Cloud computing made easy

in

Joblib

Alexandre Abadie

Outline

An overview of Joblib

Joblib for cloud computing

Future work

Joblib in a word

A Python package to make your algorithms run faster

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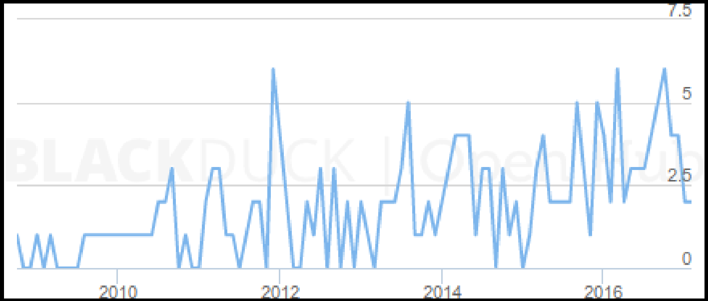
http://joblib.readthedocs.io

The ecosystem

- **54 different contributors** since the beginning in 2008



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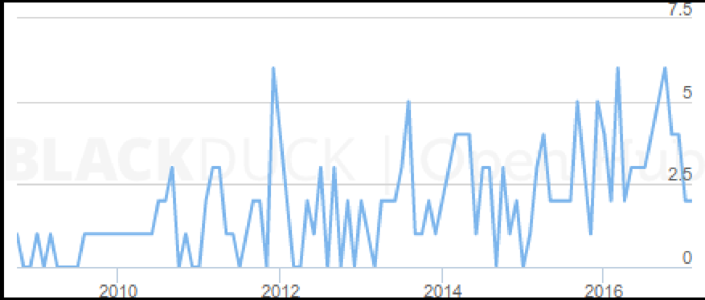

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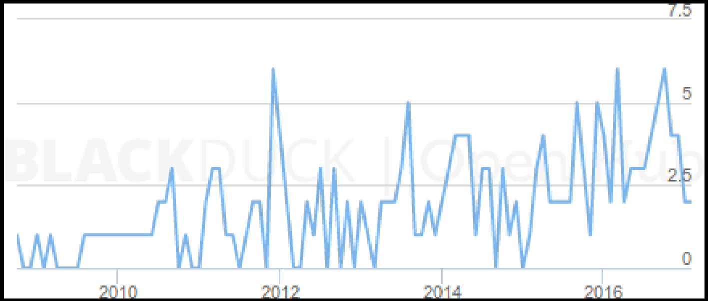

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- **Stable and mature** code base

https://github.com/joblib/joblib

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  ⇒ **And parallel programming is not user friendly in general**

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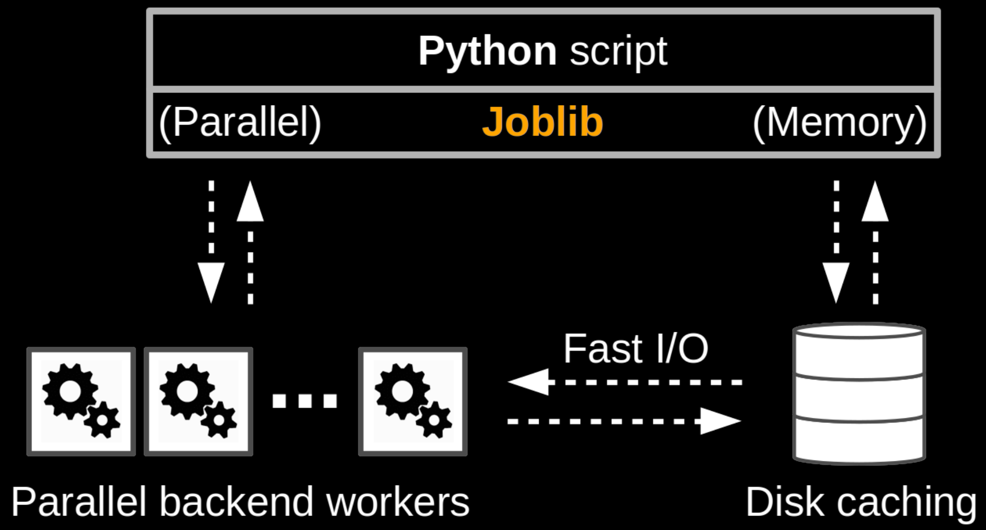
- No dependencies, optimized for numpy arrays

