

Joblib

Toward efficient computing

From laptop to cloud

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Overview of Joblib

Recent major improvements

What's next

Overview of Joblib

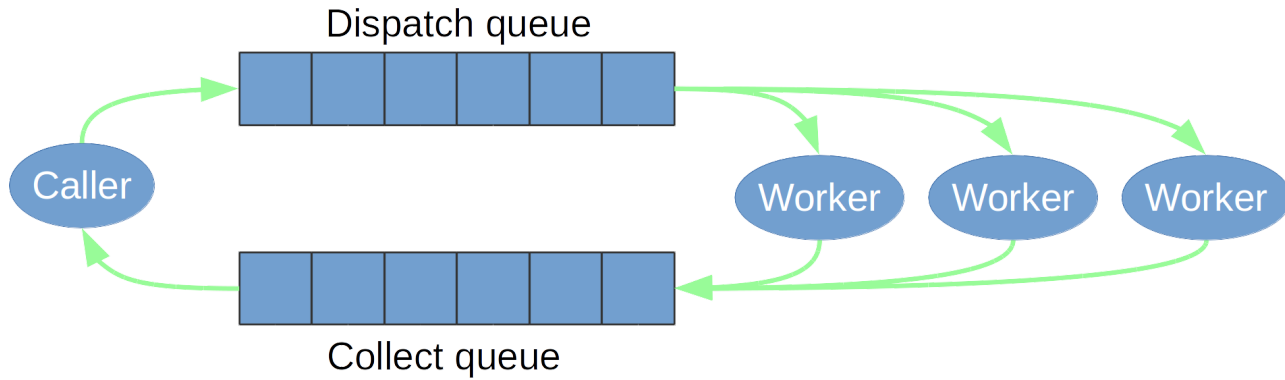
- Embarrassingly Parallel computing helper
- Efficient disk caching to avoid recomputation
- Fast I/O persistence
- No dependencies, optimized for numpy arrays



Joblib is the parallel backend used by Scikit-Learn

<https://pythonhosted.org/joblib/>

Parallel helper



Available backends: **threading** and **multiprocessing** (default)

```
>>> 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]
```

Caching on disk

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

```
>>> from joblib import Memory
>>> mem = Memory(cachedir='/tmp/joblib')
>>> import numpy as np
>>> a = np.vander(np.arange(3)).astype(np.float)
>>> square = mem.cache(np.square)
>>> b = square(a)

[Memory] Calling square...
square(array([[ 0.,  0.,  1.],
              [ 1.,  1.,  1.],
              [ 4.,  2.,  1.])))
_____square - 0...s, 0.0min

>>> c = square(a) # no recomputation
```

- Use **md5** hash of input parameters
- Results are persisted on disk

Persistence

- Convert/create **an arbitrary object** into/from a **string of bytes**
- Persistence in Joblib is based on **pickle** and **Pickler/Unpickler** subclasses

```
>>> import numpy as np
>>> import joblib
>>> obj = [('a', [1, 2, 3]), ('b', np.arange(10))]
>>> joblib.dump(obj, '/tmp/test.pkl')
['/tmp/test.pkl', '/tmp/test.pkl_01.npy']
>>> joblib.load('/tmp/test.pkl')
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
```

- Use compression for fast I/O

```
>>> joblib.dump(obj, '/tmp/test.pkl', compress=True, cache_size=0)
['/tmp/test.pkl', '/tmp/test.pkl_01.npy.z']
>>> joblib.load('/tmp/test.pkl')
```

- Access numpy arrays with **np.memmap** for **out-of-core computing** or for sharing between multiple workers

