrent.futures executor (runtime) interface

High-throughput executor (HTEX)

- Pilot job-based model with multi-threaded manager deployed on workers
- Designed for ease of use, fault-tolerance, etc.
- <2000 nodes (~60K workers), Ms tasks, task duration/nodes > 0.01

Extreme-scale executor (EXEX)*

- Distributed MPI job manages execution. Manager rank communicates workload to other worker ranks directly
- Designed for extreme scale execution on supercomputers
- >1000 nodes (>30K workers), Ms tasks, >1m task duration
- Low-latency Executor (LLEX)*
 - Direct socket communication to workers, fixed resource pool, limited features
 - 10s nodes, <1M tasks, <1m tasks

Others: WorkQueue, RADICAL-Cybertools, Flux









Parsl executors scale to 256K concurrent workers

HTEX and EXEX outperform other Python-based approaches

Parsl scales to more than 250K workers (8K nodes) and ~2M tasks

Framework	Maximum # of workers [†]	Maximum # of nodes [†]	Maximum tasks/second [‡]
Parsl-IPP	2048	64	330
Parsl-HTEX	65 536	2048*	1181
Parsl-EXEX	262 144	8192*	1176
FireWorks	1024	32	4
Dask distributed	4096	128	2617

Babuji et.al. "Parsl: Pervasive Parallel Programming in Python." ACM International Symposium on High-Performance Parallel and Distributed Computing (HPDC). 2019.

Strong scaling (50K 1s tasks)





Parsl is being used in a wide range of scientific applications

- Machine learning to predict stopping power in materials
- B Protein and biomolecule structure and interaction
- C LSST simulation and weak lensing using sky surveys
- Cosmic ray showers in QuarkNet
- E Information extraction to classify image types in papers
- Materials science at the Advanced Photon Source
- Machine learning and data analytics in materials

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https://parsl-project.org/parslfest.html

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Parsl is an open-source Python community (parsl-project.org)



+ 52 contributors



funcX: Parsl as a service for remote computing

Common Parsl use case: I want to run my computation on one or more remote clusters, clouds, supercomputers from my PC



Cloud-hosted managed compute service built on Parsl



FuncX: Fire-and-forget remote function execution

funcX Service:

- Single reliable cloud service (REST)
- Register, share, run functions
- Fire-and-forget execution: funcX will manage execution, store results in the cloud, handle errors, etc.

Endpoints:

- User-deployed and managed
- Dynamically provision resources, deploy containers, execute functions, catch exceptions, etc.
- Exploit local architecture/accelerators

Choose where to execute functions

- Closest, cheapest, fastest, accelerators ...





Parsl provides productive, safe, scalable, and flexible parallelism in Python

Productive: Python with minimal new constructs (integrated with the growing SciPy ecosystem and other scientific services)

Safe: deterministic parallel programs through immutable input/output objects, dependency task graph, etc.

Scalable and portable: efficient execution from laptops to the largest supercomputers

Flexible: programs composed from existing components and then applied to different resources/workloads



ExaWorks: ECP Workflows Project

- Community-based project to support workflows in ECP
 - Users, workflow developers, facilities, vendors
- Technical development
 - ExaWorks SDK: packaged and compatible workflows components
 - PSI/J: Asynchronous Python library for scheduler portability
- Community development

Lawrence Livermore National Laboratory

Argonne 合

- Organizing a series of summits to bring the workflows community together
- <u>https://exaworks.org/summit.html</u>

Brookhaven[®] National Laboratory **CAK RIDGE**

 Contributing to the Workflows Community Initiative (https://workflows.community)

> workflows community

> > initiatio



https://exaworks.org ExaWorks

Questions?

parsl-project.org

parsl-project.org/binder









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