  ⇒ **simple installation and integration in other projects**

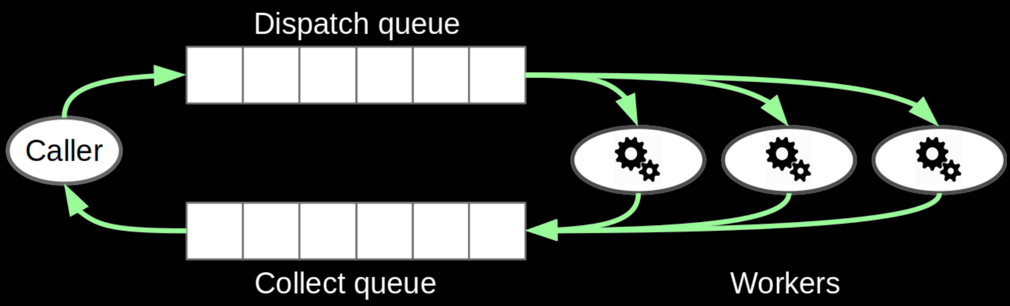
Overview


Python script
(Parallel)
Joblib
(Memory)
Fast I/O
Parallel backend workers
Disk caching

Parallel helper

```
>>> from joblib import Parallel, delayed
>>> from math import sqrt

>>> Parallel(n_jobs=3, verbose=50)(delayed(sqrt)(i**2) for i in range(6))
[Parallel(n_jobs=3)]: Done   1 tasks      | elapsed:    0.0s
[...]
[Parallel(n_jobs=3)]: Done   6 out of   6 | elapsed:    0.0s finished
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0]
```



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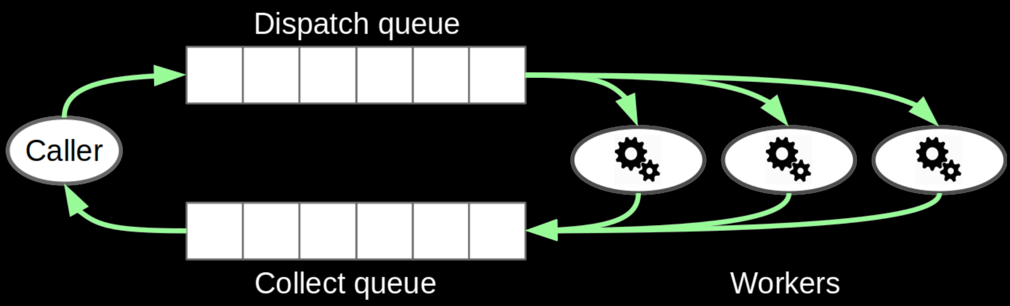

⇒ **API can be extended with external backends**

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```
>>> from distributed.joblib import DistributedBackend
>>> from joblib import (Parallel, delayed,
>>>                     register_parallel_backend, parallel_backend)

>>> register_parallel_backend('distributed', DistributedBackend)
>>> with parallel_backend('distributed', scheduler_host='dscheduler:8786'):
>>>     Parallel(n_jobs=3)(delayed(sqrt)(i**2) for i in range(6))
[...]
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- Future: new backends for **Celery**, **Spark**

Caching on disk

- Use a **memoize** pattern with the **Memory** object

```
>>> from joblib import Memory
>>> import numpy as np
>>> a = np.vander(np.arange(3)).astype(np.float)

>>> mem = Memory(cachedir='/tmp/joblib')
>>> square = mem.cache(np.square)
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>>> b = square(a)
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[Memory] Calling square...
square(array([[ 0.,  0.,  1.],
       [ 1.,  1.,  1.],
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>>> c = square(a) # no recomputation
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- **Least Recently Used (LRU)** cache replacement policy

Persistence

- Convert/create **an arbitrary object** into/from a **string of bytes**
- **Streamable persistence** to/from file or socket objects

