joblib Documentation

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Contents

CHAPTER 1

Introduction

Joblib is a set of tools to provide **lightweight pipelining in Python**. In particular:

1. transparent disk-caching of functions and lazy re-evaluation (memoize pattern)
2. easy simple parallel computing

Joblib is optimized to be **fast** and **robust** in particular on large data and has specific optimizations for *numpy* arrays. It is **BSD-licensed**.

Documentation:	https://joblib.readthedocs.io
Download:	http://pypi.python.org/pypi/joblib#downloads
Source code:	http://github.com/joblib/joblib
Report issues:	http://github.com/joblib/joblib/issues

1.1 Vision

The vision is to provide tools to easily achieve better performance and reproducibility when working with long running jobs.

- **Avoid computing twice the same thing**: code is rerun over an over, for instance when prototyping computational-heavy jobs (as in scientific development), but hand-crafted solution to alleviate this issue is error-prone and often leads to unreproducible results
- **Persist to disk transparently**: persisting in an efficient way arbitrary objects containing large data is hard. Using joblib's caching mechanism avoids hand-written persistence and implicitly links the file on disk to the execution context of the original Python object. As a result, joblib's persistence is good for resuming an application status or computational job, eg after a crash.

Joblib addresses these problems while **leaving your code and your flow control as unmodified as possible** (no framework, no new paradigms).

1.2 Main features

1. **Transparent and fast disk-caching of output value:** a memoize or make-like functionality for Python functions that works well for arbitrary Python objects, including very large numpy arrays. Separate persistence and flow-execution logic from domain logic or algorithmic code by writing the operations as a set of steps with well-defined inputs and outputs: Python functions. Joblib can save their computation to disk and rerun it only if necessary:

```
>>> from joblib import Memory
>>> cachedir = 'your_cache_dir_goes_here'
>>> mem = Memory(cachedir)
>>> 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)
>>> # The above call did not trigger an evaluation
```

2. **Embarrassingly parallel helper:** to make it easy to write readable parallel code and debug it quickly:

```
>>> from joblib import Parallel, delayed
>>> from math import sqrt
>>> Parallel(n_jobs=1)(delayed(sqrt)(i**2) for i in range(10))
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

3. **Fast compressed Persistence**: a replacement for pickle to work efficiently on Python objects containing large data (*joblib.dump* & *joblib.load*).

CHAPTER 2

User manual

2.1 Why joblib: project goals

2.1.1 Benefits of pipelines

Pipeline processing systems can provide a set of useful features:

Data-flow programming for performance

- **On-demand computing:** in pipeline systems such as labView or VTK, calculations are performed as needed by the outputs and only when inputs change.
- **Transparent parallelization:** a pipeline topology can be inspected to deduce which operations can be run in parallel (it is equivalent to purely functional programming).

Provenance tracking to understand the code

- **Tracking of data and computations:** This enables the reproducibility of a computational experiment.
- **Inspecting data flow:** Inspecting intermediate results helps debugging and understanding.

But pipeline frameworks can get in the way

Joblib's philosophy is to keep the underlying algorithm code unchanged, avoiding framework-style modifications.

2.1.2 Joblib's approach

Functions are the simplest abstraction used by everyone. Pipeline jobs (or tasks) in Joblib are made of decorated functions.

Tracking of parameters in a meaningful way requires specification of data model. Joblib gives up on that and uses hashing for performance and robustness.

2.1.3 Design choices

- No dependencies other than Python
- Robust, well-tested code, at the cost of functionality
- Fast and suitable for scientific computing on big dataset without changing the original code
- Only local imports: **embed joblib in your code by copying it**

2.2 Installing joblib

2.2.1 Using *pip*

You can use *pip* to install joblib:

- For installing for all users, you need to run:

```
pip install joblib
```

  You may need to run the above command as administrator

  On a unix environment, it is better to install outside of the hierarchy managed by the system:

```
pip install --prefix /usr/local joblib
```

- Installing only for a specific user is easy if you use Python 2.7 or above:

```
pip install --user joblib
```

2.2.2 Using distributions

Joblib is packaged for several linux distribution: archlinux, debian, ubuntu, altlinux, and fedora. For minimum administration overhead, using the package manager is the recommended installation strategy on these systems.

2.2.3 The manual way

To install joblib first download the latest tarball (follow the link on the bottom of http://pypi.python.org/pypi/joblib) and expand it.

Installing in a local environment

If you don't need to install for all users, we strongly suggest that you create a local environment and install *joblib* in it. One of the pros of this method is that you never have to become administrator, and thus all the changes are local to your account and easy to clean up. Simply move to the directory created by expanding the *joblib* tarball and run the following command:

```
python setup.py install --user
```

Installing for all users

If you have administrator rights and want to install for all users, all you need to do is to go in directory created by expanding the *joblib* tarball and run the following line:

```
python setup.py install
```

If you are under Unix, we suggest that you install in '/usr/local' in order not to interfere with your system:

```
python setup.py install --prefix /usr/local
```

2.3 On demand recomputing: the *Memory* class

2.3.1 Use case

The *Memory* class defines a context for lazy evaluation of function, by putting the results in a store, by default using a disk, and not re-running the function twice for the same arguments.

It works by explicitly saving the output to a file and it is designed to work with non-hashable and potentially large input and output data types such as numpy arrays.

A simple example:

First, define the cache directory:

```
>>> cachedir = 'your_cache_location_directory'
```

Then, instanciate a memory context that uses this cache directory:

```
>>> from joblib import Memory
>>> memory = Memory(cachedir, verbose=0)
```

After these initial steps, just decorate a function to cache its output in this context:

```
>>> @memory.cache
... def f(x):
...     print('Running f(%s)' % x)
...     return x
```

Calling this function twice with the same argument does not execute it the second time, the output is just reloaded from a pickle file in the cache directory:

```
>>> print(f(1))
Running f(1)
1
>>> print(f(1))
1
```

However, calling the function with a different parameter executes it and recomputes the output:

```
>>> print(f(2))
Running f(2)
2
```

Comparison with *memoize*

The *memoize* decorator (http://code.activestate.com/recipes/52201/) caches in memory all the inputs and outputs of a function call. It can thus avoid running twice the same function, with a very small overhead. However, it compares input objects with those in cache on each call. As a result, for big objects there is a huge overhead. Moreover this approach does not work with numpy arrays, or other objects subject to non-significant fluctuations. Finally, using *memoize* with large objects will consume all the memory, where with *Memory*, objects are persisted to disk, using a persister optimized for speed and memory usage (*joblib.dump()*).

In short, *memoize* is best suited for functions with "small" input and output objects, whereas *Memory* is best suited for functions with complex input and output objects, and aggressive persistence to disk.

2.3.2 Using with *numpy*

The original motivation behind the *Memory* context was to have a memoize-like pattern on numpy arrays. *Memory* uses fast cryptographic hashing of the input arguments to check if they have been computed;

An example

Define two functions: the first with a number as an argument, outputting an array, used by the second one. Both functions are decorated with *Memory.cache*:

```
>>> import numpy as np

>>> @memory.cache
... def g(x):
...     print('A long-running calculation, with parameter %s' % x)
...     return np.hamming(x)

>>> @memory.cache
... def h(x):
...     print('A second long-running calculation, using g(x)')
...     return np.vander(x)
```

If the function *h* is called with the array created by the same call to *g*, *h* is not re-run:

```
>>> a = g(3)
A long-running calculation, with parameter 3
>>> a
array([0.08, 1.  , 0.08])
```

```
>>> g(3)
array([0.08, 1.  , 0.08])
>>> b = h(a)
A second long-running calculation, using g(x)
>>> b2 = h(a)
>>> b2
array([[0.0064, 0.08  , 1.    ],
       [1.    , 1.    , 1.    ],
       [0.0064, 0.08  , 1.    ]])
>>> np.allclose(b, b2)
True
```

Using memmapping

Memmapping (memory mapping) speeds up cache looking when reloading large numpy arrays:

```
>>> cachedir2 = 'your_cachedir2_location'
>>> memory2 = Memory(cachedir2, mmap_mode='r')
>>> square = memory2.cache(np.square)
>>> a = np.vander(np.arange(3)).astype(np.float)
>>> square(a)
________________________________________________________________________________
↪___
[Memory] Calling square...
square(array([[0., 0., 1.],
       [1., 1., 1.],
       [4., 2., 1.]]))
_____________________________________________________________square - 0.0s, 0.
↪0min
memmap([[ 0.,  0.,  1.],
        [ 1.,  1.,  1.],
        [16.,  4.,  1.]])
```

Note: Notice the debug mode used in the above example. It is useful for tracing of what is being reexecuted, and where the time is spent.

If the *square* function is called with the same input argument, its return value is loaded from the disk using memmapping:

```
>>> res = square(a)
>>> print(repr(res))
memmap([[ 0.,  0.,  1.],
        [ 1.,  1.,  1.],
        [16.,  4.,  1.]])
```

The memmap file must be closed to avoid file locking on Windows; closing numpy.memmap objects is done with del, which flushes changes to the disk

```
>>> del res
```

Note: If the memory mapping mode used was 'r', as in the above example, the array will be read only, and will be impossible to modified in place.

On the other hand, using 'r+' or 'w+' will enable modification of the array, but will propagate these modification to the disk, which will corrupt the cache. If you want modification of the array in memory, we suggest you use the 'c' mode: copy on write.

2.3.3 Shelving: using references to cached values

In some cases, it can be useful to get a reference to the cached result, instead of having the result itself. A typical example of this is when a lot of large numpy arrays must be dispatched accross several workers: instead of sending the data themselves over the network, send a reference to the joblib cache, and let the workers read the data from a network filesystem, potentially taking advantage of some system-level caching too.

Getting a reference to the cache can be done using the *call_and_shelve* method on the wrapped function:

```
>>> result = g.call_and_shelve(4)
A long-running calculation, with parameter 4
>>> result
MemorizedResult(location="...", func="...g...", args_id="...")
```

Once computed, the output of *g* is stored on disk, and deleted from memory. Reading the associated value can then be performed with the *get* method:

```
>>> result.get()
array([0.08, 0.77, 0.77, 0.08])
```

The cache for this particular value can be cleared using the *clear* method. Its invocation causes the stored value to be erased from disk. Any subsequent call to *get* will cause a *KeyError* exception to be raised:

```
>>> result.clear()
>>> result.get()
Traceback (most recent call last):
...
KeyError: 'Non-existing cache value (may have been cleared).\nFile ... does␣
↪not exist'
```

A *MemorizedResult* instance contains all that is necessary to read the cached value. It can be pickled for transmission or storage, and the printed representation can even be copy-pasted to a different python interpreter.

Shelving when cache is disabled

In the case where caching is disabled (e.g. *Memory(None)*), the *call_and_shelve* method returns a *NotMemorizedResult* instance, that stores the full function output, instead of just a reference (since there is nothing to point to). All the above remains valid though, except for the copy-pasting feature.

2.3.4 Gotchas

- **Across sessions, function cache is identified by the function's name**. Thus assigning the same name to different functions, their cache will override each-others (e.g. there are 'name collisions'), and unwanted re-run will happen:

```
>>> @memory.cache
... def func(x):
...     print('Running func(%s)' % x)

>>> func2 = func

>>> @memory.cache
... def func(x):
...     print('Running a different func(%s)' % x)
```

As long as the same session is used, there are no collisions (in joblib 0.8 and above), altough joblib does warn you that you are doing something dangerous:

```
>>> func(1)
Running a different func(1)

>>> # FIXME: The next line should create a JolibCollisionWarning but␣
↪does not
>>> # memory.rst:0: JobLibCollisionWarning: Possible name collisions␣
↪between functions 'func' (<doctest memory.rst>:...) and 'func' (
↪<doctest memory.rst>:...)
>>> func2(1)
Running func(1)

>>> func(1) # No recomputation so far
>>> func2(1) # No recomputation so far
```

But suppose the interpreter is exited and then restarted, the cache will not be identified properly, and the functions will be rerun:

```
>>> # FIXME: The next line will should create a JoblibCollisionWarning␣
↪but does not. Also it is skipped because it does not produce any output
>>> # memory.rst:0: JobLibCollisionWarning: Possible name collisions␣
↪between functions 'func' (<doctest memory.rst>:...) and 'func' (
↪<doctest memory.rst>:...)
>>> func(1)
Running a different func(1)
>>> func2(1)
Running func(1)
```

As long as the same session is used, there are no needless recomputation:

```
>>> func(1) # No recomputation now
>>> func2(1) # No recomputation now
```

- **lambda functions**

  Beware that with Python 2.7 lambda functions cannot be separated out:

```
>>> def my_print(x):
...     print(x)

>>> f = memory.cache(lambda : my_print(1))
>>> g = memory.cache(lambda : my_print(2))

>>> f()
1
>>> f()
```

```
>>> g()
memory.rst:0: JobLibCollisionWarning: Cannot detect name collisions for␣
↪function '<lambda>'
2
>>> g()
>>> f()
1
```

- **memory cannot be used on some complex objects**, e.g. a callable object with a *__call__* method.

  However, it works on numpy ufuncs:

```
>>> sin = memory.cache(np.sin)
>>> print(sin(0))
0.0
```

- **caching methods: memory is designed for pure functions and it is not recommended to use it for methods**. If one wants to use cache inside a class the recommended pattern is to cache a pure function and use the cached function inside your class, i.e. something like this:

```
@memory.cache
def compute_func(arg1, arg2, arg3):
    # long computation
    return result


class Foo(object):
    def __init__(self, args):
        self.data = None

    def compute(self):
        self.data = compute_func(self.arg1, self.arg2, 40)
```

  Using `Memory` for methods is not recommended and has some caveats that make it very fragile from a maintenance point of view because it is very easy to forget about these caveats when a software evolves. If this cannot be avoided (we would be interested about your use case by the way), here are a few known caveats:

  1. a method cannot be decorated at class definition, because when the class is instantiated, the first argument (self) is *bound*, and no longer accessible to the *Memory* object. The following code won't work:

```
class Foo(object):

    @memory.cache  # WRONG
    def method(self, args):
        pass
```

     The right way to do this is to decorate at instantiation time:

```
class Foo(object):

    def __init__(self, args):
        self.method = memory.cache(self.method)

    def method(self, ...):
        pass
```

2. The cached method will have `self` as one of its arguments. That means that the result will be recomputed if anything with `self` changes. For example if `self.attr` has changed calling `self.method` will recompute the result even if `self.method` does not use `self.attr` in its body. Another example is changing `self` inside the body of `self.method`. The consequence is that `self.method` will create cache that will not be reused in subsequent calls. To alleviate these problems and if you *know* that the result of `self.method` does not depend on `self` you can use `self.method = memory.cache(self.method, ignore=['self'])`.

2.3.5 Ignoring some arguments

It may be useful not to recalculate a function when certain arguments change, for instance a debug flag. *Memory* provides the *ignore* list:

```
>>> @memory.cache(ignore=['debug'])
... def my_func(x, debug=True):
...     print('Called with x = %s' % x)
>>> my_func(0)
Called with x = 0
>>> my_func(0, debug=False)
>>> my_func(0, debug=True)
>>> # my_func was not reevaluated
```

2.3.6 Reference documentation of the *Memory* class

class joblib.memory.**Memory**(*location=None*, *backend='local'*, *cachedir=None*, *mmap_mode=None*, *compress=False*, *verbose=1*, *bytes_limit=None*, *backend_options=None*)

A context object for caching a function's return value each time it is called with the same input arguments.

All values are cached on the filesystem, in a deep directory structure.

Read more in the *User Guide*.

Parameters

location: str or None The path of the base directory to use as a data store or None. If None is given, no caching is done and the Memory object is completely transparent. This option replaces cachedir since version 0.12.

backend: str, optional Type of store backend for reading/writing cache files. Default: 'local'. The 'local' backend is using regular filesystem operations to manipulate data (open, mv, etc) in the backend.

cachedir: str or None, optional

mmap_mode: {None, 'r+', 'r', 'w+', 'c'}, optional The memmapping mode used when loading from cache numpy arrays. See numpy.load for the meaning of the arguments.

compress: boolean, or integer, optional Whether to zip the stored data on disk. If an integer is given, it should be between 1 and 9, and sets the amount of compression. Note that compressed arrays cannot be read by memmapping.

verbose: int, optional Verbosity flag, controls the debug messages that are issued as functions are evaluated.

bytes_limit: int, optional Limit in bytes of the size of the cache.

backend_options: dict, optional Contains a dictionnary of named parameters used to configure the store backend.

cache (*func=None*, *ignore=None*, *verbose=None*, *mmap_mode=False*)
Decorates the given function func to only compute its return value for input arguments not cached on disk.

Parameters

func: callable, optional The function to be decorated

ignore: list of strings A list of arguments name to ignore in the hashing

verbose: integer, optional The verbosity mode of the function. By default that of the memory object is used.

mmap_mode: {None, 'r+', 'r', 'w+', 'c'}, optional The memmapping mode used when loading from cache numpy arrays. See numpy.load for the meaning of the arguments. By default that of the memory object is used.

Returns

decorated_func: MemorizedFunc object The returned object is a MemorizedFunc object, that is callable (behaves like a function), but offers extra methods for cache lookup and management. See the documentation for *joblib.memory.MemorizedFunc*.

clear (*warn=True*)
Erase the complete cache directory.

eval (*func*, **args*, ***kwargs*)
Eval function func with arguments **args* and ***kwargs*, in the context of the memory.

This method works similarly to the builtin *apply*, except that the function is called only if the cache is not up to date.

2.3.7 Useful methods of decorated functions

Function decorated by *Memory.cache()* are *MemorizedFunc* objects that, in addition of behaving like normal functions, expose methods useful for cache exploration and management.

class joblib.memory.**MemorizedFunc** (*func*, *location*, *backend='local'*, *ignore=None*, *mmap_mode=None*, *compress=False*, *verbose=1*, *timestamp=None*)
Callable object decorating a function for caching its return value each time it is called.

Methods are provided to inspect the cache or clean it.

Attributes

func: callable The original, undecorated, function.

location: string The location of joblib cache. Depends on the store backend used.

backend: str Type of store backend for reading/writing cache files. Default is 'local', in which case the location is the path to a disk storage.

ignore: list or None List of variable names to ignore when choosing whether to recompute.

mmap_mode: {None, 'r+', 'r', 'w+', 'c'} The memmapping mode used when loading from cache numpy arrays. See numpy.load for the meaning of the different values.

compress: boolean, or integer Whether to zip the stored data on disk. If an integer is given, it should be between 1 and 9, and sets the amount of compression. Note that compressed arrays cannot be read by memmapping.

verbose: int, optional The verbosity flag, controls messages that are issued as the function is evaluated.

call(**args*, ***kwargs*)
Force the execution of the function with the given arguments and persist the output values.

clear(*warn=True*)
Empty the function's cache.

2.4 Embarrassingly parallel for loops

2.4.1 Common usage

Joblib provides a simple helper class to write parallel for loops using multiprocessing. The core idea is to write the code to be executed as a generator expression, and convert it to parallel computing:

```
>>> from math import sqrt
>>> [sqrt(i ** 2) for i in range(10)]
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

can be spread over 2 CPUs using the following:

```
>>> from math import sqrt
>>> from joblib import Parallel, delayed
>>> Parallel(n_jobs=2)(delayed(sqrt)(i ** 2) for i in range(10))
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

2.4.2 Thread-based parallelism vs process-based parallelism

By default *joblib.Parallel* uses the `'loky'` backend module to start separate Python worker processes to execute tasks concurrently on separate CPUs. This is a reasonable default for generic Python programs but can induce a significant overhead as the input and output data need to be serialized in a queue for communication with the worker processes.

When you know that the function you are calling is based on a compiled extension that releases the Python Global Interpreter Lock (GIL) during most of its computation then it is more efficient to use threads instead of Python processes as concurrent workers. For instance this is the case if you write the CPU intensive part of your code inside a with nogil block of a Cython function.

To hint that your code can efficiently use threads, just pass `prefer="threads"` as parameter of the *joblib.Parallel* constructor. In this case joblib will automatically use the `"threading"` backend instead of the default `"loky"` backend:

```
>>> Parallel(n_jobs=2, prefer="threads")(
...     delayed(sqrt)(i ** 2) for i in range(10))
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

It is also possible to manually select a specific backend implementation with the help of a context manager:

```
>>> from joblib import parallel_backend
>>> with parallel_backend('threading', n_jobs=2):
...     Parallel()(delayed(sqrt)(i ** 2) for i in range(10))
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

The latter is especially useful when calling a library that uses *joblib.Parallel* internally without exposing backend selection as part of its public API.

Note that the `prefer="threads"` option was introduced in joblib 0.12. In prior versions, the same effect could be achieved by hardcoding a specific backend implementation such as `backend="threading"` in the call to *joblib.Parallel* but this is now considered a bad pattern (when done in a library) as it does not make it possible to override that choice with the `parallel_backend` context manager.

2.4.3 Shared-memory semantics

The default backend of joblib will run each function call in isolated Python processes, therefore they cannot mutate a common Python object defined in the main program.

However if the parallel function really needs to rely on the shared memory semantics of threads, it should be made explicit with `require='sharedmem'`, for instance:

```
>>> shared_set = set()
>>> def collect(x):
...     shared_set.add(x)
...
>>> Parallel(n_jobs=2, require='sharedmem')(
...      delayed(collect)(i) for i in range(5))
[None, None, None, None, None]
>>> sorted(shared_set)
[0, 1, 2, 3, 4]
```

Keep in mind that relying a on the shared-memory semantics is probably suboptimal from a performance point of view as concurrent access to a shared Python object will suffer from lock contention.

2.4.4 Reusing a pool of workers

Some algorithms require to make several consecutive calls to a parallel function interleaved with processing of the intermediate results. Calling *joblib.Parallel* several times in a loop is sub-optimal because it will create and destroy a pool of workers (threads or processes) several times which can cause a significant overhead.

For this case it is more efficient to use the context manager API of the *joblib.Parallel* class to re-use the same pool of workers for several calls to the *joblib.Parallel* object:

```
>>> with Parallel(n_jobs=2) as parallel:
...     accumulator = 0.
...     n_iter = 0
...     while accumulator < 1000:
...         results = parallel(delayed(sqrt)(accumulator + i ** 2)
...                            for i in range(5))
...         accumulator += sum(results)  # synchronization barrier
...         n_iter += 1
...
```

```
>>> (accumulator, n_iter)
(1136.596..., 14)
```

2.4.5 Working with numerical data in shared memory (memmapping)

By default the workers of the pool are real Python processes forked using the `multiprocessing` module of the Python standard library when `n_jobs != 1`. The arguments passed as input to the `Parallel` call are serialized and reallocated in the memory of each worker process.

This can be problematic for large arguments as they will be reallocated `n_jobs` times by the workers.

As this problem can often occur in scientific computing with `numpy` based datastructures, *joblib.Parallel* provides a special handling for large arrays to automatically dump them on the filesystem and pass a reference to the worker to open them as memory map on that file using the `numpy.memmap` subclass of `numpy.ndarray`. This makes it possible to share a segment of data between all the worker processes.

Note: The following only applies with the "loky"` and ``'multiprocessing' process-backends. If your code can release the GIL, then using a thread-based backend backend by passing `prefer='threads'` is even more efficient because it makes it possible to avoid the communication overhead of process-based parallelism.

Scientific Python libraries such as numpy, scipy, pandas and scikit-learn often release the GIL in performance critical code paths. It is therefore advised to always measure the speed of thread-based parallelism and use it when the scalability is not limited by the GIL.

Automated array to memmap conversion

The automated array to memmap conversion is triggered by a configurable threshold on the size of the array:

```
>>> import numpy as np
>>> from joblib import Parallel, delayed
>>> def is_memmap(obj):
...     return isinstance(obj, np.memmap)

>>> Parallel(n_jobs=2, max_nbytes=1e6)(
...     delayed(is_memmap)(np.ones(int(i)))
...     for i in [1e2, 1e4, 1e6])
[False, False, True]
```

By default the data is dumped to the `/dev/shm` shared-memory partition if it exists and is writable (typically the case under Linux). Otherwise the operating system's temporary folder is used. The location of the temporary data files can be customized by passing a `temp_folder` argument to the `Parallel` constructor.

Passing `max_nbytes=None` makes it possible to disable the automated array to memmap conversion.

Manual management of memmaped input data

For even finer tuning of the memory usage it is also possible to dump the array as a memmap directly from the parent process to free the memory before forking the worker processes. For instance let's allocate a

large array in the memory of the parent process:

```
>>> large_array = np.ones(int(1e6))
```

Dump it to a local file for memmapping:

```
>>> import tempfile
>>> import os
>>> from joblib import load, dump

>>> temp_folder = tempfile.mkdtemp()
>>> filename = os.path.join(temp_folder, 'joblib_test.mmap')
>>> if os.path.exists(filename): os.unlink(filename)
>>> _ = dump(large_array, filename)
>>> large_memmap = load(filename, mmap_mode='r+')
```

The `large_memmap` variable is pointing to a `numpy.memmap` instance:

```
>>> large_memmap.__class__.__name__, large_array.nbytes, large_array.shape
('memmap', 8000000, (1000000,))

>>> np.allclose(large_array, large_memmap)
True
```

The original array can be freed from the main process memory:

```
>>> del large_array
>>> import gc
>>> _ = gc.collect()
```

It is possible to slice `large_memmap` into a smaller memmap:

```
>>> small_memmap = large_memmap[2:5]
>>> small_memmap.__class__.__name__, small_memmap.nbytes, small_memmap.shape
('memmap', 24, (3,))
```

Finally a `np.ndarray` view backed on that same memory mapped file can be used:

```
>>> small_array = np.asarray(small_memmap)
>>> small_array.__class__.__name__, small_array.nbytes, small_array.shape
('ndarray', 24, (3,))
```

All those three datastructures point to the same memory buffer and this same buffer will also be reused directly by the worker processes of a `Parallel` call:

```
>>> Parallel(n_jobs=2, max_nbytes=None)(
...     delayed(is_memmap)(a)
...     for a in [large_memmap, small_memmap, small_array])
[True, True, True]
```

Note that here `max_nbytes=None` is used to disable the auto-dumping feature of `Parallel`. `small_array` is still in shared memory in the worker processes because it was already backed by shared memory in the parent process. The pickling machinery of `Parallel` multiprocessing queues are able to detect this situation and optimize it on the fly to limit the number of memory copies.

Writing parallel computation results in shared memory

If data are opened using the `w+` or `r+` mode in the main program, the worker will get `r+` mode access. Thus the worker will be able to write its results directly to the original data, alleviating the need of the serialization to send back the results to the parent process.

Here is an example script on parallel processing with preallocated `numpy.memmap` datastructures *NumPy memmap in joblib.Parallel*.

Warning: Having concurrent workers write on overlapping shared memory data segments, for instance by using inplace operators and assignments on a *numpy.memmap* instance, can lead to data corruption as numpy does not offer atomic operations. The previous example does not risk that issue as each task is updating an exclusive segment of the shared result array.

Some C/C++ compilers offer lock-free atomic primitives such as add-and-fetch or compare-and-swap that could be exposed to Python via CFFI for instance. However providing numpy-aware atomic constructs is outside of the scope of the joblib project.

A final note: don't forget to clean up any temporary folder when you are done with the computation:

```
>>> import shutil
>>> try:
...     shutil.rmtree(temp_folder)
... except OSError:
...     pass  # this can sometimes fail under Windows
```

Note that the `'loky'` backend now used by default for process-based parallelism automatically tries to maintain and reuse a pool of workers by it-self even for calls without the context manager.

2.4.6 Avoiding over-subscription of CPU ressources

The computation parallelism relies on the usage of multiple CPUs to perform the operation simultaneously. When using more processes than the number of CPU on a machine, the performance of each process is degraded as there is less computational power available for each process. Moreover, when many processes are running, the time taken by the OS scheduler to switch between them can further hinder the performance of the computation. It is generally better to avoid using significantly more processes or threads than the number of CPUs on a machine.

Some third-partiy libraries – *e.g.* the BLAS runtime used by `numpy` – manage internally a thread-pool to perform their computations. The default behavior is generally to use number of thread equals to the number of CPU available. When these libraries are used with *`joblib.Parallel`*, each worker will spawn its thread-pools, resulting in a massive over-subscription of the ressources that can slow down the computation compared to sequential one. To cope with this problem, joblib forces by default supported third-party libraries to use only one thread in workers with the `'loky'` backend. This behavior can be overwritten by setting the proper environment variable to the desired number of threads. This limitation is supported for the following libraries:

- OpenMP with the environment variable `'OMP_NUM_THREADS'`,
- OpenBLAS with the `'OPENBLAS_NUM_THREADS'`,
- MKL with the environment variable `'MKL_NUM_THREADS'`,
- Accelerated with the environment variable `'VECLIB_MAXIMUM_THREADS'`,
- Numexpr with the environment variable `'NUMEXPR_NUM_THREADS'`.

2.4.7 Custom backend API (experimental)

New in version 0.10.

Warning: The custom backend API is experimental and subject to change without going through a deprecation cycle.

User can provide their own implementation of a parallel processing backend in addition to the `'loky'`, `'threading'`, `'multiprocessing'` backends provided by default. A backend is registered with the *joblib.register_parallel_backend()* function by passing a name and a backend factory.

The backend factory can be any callable that returns an instance of `ParallelBackendBase`. Please refer to the default backends source code as a reference if you want to implement your own custom backend.

Note that it is possible to register a backend class that has some mandatory constructor parameters such as the network address and connection credentials for a remote cluster computing service:

```
class MyCustomBackend(ParallelBackendBase):

    def __init__(self, endpoint, api_key):
        self.endpoint = endpoint
        self.api_key = api_key

    ...
    # Do something with self.endpoint and self.api_key somewhere in
    # one of the method of the class

register_parallel_backend('custom', MyCustomBackend)
```

The connection parameters can then be passed to the *joblib.parallel_backend()* context manager:

```
with parallel_backend('custom', endpoint='http://compute', api_key='42'):
    Parallel()(delayed(some_function)(i) for i in range(10))
```

Using the context manager can be helpful when using a third-party library that uses *joblib.Parallel* internally while not exposing the `backend` argument in its own API.

A problem exists that external packages that register new parallel backends must now be imported explicitly for their backends to be identified by joblib:

```
>>> import joblib
>>> with joblib.parallel_backend('custom'):
...     ...  # this fails
KeyError: 'custom'

# Import library to register external backend
>>> import my_custom_backend_library
>>> with joblib.parallel_backend('custom'):
...     ... # this works
```

This can be confusing for users. To resolve this, external packages can safely register their backends directly within the joblib codebase by creating a small function that registers their backend, and including this function within the `joblib.parallel.EXTERNAL_PACKAGES` dictionary:

```
def _register_custom():
    try:
        import my_custom_library
    except ImportError:
        raise ImportError("an informative error message")

EXTERNAL_BACKENDS['custom'] = _register_custom
```

This is subject to community review, but can reduce the confusion for users when relying on side effects of external package imports.

2.4.8 Old multiprocessing backend

Prior to version 0.12, joblib used the `'multiprocessing'` backend as default backend instead of `'loky'`.

This backend creates an instance of *multiprocessing.Pool* that forks the Python interpreter in multiple processes to execute each of the items of the list. The *delayed* function is a simple trick to be able to create a tuple *(function, args, kwargs)* with a function-call syntax.

Warning: Under Windows, the use of `multiprocessing.Pool` requires to protect the main loop of code to avoid recursive spawning of subprocesses when using *joblib.Parallel*. In other words, you should be writing code like this when using the `'multiprocessing'` backend:

```
import ....

def function1(...):
    ...

def function2(...):
    ...