Recent major improvements

Persistence

Custom parallel backends

arriving in version 0.10.0

Persistence refactoring

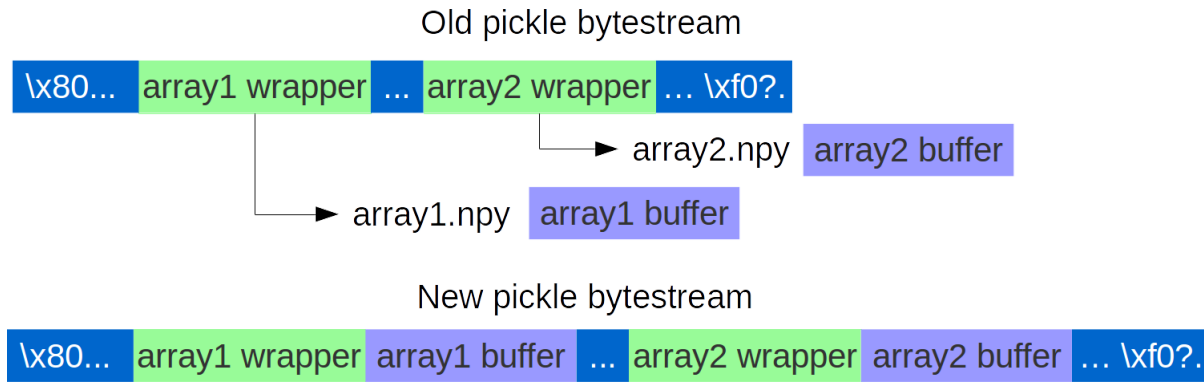
- *Until 0.9.4:*
 - An object with **multiple arrays** is persisted in **multiple files**
 - **Only zlib** compression available
 - **Memory copies** with compression

Persistence refactoring

- *Until 0.9.4:*
 - An object with **multiple arrays** is persisted in **multiple files**
 - **Only zlib** compression available
 - **Memory copies** with compression
- *In 0.10.0 (not released yet):*
 - An object with **multiple arrays** goes in a **single file**
 - Support of **all compression methods** provided by the python standard library
 - **No memory copies** with compression