```
>>> import numpy as np
>>> import joblib
>>> obj = [('a', [1, 2, 3]), ('b', np.arange(10))]
>>> joblib.dump(obj, '/tmp/test.pkl')
['/tmp/test.pkl']
>>> with open('/tmp/test.pkl', 'rb') as f:
>>>     joblib.load(f)
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
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- Use **compression for fast I/O**:
  support for **zlib, gz, bz2, xz and lzma** compressors

```
>>> joblib.dump(obj, '/tmp/test.pkl.gz', compress=True, cache_size=0)
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Outline

Joblib in a word

⇒**Joblib for cloud computing**

Future work

The Cloud trend

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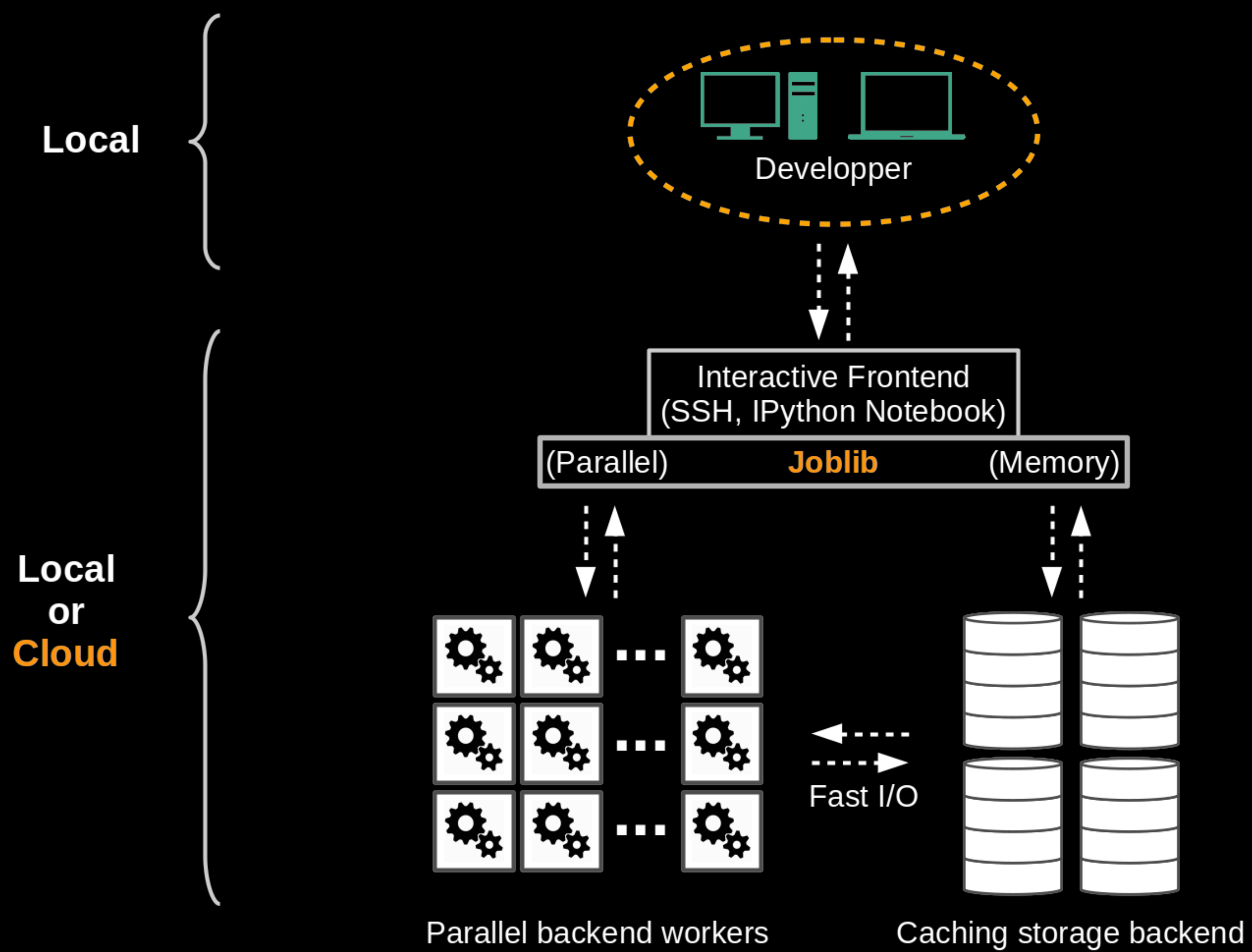
How can Joblib be used with them?

The general idea



Use pluggable multi-machine parallel backends

Principle: configure your backend and wrap the calls to Parallel