...
if __name__ == '__main__':
    # do stuff with imports and functions defined about
    ...
```

No code should *run* outside of the `"if __name__ == '__main__'"` blocks, only imports and definitions.

The `'loky'` backend used by default in joblib 0.12 and later does not impose this anymore.

2.4.9 Bad interaction of multiprocessing and third-party libraries

Using the `'multiprocessing'` backend can cause a crash when using third party libraries that manage their own native thread-pool if the library is first used in the main process and subsequently called again in a worker process (inside the *joblib.Parallel* call).

Joblib version 0.12 and later are no longer subject to this problem thanks to the use of loky as the new default backend for process-based parallelism.

Prior to Python 3.4 the `'multiprocessing'` backend of joblib can only use the `fork` strategy to create worker processes under non-Windows systems. This can cause some third-party libraries to crash or freeze. Such libraries include Apple vecLib / Accelerate (used by NumPy under OSX), some old

version of OpenBLAS (prior to 0.2.10) or the OpenMP runtime implementation from GCC which is used internally by third-party libraries such as XGBoost, spaCy, OpenCV...

The best way to avoid this problem is to use the `'loky'` backend instead of the `multiprocessing` backend. Prior to joblib 0.12, it is also possible to get *joblib.Parallel* configured to use the `'forkserver'` start method on Python 3.4 and later. The start method has to be configured by setting the `JOBLIB_START_METHOD` environment variable to `'forkserver'` instead of the default `'fork'` start method. However the user should be aware that using the `'forkserver'` method prevents *joblib.Parallel* to call function interactively defined in a shell session.

You can read more on this topic in the multiprocessing documentation.

Under Windows the `fork` system call does not exist at all so this problem does not exist (but multiprocessing has more overhead).

2.4.10 *Parallel* reference documentation

class joblib.**Parallel**(*n_jobs=None*, *backend=None*, *verbose=0*, *timeout=None*, *pre_dispatch='2 * n_jobs'*, *batch_size='auto'*, *temp_folder=None*, *max_nbytes='1M'*, *mmap_mode='r'*, *prefer=None*, *require=None*)

Helper class for readable parallel mapping.

Read more in the *User Guide*.

Parameters

n_jobs: int, default: None The maximum number of concurrently running jobs, such as the number of Python worker processes when backend="multiprocessing" or the size of the thread-pool when backend="threading". If -1 all CPUs are used. If 1 is given, no parallel computing code is used at all, which is useful for debugging. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Thus for n_jobs = -2, all CPUs but one are used. None is a marker for 'unset' that will be interpreted as n_jobs=1 (sequential execution) unless the call is performed under a parallel_backend context manager that sets another value for n_jobs.

backend: str, ParallelBackendBase instance or None, default: 'loky' Specify the parallelization backend implementation. Supported backends are:

- "loky" used by default, can induce some communication and memory overhead when exchanging input and output data with the worker Python processes.
- "multiprocessing" previous process-based backend based on *multiprocessing.Pool*. Less robust than *loky*.
- "threading" is a very low-overhead backend but it suffers from the Python Global Interpreter Lock if the called function relies a lot on Python objects. "threading" is mostly useful when the execution bottleneck is a compiled extension that explicitly releases the GIL (for instance a Cython loop wrapped in a "with nogil" block or an expensive call to a library such as NumPy).
- finally, you can register backends by calling register_parallel_backend. This will allow you to implement a backend of your liking.

It is not recommended to hard-code the backend name in a call to Parallel in a library. Instead it is recommended to set soft hints (prefer) or hard constraints (require) so as to make it possible for library users to change the backend from the outside using the parallel_backend context manager.

prefer: str in {'processes', 'threads'} or None, default: None Soft hint to choose the default backend if no specific backend was selected with the parallel_backend context manager. The default process-based backend is 'loky' and the default thread-based backend is 'threading'.

require: 'sharedmem' or None, default None Hard constraint to select the backend. If set to 'sharedmem', the selected backend will be single-host and thread-based even if the user asked for a non-thread based backend with parallel_backend.

verbose: int, optional The verbosity level: if non zero, progress messages are printed. Above 50, the output is sent to stdout. The frequency of the messages increases with the verbosity level. If it more than 10, all iterations are reported.

timeout: float, optional Timeout limit for each task to complete. If any task takes longer a TimeOutError will be raised. Only applied when n_jobs != 1

pre_dispatch: {'all', integer, or expression, as in '3*n_jobs'} The number of batches (of tasks) to be pre-dispatched. Default is '2*n_jobs'. When batch_size="auto" this is reasonable default and the workers should never starve.

batch_size: int or 'auto', default: 'auto' The number of atomic tasks to dispatch at once to each worker. When individual evaluations are very fast, dispatching calls to workers can be slower than sequential computation because of the overhead. Batching fast computations together can mitigate this. The `'auto'` strategy keeps track of the time it takes for a batch to complete, and dynamically adjusts the batch size to keep the time on the order of half a second, using a heuristic. The initial batch size is 1. `batch_size="auto"` with `backend="threading"` will dispatch batches of a single task at a time as the threading backend has very little overhead and using larger batch size has not proved to bring any gain in that case.

temp_folder: str, optional Folder to be used by the pool for memmapping large arrays for sharing memory with worker processes. If None, this will try in order:

- a folder pointed by the JOBLIB_TEMP_FOLDER environment variable,
- /dev/shm if the folder exists and is writable: this is a RAM disk filesystem available by default on modern Linux distributions,
- the default system temporary folder that can be overridden with TMP, TMPDIR or TEMP environment variables, typically /tmp under Unix operating systems.

Only active when backend="loky" or "multiprocessing".

max_nbytes int, str, or None, optional, 1M by default Threshold on the size of arrays passed to the workers that triggers automated memory mapping in temp_folder. Can be an int in Bytes, or a human-readable string, e.g., '1M' for 1 megabyte. Use None to disable memmapping of large arrays. Only active when backend="loky" or "multiprocessing".

mmap_mode: {None, 'r+', 'r', 'w+', 'c'} Memmapping mode for numpy arrays passed to workers. See 'max_nbytes' parameter documentation for more details.

Notes

This object uses workers to compute in parallel the application of a function to many different arguments. The main functionality it brings in addition to using the raw multiprocessing or concurrent.futures API are (see examples for details):

- More readable code, in particular since it avoids constructing list of arguments.

- **Easier debugging:**
  - informative tracebacks even when the error happens on the client side
  - using 'n_jobs=1' enables to turn off parallel computing for debugging without changing the codepath
  - early capture of pickling errors
- An optional progress meter.
- Interruption of multiprocesses jobs with 'Ctrl-C'
- Flexible pickling control for the communication to and from the worker processes.
- Ability to use shared memory efficiently with worker processes for large numpy-based datastructures.

Examples

A simple example:

```
>>> from math import sqrt
>>> from joblib import Parallel, delayed
>>> Parallel(n_jobs=1)(delayed(sqrt)(i**2) for i in range(10))
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

Reshaping the output when the function has several return values:

```
>>> from math import modf
>>> from joblib import Parallel, delayed
>>> r = Parallel(n_jobs=1)(delayed(modf)(i/2.) for i in range(10))
>>> res, i = zip(*r)
>>> res
(0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5)
>>> i
(0.0, 0.0, 1.0, 1.0, 2.0, 2.0, 3.0, 3.0, 4.0, 4.0)
```

The progress meter: the higher the value of *verbose*, the more messages:

```
>>> from time import sleep
>>> from joblib import Parallel, delayed
>>> r = Parallel(n_jobs=2, verbose=10)(delayed(sleep)(.2) for _ in␣
↪range(10))
[Parallel(n_jobs=2)]: Done   1 tasks      | elapsed:    0.6s
[Parallel(n_jobs=2)]: Done   4 tasks      | elapsed:    0.8s
[Parallel(n_jobs=2)]: Done  10 out of  10 | elapsed:    1.4s finished
```

Traceback example, note how the line of the error is indicated as well as the values of the parameter passed to the function that triggered the exception, even though the traceback happens in the child process:

```
>>> from heapq import nlargest
>>> from joblib import Parallel, delayed
>>> Parallel(n_jobs=2)(delayed(nlargest)(2, n) for n in (range(4), 'abcde
↪', 3))
#...
---------------------------------------------------------------------------
↪--
```

```
Sub-process traceback:
---------------------------------------------------------------------------
↪--
TypeError                                          Mon Nov 12 11:37:46␣
↪2012
PID: 12934                                     Python 2.7.3: /usr/bin/
↪python
...........................................................................
↪..
/usr/lib/python2.7/heapq.pyc in nlargest(n=2, iterable=3, key=None)
    419         if n >= size:
    420             return sorted(iterable, key=key, reverse=True)[:n]
    421
    422     # When key is none, use simpler decoration
    423     if key is None:
--> 424         it = izip(iterable, count(0,-1))                    #␣
↪decorate
    425         result = _nlargest(n, it)
    426         return map(itemgetter(0), result)                   #␣
↪undecorate
    427
    428     # General case, slowest method
 TypeError: izip argument #1 must support iteration
___________________________________________________________________________
↪__
```