<https://github.com/joblib/joblib/pull/260>

Persistence refactoring strategy

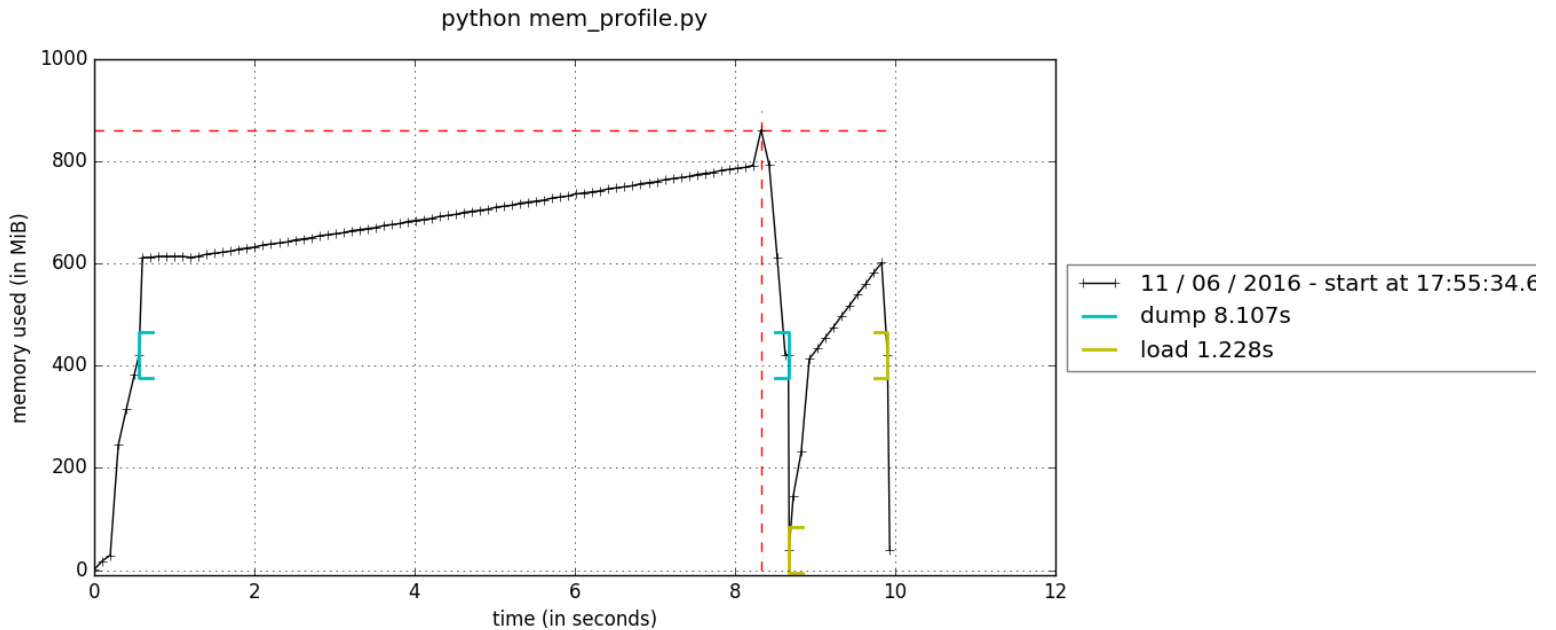


- Write numpy array buffer interleaved in the pickle stream
⇒ **all arrays in a single file**

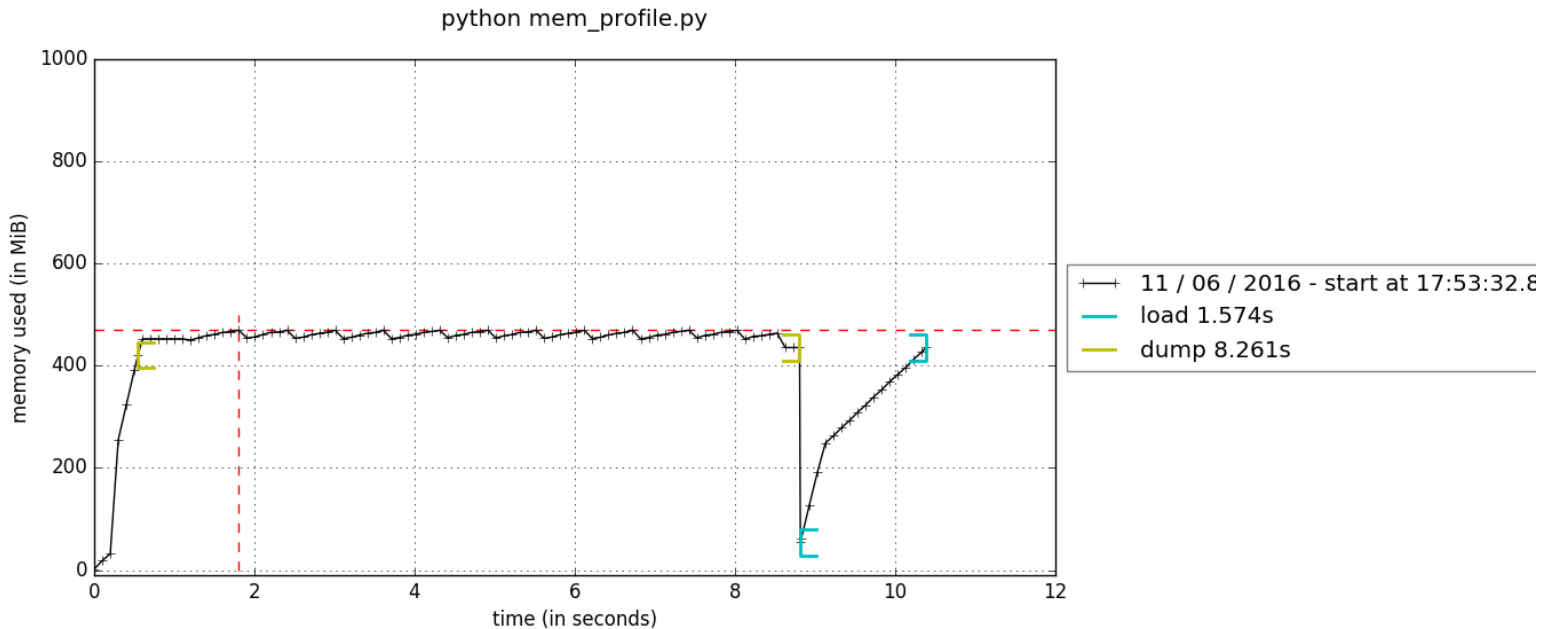
Caveat: Not compatible with pickle format