```
>>> import time
>>> import ipyparallel as ipp
>>> from ipyparallel.joblib import register as register_joblib
>>> from joblib import parallel_backend, Parallel, delayed

# Setup ipyparallel backend
>>> register_joblib()
>>> dview = ipp.Client()[:]

# Start the job
>>> with parallel_backend("ipyparallel", view=dview):
>>>     Parallel(n_jobs=20, verbose=50)(delayed(time.sleep)(1) for i in range(10))
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Complete examples exist for:

- Dask distributed: https://github.com/ogrisel/docker-distributed
- Hadoop Yarn: https://github.com/joblib/joblib-hadoop

Use pluggable store backends

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```
>>> import numpy as np
>>> from joblib import Memory
>>> from joblibhadoop.hdfs import register_hdfs_store_backend

# Register HDFS store backend provider
>>> register_hdfs_store_backend()
# Persist data in hdfs://namenode:9000/user/john/cache/joblib
>>> mem = Memory(location='cache', backend='hdfs',
>>>              host='namenode', port=9000, user='john', compress=True)
multiply = mem.cache(np.multiply)
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Store backends available:

- Amazon S3: https://github.com/aabadie/joblib-s3
- Hadoop HDFS: https://github.com/joblib/joblib-hadoop

Using Hadoop with Joblib

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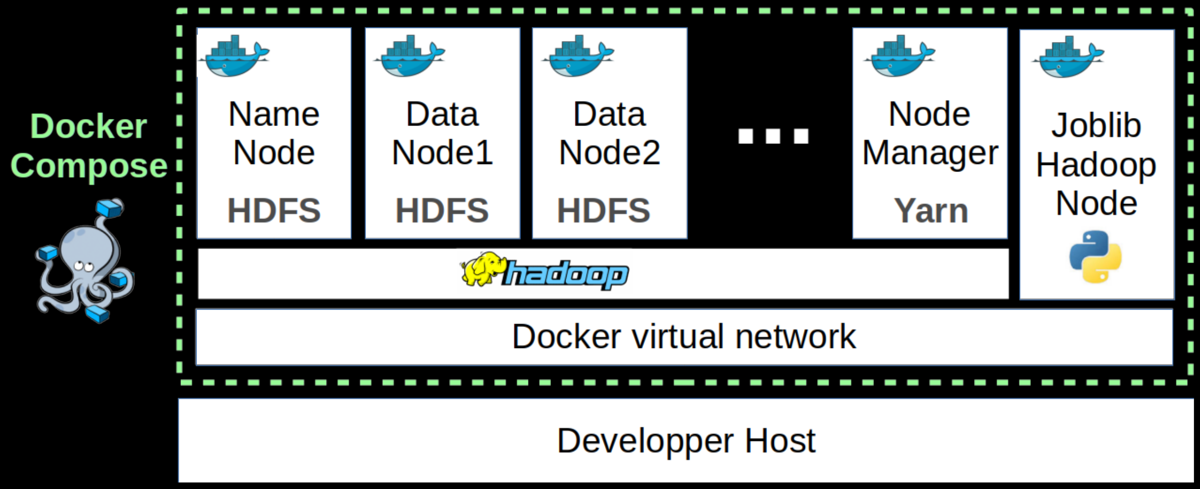