Using pre_dispatch in a producer/consumer situation, where the data is generated on the fly. Note how the producer is first called 3 times before the parallel loop is initiated, and then called to generate new data on the fly:

```
>>> from math import sqrt
>>> from joblib import Parallel, delayed
>>> def producer():
...     for i in range(6):
...         print('Produced %s' % i)
...         yield i
>>> out = Parallel(n_jobs=2, verbose=100, pre_dispatch='1.5*n_jobs')(
...                delayed(sqrt)(i) for i in producer())
Produced 0
Produced 1
Produced 2
[Parallel(n_jobs=2)]: Done 1 jobs     | elapsed:  0.0s
Produced 3
[Parallel(n_jobs=2)]: Done 2 jobs     | elapsed:  0.0s
Produced 4
[Parallel(n_jobs=2)]: Done 3 jobs     | elapsed:  0.0s
Produced 5
[Parallel(n_jobs=2)]: Done 4 jobs     | elapsed:  0.0s
[Parallel(n_jobs=2)]: Done 6 out of 6 | elapsed:  0.0s remaining: 0.0s
[Parallel(n_jobs=2)]: Done 6 out of 6 | elapsed:  0.0s finished
```

joblib.**delayed**(*function*, *check_pickle=None*)
Decorator used to capture the arguments of a function.

joblib.**register_parallel_backend**(*name*, *factory*, *make_default=False*)
Register a new Parallel backend factory.

The new backend can then be selected by passing its name as the backend argument to the Parallel

class. Moreover, the default backend can be overwritten globally by setting make_default=True.

The factory can be any callable that takes no argument and return an instance of `ParallelBackendBase`.

Warning: this function is experimental and subject to change in a future version of joblib.

New in version 0.10.

joblib.**parallel_backend**(*backend*, *n_jobs=-1*, ***backend_params*)

Change the default backend used by Parallel inside a with block.

If `backend` is a string it must match a previously registered implementation using the `register_parallel_backend` function.

By default the following backends are available:

- 'loky': single-host, process-based parallelism (used by default),
- 'threading': single-host, thread-based parallelism,
- 'multiprocessing': legacy single-host, process-based parallelism.

'loky' is recommended to run functions that manipulate Python objects. 'threading' is a low-overhead alternative that is most efficient for functions that release the Global Interpreter Lock: e.g. I/O-bound code or CPU-bound code in a few calls to native code that explicitly releases the GIL.

In addition, if the *dask* and *distributed* Python packages are installed, it is possible to use the 'dask' backend for better scheduling of nested parallel calls without over-subscription and potentially distribute parallel calls over a networked cluster of several hosts.

Alternatively the backend can be passed directly as an instance.

By default all available workers will be used (`n_jobs=-1`) unless the caller passes an explicit value for the `n_jobs` parameter.

This is an alternative to passing a `backend='backend_name'` argument to the `Parallel` class constructor. It is particularly useful when calling into library code that uses joblib internally but does not expose the backend argument in its own API.

```
>>> from operator import neg
>>> with parallel_backend('threading'):
...     print(Parallel()(delayed(neg)(i + 1) for i in range(5)))
...
[-1, -2, -3, -4, -5]
```

Warning: this function is experimental and subject to change in a future version of joblib.

New in version 0.10.

2.5 Persistence

2.5.1 Use case

joblib.dump() and *joblib.load()* provide a replacement for pickle to work efficiently on arbitrary Python objects containing large data, in particular large numpy arrays.

2.5.2 A simple example

First create a temporary directory:

```
>>> from tempfile import mkdtemp
>>> savedir = mkdtemp()
>>> import os
>>> filename = os.path.join(savedir, 'test.joblib')
```

Then create an object to be persisted:

```
>>> import numpy as np
>>> to_persist = [('a', [1, 2, 3]), ('b', np.arange(10))]
```

which is saved into *filename*:

```
>>> import joblib
>>> joblib.dump(to_persist, filename)
['...test.joblib']
```

The object can then be reloaded from the file:

```
>>> joblib.load(filename)
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
```

2.5.3 Persistence in file objects

Instead of filenames, *joblib.dump()* and *joblib.load()* functions also accept file objects:

```
>>> with open(filename, 'wb') as fo:
...     joblib.dump(to_persist, fo)
>>> with open(filename, 'rb') as fo:
...     joblib.load(fo)
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
```

2.5.4 Compressed joblib pickles

Setting the *compress* argument to *True* in *joblib.dump()* will allow to save space on disk:

```
>>> joblib.dump(to_persist, filename + '.compressed', compress=True)
['...test.joblib.compressed']
```

If the filename extension corresponds to one of the supported compression methods, the compressor will be used automatically:

```
>>> joblib.dump(to_persist, filename + '.z')
['...test.joblib.z']
```

By default, *joblib.dump()* uses the zlib compression method as it gives the best tradeoff between speed and disk space. The other supported compression methods are 'gzip', 'bz2', 'lzma' and 'xz':

```
>>> # Dumping in a gzip compressed file using a compress level of 3.
>>> joblib.dump(to_persist, filename + '.gz', compress=('gzip', 3))
['...test.joblib.gz']
```

```
>>> joblib.load(filename + '.gz')
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
>>> joblib.dump(to_persist, filename + '.bz2', compress=('bz2', 3))
['...test.joblib.bz2']
>>> joblib.load(filename + '.bz2')
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
```

The `compress` parameter of the *joblib.dump()* function also accepts a string corresponding to the name of the compressor used. When using this, the default compression level is used by the compressor:

```
>>> joblib.dump(to_persist, filename + '.gz', compress='gzip')
['...test.joblib.gz']
```

Note: Lzma and Xz compression methods are only available for python versions >= 3.3.

Compressor files provided by the python standard library can also be used to compress pickle, e.g `gzip.GzipFile`, `bz2.BZ2File`, `lzma.LZMAFile`:

```
>>> # Dumping in a gzip.GzipFile object using a compression level of 3.
>>> import gzip
>>> with gzip.GzipFile(filename + '.gz', 'wb', compresslevel=3) as fo:
...     joblib.dump(to_persist, fo)
>>> with gzip.GzipFile(filename + '.gz', 'rb') as fo:
...     joblib.load(fo)
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
```

If the `lz4` package is installed, this compression method is automatically available with the dump function.

```
>>> joblib.dump(to_persist, filename + '.lz4')
['...test.joblib.lz4']
>>> joblib.load(filename + '.lz4')
[('a', [1, 2, 3]), ('b', array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]))]
```

Note: LZ4 compression is only available with python major versions >= 3

More details can be found in the *joblib.dump()* and *joblib.load()* documentation.

Registering extra compressors

Joblib provides *joblib.register_compressor()* in order to extend the list of default compressors available. To fit with Joblib internal implementation and features, such as *joblib.load()* and *joblib.Memory*, the registered compressor should implement the Python file object interface.

Compatibility across python versions

Compatibility of joblib pickles across python versions is not fully supported. Note that, for a very restricted set of objects, this may appear to work when saving a pickle with python 2 and loading it with python 3 but relying on it is strongly discouraged.

If you are switching between python versions, you will need to save a different joblib pickle for each python version.

Here are a few examples or exceptions:

- Saving joblib pickle with python 2, trying to load it with python 3:

```
Traceback (most recent call last):
  File "/home/lesteve/dev/joblib/joblib/numpy_pickle.py", line 453, in␣
↪load
    obj = unpickler.load()
  File "/home/lesteve/miniconda3/lib/python3.4/pickle.py", line 1038, in␣
↪load
    dispatch[key[0]](self)
  File "/home/lesteve/miniconda3/lib/python3.4/pickle.py", line 1176, in␣
↪load_binstring
    self.append(self._decode_string(data))
  File "/home/lesteve/miniconda3/lib/python3.4/pickle.py", line 1158, in␣
↪_decode_string
    return value.decode(self.encoding, self.errors)
UnicodeDecodeError: 'ascii' codec can't decode byte 0x80 in position␣
↪1024: ordinal not in range(128)

Traceback (most recent call last):
  File "<string>", line 1, in <module>
  File "/home/lesteve/dev/joblib/joblib/numpy_pickle.py", line 462, in␣
↪load
    raise new_exc
  ValueError: You may be trying to read with python 3 a joblib pickle␣
↪generated with python 2. This is not feature supported by joblib.
```

- Saving joblib pickle with python 3, trying to load it with python 2:

```
Traceback (most recent call last):
  File "<string>", line 1, in <module>
  File "joblib/numpy_pickle.py", line 453, in load
    obj = unpickler.load()
  File "/home/lesteve/miniconda3/envs/py27/lib/python2.7/pickle.py",␣
↪line 858, in load
    dispatch[key](self)
  File "/home/lesteve/miniconda3/envs/py27/lib/python2.7/pickle.py",␣
↪line 886, in load_proto
    raise ValueError, "unsupported pickle protocol: %d" % proto
ValueError: unsupported pickle protocol: 3
```

2.6 Examples

2.6.1 General examples

General-purpose and introductory examples for joblib.