- Dump/reconstruct the array by chunks of bytes using numpy functions
⇒ **avoid memory copies**

Before: memory copies



Now: **no** memory copies



Credits: Memory profiler

Persistence in a single file

```
>>> import numpy as np
>>> import joblib
>>> obj = [np.ones((5000, 5000)), np.random.random((5000, 5000))]

# only 1 file is generated:
>>> joblib.dump(obj, '/tmp/test.pkl', compress=True)
['/tmp/test.pkl']
>>> joblib.load('/tmp/test.pkl')
[array([[ 1.,  1., ...,  1.,  1.]],
       array([[ 0.47006195,  0.5436392 , ...,  0.1218267 ,  0.48592789]])]
```

- useful with scikit-learn estimators
- simpler management of backup files
- robust when using memory map on distributed file systems

Compression formats

- New supported compression formats

⇒ **gzip, bz2, lzma and xz**

- Automatic compression based on file extension
- Automatic detection of compression format when loading
- Valid compression file formats
- Slower than **zlib**

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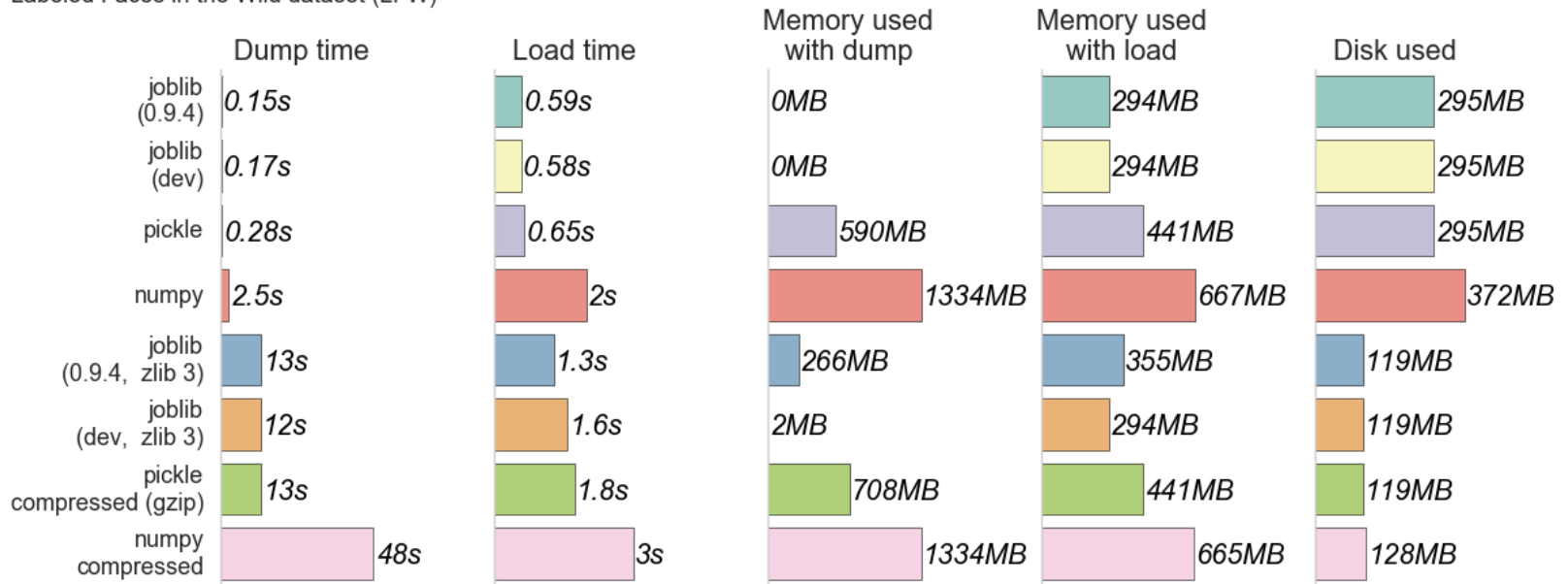
- Automatic compression based on file extension
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Example with **gzip** compression:

```
>>> joblib.dump(obj, '/tmp/test.pkl.gz', compress=('gzip', 3))
>>> joblib.load('/tmp/test.pkl.gz')
[array([[ 1.,  1., ...,  1.,  1.]),
 array([[ 0.47006195,  0.5436392, ...,  0.1218267,  0.48592789]])]
>>> # or with file extension detection
>>> joblib.dump(obj, '/tmp/test.pkl.gz')
```