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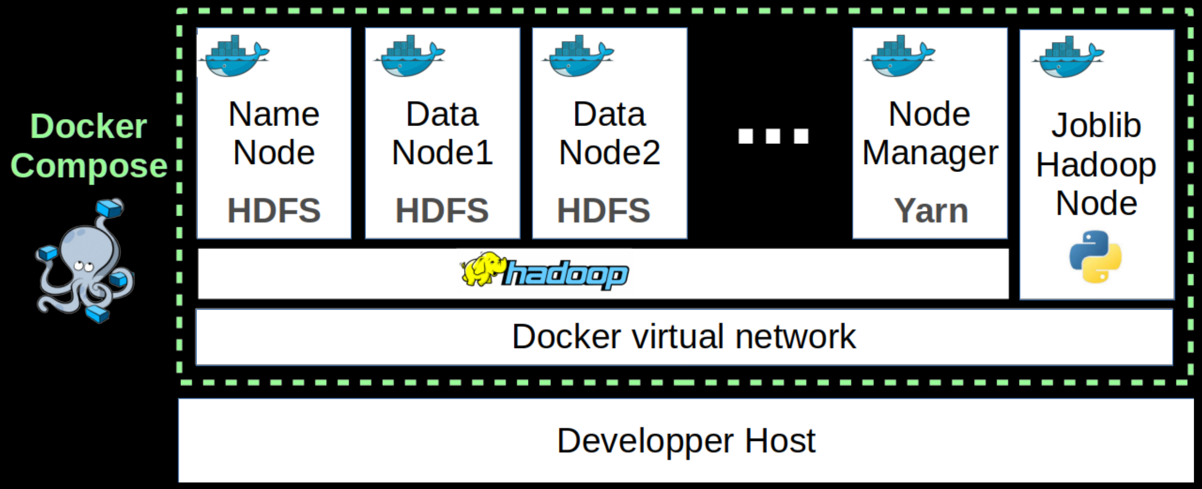

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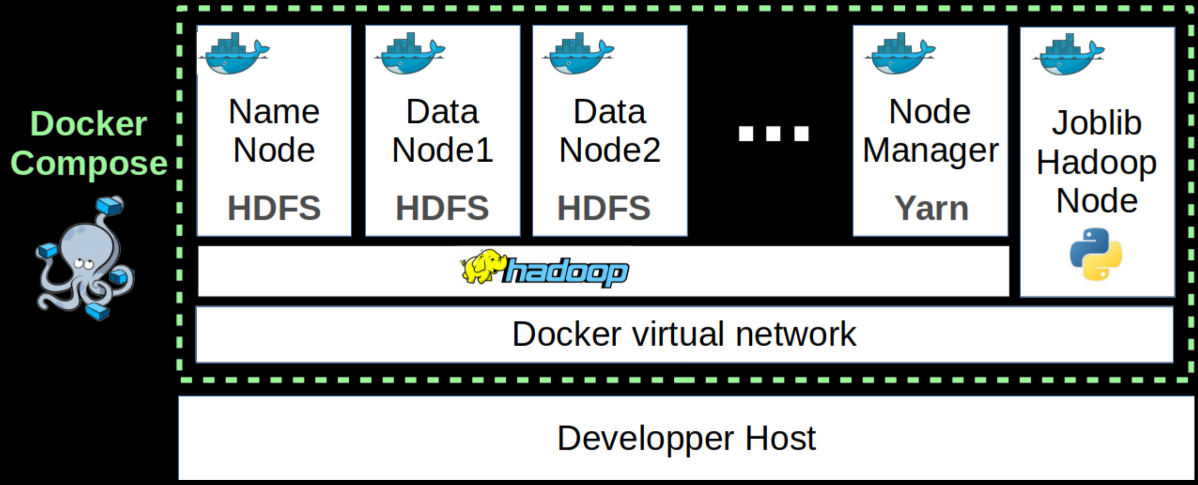

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⇒**Future work and conclusion**

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Future work

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- Replace multiprocessing parallel backend with **Loky**

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- Extend Cloud providers support

  ⇒ Using **Apache libcloud**: give access to a lot more Cloud providers

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- Use Joblib either **on your laptop** or **in a Cloud** with **very few code changes**

Thanks!