Note: Click *here* to download the full example code

Random state within joblib.Parallel

Randomness is affected by parallel execution differently by the different backends.

In particular, when using multiple processes, the random sequence can be the same in all processes. This example illustrates the problem and shows how to work around it.

```
import numpy as np
from joblib import Parallel, delayed
```

A utility function for the example

```
def print_vector(vector, backend):
    """Helper function to print the generated vector with a given backend."""
    print('\nThe different generated vectors using the {} backend are:\n {}'
          .format(backend, np.array(vector)))
```

Sequential behavior

`stochastic_function` will generate five random integers. When calling the function several times, we are expecting to obtain different vectors. For instance, we will call the function five times in a sequential manner, we can check that the generated vectors are all different.

```
def stochastic_function(max_value):
    """Randomly generate integer up to a maximum value."""
    return np.random.randint(max_value, size=5)


n_vectors = 5
random_vector = [stochastic_function(10) for _ in range(n_vectors)]
print('\nThe different generated vectors in a sequential manner are:\n {}'
      .format(np.array(random_vector)))
```

Out:

```
The different generated vectors in a sequential manner are:
 [[9 5 5 4 0]
 [8 7 5 9 7]
 [7 2 5 3 5]
 [8 6 2 2 9]
 [9 8 4 8 9]]
```

Parallel behavior

Joblib provides three different backend: loky (default), threading, and multiprocessing.

```
backend = 'loky'
random_vector = Parallel(n_jobs=2, backend=backend)(delayed(
    stochastic_function)(10) for _ in range(n_vectors))
print_vector(random_vector, backend)
```

Out:

```
The different generated vectors using the loky backend are:
 [[3 8 1 3 2]
 [8 4 8 3 4]
 [4 6 1 3 8]
```

```
 [2 2 2 7 0]
 [8 9 6 5 9]]
```

```
backend = 'threading'
random_vector = Parallel(n_jobs=2, backend=backend)(delayed(
    stochastic_function)(10) for _ in range(n_vectors))
print_vector(random_vector, backend)
```

Out:

```
The different generated vectors using the threading backend are:
 [[5 8 1 5 4]
 [7 0 0 8 9]
 [5 1 3 1 5]
 [0 4 7 2 0]
 [6 6 0 0 0]]
```

Loky and the threading backends behave exactly as in the sequential case and do not require more care. However, this is not the case regarding the multiprocessing backend.

```
backend = 'multiprocessing'
random_vector = Parallel(n_jobs=2, backend=backend)(delayed(
    stochastic_function)(10) for _ in range(n_vectors))
print_vector(random_vector, backend)
```

Out:

```
The different generated vectors using the multiprocessing backend are:
 [[9 2 6 4 8]
 [9 2 6 4 8]
 [6 5 8 5 8]
 [6 5 8 5 8]
 [8 1 7 5 1]]
```

Some of the generated vectors are exactly the same, which can be a problem for the application.

Technically, the reason is that all forked Python processes share the same exact random seed. As a results, we obtain twice the same randomly generated vectors because we are using `n_jobs=2`. A solution is to set the random state within the function which is passed to *joblib.Parallel*.

```
def stochastic_function_seeded(max_value, random_state):
    rng = np.random.RandomState(random_state)
    return rng.randint(max_value, size=5)
```

`stochastic_function_seeded` accepts as argument a random seed. We can reset this seed by passing `None` at every function call. In this case, we see that the generated vectors are all different.

```
random_vector = Parallel(n_jobs=2, backend=backend)(delayed(
    stochastic_function_seeded)(10, None) for _ in range(n_vectors))
print_vector(random_vector, backend)
```

Out:

```
The different generated vectors using the multiprocessing backend are:
 [[6 1 0 0 5]
 [4 1 7 1 1]
 [0 1 9 5 0]
```

```
 [9 9 4 0 2]
 [8 9 4 6 1]]
```

Fixing the random state to obtain deterministic results

The pattern of `stochastic_function_seeded` has another advantage: it allows to control the random_state by passing a known seed. So for instance, we can replicate the same generation of vectors by passing a fixed state as follows.

```
random_state = np.random.randint(np.iinfo(np.int32).max, size=n_vectors)

random_vector = Parallel(n_jobs=2, backend=backend)(delayed(
    stochastic_function_seeded)(10, rng) for rng in random_state)
print_vector(random_vector, backend)

random_vector = Parallel(n_jobs=2, backend=backend)(delayed(
    stochastic_function_seeded)(10, rng) for rng in random_state)
print_vector(random_vector, backend)
```

Out:

```
The different generated vectors using the multiprocessing backend are:
 [[8 4 2 3 5]
 [5 0 0 6 6]
 [7 7 6 0 1]
 [3 7 1 6 7]
 [3 7 7 3 3]]

The different generated vectors using the multiprocessing backend are:
 [[8 4 2 3 5]
 [5 0 0 6 6]
 [7 7 6 0 1]
 [3 7 1 6 7]
 [3 7 7 3 3]]
```

Total running time of the script: (0 minutes 1.225 seconds)

Note: Click *here* to download the full example code

Checkpoint using joblib.Memory and joblib.Parallel

This example illustrates how to cache intermediate computing results using *joblib.Memory* within *joblib.Parallel*.

Embed caching within parallel processing

It is possible to cache a computationally expensive function executed during a parallel process. `costly_compute` emulates such time consuming function.

```
import time
```

```
def costly_compute(data, column):
    """Emulate a costly function by sleeping and returning a column."""
    time.sleep(2)
    return data[column]


def data_processing_mean(data, column):
    """Compute the mean of a column."""
    return costly_compute(data, column).mean()
```

Create some data. The random seed is fixed to generate deterministic data across Python session. Note that this is not necessary for this specific example since the memory cache is cleared at the end of the session.

```
import numpy as np
rng = np.random.RandomState(42)
data = rng.randn(int(1e4), 4)
```

It is first possible to make the processing without caching or parallel processing.

```
start = time.time()
results = [data_processing_mean(data, col) for col in range(data.shape[1])]
stop = time.time()

print('\nSequential processing')
print('Elapsed time for the entire processing: {:.2f} s'
      .format(stop - start))
```

Out:

```
Sequential processing
Elapsed time for the entire processing: 8.01 s
```

`costly_compute` is expensive to compute and it is used as an intermediate step in `data_processing_mean`. Therefore, it is interesting to store the intermediate results from `costly_compute` using *joblib.Memory*.

```
from joblib import Memory

location = './cachedir'
memory = Memory(location, verbose=0)
costly_compute_cached = memory.cache(costly_compute)
```

Now, we define `data_processing_mean_using_cache` which benefits from the cache by calling `costly_compute_cached`

```
def data_processing_mean_using_cache(data, column):
    """Compute the mean of a column."""
    return costly_compute_cached(data, column).mean()
```

Then, we execute the same processing in parallel and caching the intermediate results.

```
from joblib import Parallel, delayed

start = time.time()
results = Parallel(n_jobs=2)(
```

```
    delayed(data_processing_mean_using_cache)(data, col)
    for col in range(data.shape[1]))
stop = time.time()

print('\nFirst round - caching the data')
print('Elapsed time for the entire processing: {:.2f} s'
      .format(stop - start))
```

Out:

```
First round - caching the data
Elapsed time for the entire processing: 4.03 s
```