Performance comparison: Memory footprint and Speed

Labeled Faces in the Wild dataset (LFW)



- Joblib persists **faster** and with **low extra memory consumption**
- Performance is data dependent

<http://gael-varoquaux.info/programming/new-low-overhead-persistence-in-joblib-for-big-data.html>

Parallel backends

Custom parallel backends

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 - Not extensible
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Custom parallel backends

- *Until 0.9.4:*
 - Only **threading** and **multiprocessing** backends
 - Not extensible
 - Active backend cannot be changed easily at a high level
- *In 0.10.0:*
 - Common API using **ParallelBackendBase** interface
 - Use **with** to set the active backend in a context manager
 - New backends for:
 - **distributed** implemented by Matthieu Rocklin
 - **ipyparallel** implemented by Min RK
 - **YARN** implemented by Niels Zielemaker

<https://github.com/joblib/joblib/pull/306> contributed by Niels Zielemaker

Principle

1. Subclass **ParallelBackendBase**:

```
class ExampleParallelBackend(ParallelBackendBase):
    """Example of minimum parallel backend."""

    def configure(self, n_jobs=1, parallel=None, **backend_args):
        self.n_jobs = self.effective_n_jobs(n_jobs)
        self.parallel = parallel
        return n_jobs

    def apply_async(self, func, callback=None):
        """Schedule a func to be run"""
        result = func() # depends on the backend
        if callback:
            callback(result)
        return result
```

2. Register your backend:

```
>>> register_parallel_backend("example_backend", ExampleParallelBackend)
```

IPython parallel backend

Integration for Joblib available in version 5.1

1. Launch a 5 engines cluster:

```
$ ipcontroller &  
$ ipcluster engines -n 5
```

2. Run the following script:

```
import time  
import ipyparallel as ipp  
from ipyparallel.joblib import register as register_joblib  
from joblib import parallel_backend, Parallel, delayed  
  
# Register ipyparallel backend  
register_joblib()  
# Start the job  
with parallel_backend("ipyparallel"):  
    Parallel(n_jobs=20, verbose=50)(delayed(time.sleep)(1) for i in range(10))
```

Demo

https://github.com/aabadie/ipyparallel-cloud/blob/master/examples/sklearn_parameter_search_local_ipyparallel.ipynb

What's next

Persistence in file objects

1. With regular file object:

```
>>> with open('/tmp/test.pkl', 'wb') as fo:  
...     joblib.dump(obj, fo)  
>>> with open('/tmp/test.pkl', 'rb') as fo:  
...     joblib.load(fo)
```

Also works with **gzip.GzipFile**, **bz2.BZ2File** and **lzma.LZMAFile**

<https://github.com/joblib/joblib/pull/351>

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Also works with **gzip.GzipFile**, **bz2.BZ2File** and **lzma.LZMAFile**

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2. Or with any file-like object, e.g exposing read/write functions:

```
>>> with RemoteStoreObject(hostname, port, obj_id) as rso:  
...     joblib.dump(obj, rso)  
>>> with RemoteStoreObject(hostname, port, obj_id) as rso:  
...     joblib.load(rso)
```

⇒Example: blob databases, remote storage

Joblib in the cloud

- Share persistence files



- Use computing resources



Conclusion

- Persistence of numpy arrays in **a single file**...
... and soon in file objects
- New compression formats: **gzip, bz2, xz, lzma**
... extend to faster implementations (**blosc**) ?
- Persists **without memory copies**
... manipulate bigger data
- New parallel backends: **distributed, ipyparallel, YARN**...
... new ones to come ?

Thanks !

