

Dask

Contents

- · Familiar user interface
- Scales from laptops to clusters
- · Complex Algorithms

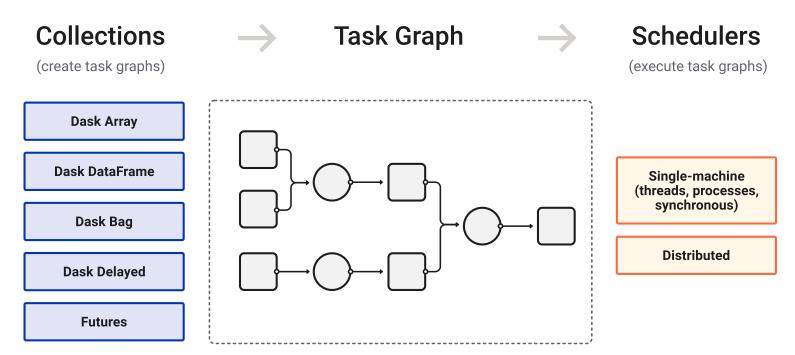
Dask is a flexible library for parallel computing in Python.

Dask is composed of two parts:

- 1. **Dynamic task scheduling** optimized for computation. This is similar to *Airflow, Luigi, Celery, or Make*, but optimized for interactive computational workloads.
- 2. "Big Data" collections like parallel arrays, dataframes, and lists that extend common interfaces like *NumPy*, *Pandas*, *or Python iterators* to larger-than-memory or distributed environments. These parallel collections run on top of dynamic task schedulers.

Dask emphasizes the following virtues:

- Familiar: Provides parallelized NumPy array and Pandas DataFrame objects
- Flexible: Provides a task scheduling interface for more custom workloads and integration with other projects.
- Native: Enables distributed computing in pure Python with access to the PyData stack.
- Fast: Operates with low overhead, low latency, and minimal serialization necessary for fast numerical algorithms
- Scales up: Runs resiliently on clusters with 1000s of cores
- Scales down: Trivial to set up and run on a laptop in a single process
- Responsive: Designed with interactive computing in mind, it provides rapid feedback and diagnostics to aid humans



High level collections are used to generate task graphs which can be executed by schedulers on a single machine or a cluster.

<u>Dask</u> <u>Distributed</u> <u>Dask ML</u> <u>Examples</u> <u>Ecosystem</u> <u>Community</u>

Dask Data-rame mimics Pandas - documentation

Dask Array mimics NumPy - documentation

Dask Bag mimics iterators, Toolz, and PySpark - documentation

```
import dask.bag as db
b = db.read_text('2015-*-*.json.gz').map(json.loads)
b.pluck('name').frequencies().topk(10, lambda pair: pair[1]).compute()
```

Dask Delayed mimics for loops and wraps custom code - documentation

The concurrent.futures interface provides general submission of custom tasks: - documentation

```
from dask.distributed import Client
client = Client('scheduler:port')

futures = []
for fn in filenames:
    future = client.submit(load, fn)
    futures.append(future)

summary = client.submit(summarize, futures)
summary.result()
```

Scales from laptops to clusters

Dask is convenient on a laptop. It <u>installs</u> trivially with conda or pip and extends the size of convenient datasets from "fits in memory" to "fits on disk".

Dask can scale to a cluster of 100s of machines. It is resilient, elastic, data local, and low latency. For more information, see the documentation about the <u>distributed scheduler</u>.

This ease of transition between single-machine to moderate cluster enables users to both start simple and grow when necessary.

Complex Algorithms

Dask represents parallel computations with <u>task graphs</u>. These directed acyclic graphs may have arbitrary structure, which enables both developers and users the freedom to build sophisticated algorithms and to handle messy situations not easily managed by the <u>map/filter/groupby</u> paradigm common in most data engineering frameworks.

We originally needed this complexity to build complex algorithms for n-dimensional arrays but have found it to be equally valuable when dealing with messy situations in everyday problems.