By using 2 workers, the parallel processing gives a x2 speed-up compared to the sequential case. By executing again the same process, the intermediate results obtained by calling `costly_compute_cached` will be loaded from the cache instead of executing the function.

```
start = time.time()
results = Parallel(n_jobs=2)(
    delayed(data_processing_mean_using_cache)(data, col)
    for col in range(data.shape[1]))
stop = time.time()

print('\nSecond round - reloading from the cache')
print('Elapsed time for the entire processing: {:.2f} s'
      .format(stop - start))
```

Out:

```
Second round - reloading from the cache
Elapsed time for the entire processing: 0.01 s
```

Reuse intermediate checkpoints

Having cached the intermediate results of the `costly_compute_cached` function, they are reusable by calling the function. We define a new processing which will take the maximum of the array returned by `costly_compute_cached` instead of previously the mean.

```
def data_processing_max_using_cache(data, column):
    """Compute the max of a column."""
    return costly_compute_cached(data, column).max()


start = time.time()
results = Parallel(n_jobs=2)(
    delayed(data_processing_max_using_cache)(data, col)
    for col in range(data.shape[1]))
stop = time.time()

print('\nReusing intermediate checkpoints')
print('Elapsed time for the entire processing: {:.2f} s'
      .format(stop - start))
```

Out:

```
Reusing intermediate checkpoints
Elapsed time for the entire processing: 0.01 s
```

The processing time only corresponds to the execution of the `max` function. The internal call to `costly_compute_cached` is reloading the results from the cache.

Clean-up the cache folder

```
memory.clear(warn=False)
```

Total running time of the script: (0 minutes 12.069 seconds)

Note: Click *here* to download the full example code

How to use joblib.Memory

This example illustrates the usage of *joblib.Memory* with both functions and methods.

Without `joblib.Memory`

`costly_compute` emulates a computationally expensive process which later will benefit from caching using *joblib.Memory*.

```
import time
import numpy as np


def costly_compute(data, column_index=0):
    """Simulate an expensive computation"""
    time.sleep(5)
    return data[column_index]
```

Be sure to set the random seed to generate deterministic data. Indeed, if the data is not deterministic, the *joblib.Memory* instance will not be able to reuse the cache from one run to another.

```
rng = np.random.RandomState(42)
data = rng.randn(int(1e5), 10)
start = time.time()
data_trans = costly_compute(data)
end = time.time()

print('\nThe function took {:.2f} s to compute.'.format(end - start))
print('\nThe transformed data are:\n {}'.format(data_trans))
```

Out:

```
The function took 5.00 s to compute.

The transformed data are:
 [ 0.49671415 -0.1382643   0.64768854  1.52302986 -0.23415337 -0.23413696
  1.57921282  0.76743473 -0.46947439  0.54256004]
```

Caching the result of a function to avoid recomputing

If we need to call our function several time with the same input data, it is beneficial to avoid recomputing the same results over and over since it is expensive. *joblib.Memory* enables to cache results from a function into a specific location.

```
from joblib import Memory
location = './cachedir'
memory = Memory(location, verbose=0)


def costly_compute_cached(data, column_index=0):
    """Simulate an expensive computation"""
    time.sleep(5)
    return data[column_index]


costly_compute_cached = memory.cache(costly_compute_cached)
start = time.time()
data_trans = costly_compute_cached(data)
end = time.time()

print('\nThe function took {:.2f} s to compute.'.format(end - start))
print('\nThe transformed data are:\n {}'.format(data_trans))
```

Out:

```
The function took 5.06 s to compute.

The transformed data are:
 [ 0.49671415 -0.1382643   0.64768854  1.52302986 -0.23415337 -0.23413696
  1.57921282  0.76743473 -0.46947439  0.54256004]
```

At the first call, the results will be cached. Therefore, the computation time corresponds to the time to compute the results plus the time to dump the results into the disk.

```
start = time.time()
data_trans = costly_compute_cached(data)
end = time.time()

print('\nThe function took {:.2f} s to compute.'.format(end - start))
print('\nThe transformed data are:\n {}'.format(data_trans))
```

Out:

```
The function took 0.01 s to compute.

The transformed data are:
 [ 0.49671415 -0.1382643   0.64768854  1.52302986 -0.23415337 -0.23413696
  1.57921282  0.76743473 -0.46947439  0.54256004]
```

At the second call, the computation time is largely reduced since the results are obtained by loading the data previously dumped to the disk instead of recomputing the results.

Using `joblib.Memory` with a method

joblib.Memory is designed to work with functions with no side effects. When dealing

with class, the computationally expensive part of a method has to be moved to a function and decorated in the class method.

```
def _costly_compute_cached(data, column):
    time.sleep(5)
    return data[column]


class Algorithm(object):
    """A class which is using the previous function."""

    def __init__(self, column=0):
        self.column = column

    def transform(self, data):
        costly_compute = memory.cache(_costly_compute_cached)
        return costly_compute(data, self.column)


transformer = Algorithm()
start = time.time()
data_trans = transformer.transform(data)
end = time.time()

print('\nThe function took {:.2f} s to compute.'.format(end - start))
print('\nThe transformed data are:\n {}'.format(data_trans))
```

Out:

```
The function took 5.05 s to compute.

The transformed data are:
 [ 0.49671415 -0.1382643   0.64768854  1.52302986 -0.23415337 -0.23413696
  1.57921282  0.76743473 -0.46947439  0.54256004]
```

```
start = time.time()
data_trans = transformer.transform(data)
end = time.time()

print('\nThe function took {:.2f} s to compute.'.format(end - start))
print('\nThe transformed data are:\n {}'.format(data_trans))
```

Out:

```
The function took 0.02 s to compute.

The transformed data are:
 [ 0.49671415 -0.1382643   0.64768854  1.52302986 -0.23415337 -0.23413696
  1.57921282  0.76743473 -0.46947439  0.54256004]
```

As expected, the second call to the `transform` method load the results which have been cached.

Clean up cache directory

```
memory.clear(warn=False)
```

Total running time of the script: (0 minutes 15.198 seconds)

Note: Click *here* to download the full example code

NumPy memmap in joblib.Parallel

This example illustrates some features enabled by using a memory map (`numpy.memmap`) within *`joblib.Parallel`*. First, we show that dumping a huge data array ahead of passing it to *`joblib.Parallel`* speeds up computation. Then, we show the possibility to provide write access to original data.

Speed up processing of a large data array

We create a large data array for which the average is computed for several slices.

```
import numpy as np

data = np.random.random((int(1e7),))
window_size = int(5e5)
slices = [slice(start, start + window_size)
          for start in range(0, data.size - window_size, int(1e5))]
```

The `slow_mean` function introduces a `time.sleep()` call to simulate a more expensive computation cost for which parallel computing is beneficial. Parallel may not be beneficial for very fast operation, due to extra overhead (workers creations, communication, etc.).

```
import time


def slow_mean(data, sl):
    """Simulate a time consuming processing."""
    time.sleep(0.01)
    return data[sl].mean()
```

First, we will evaluate the sequential computing on our problem.

```
tic = time.time()
results = [slow_mean(data, sl) for sl in slices]
toc = time.time()
print('\nElapsed time computing the average of couple of slices {:.2f} s'
      .format(toc - tic))
```

Out:

```
Elapsed time computing the average of couple of slices 1.00 s
```

`joblib.Parallel` is used to compute in parallel the average of all slices using 2 workers.

```
from joblib import Parallel, delayed


tic = time.time()
results = Parallel(n_jobs=2)(delayed(slow_mean)(data, sl) for sl in slices)
toc = time.time()
```

```
print('\nElapsed time computing the average of couple of slices {:.2f} s'
      .format(toc - tic))
```

Out:

```
Elapsed time computing the average of couple of slices 0.64 s
```

Parallel processing is already faster than the sequential processing. It is also possible to remove a bit of overhead by dumping the `data` array to a memmap and pass the memmap to *joblib.Parallel*.

```
import os
from joblib import dump, load

folder = './joblib_memmap'
try:
    os.mkdir(folder)
except FileExistsError:
    pass

data_filename_memmap = os.path.join(folder, 'data_memmap')
dump(data, data_filename_memmap)
data = load(data_filename_memmap, mmap_mode='r')

tic = time.time()
results = Parallel(n_jobs=2)(delayed(slow_mean)(data, sl) for sl in slices)
toc = time.time()
print('\nElapsed time computing the average of couple of slices {:.2f} s\n'
      .format(toc - tic))
```

Out:

```
Elapsed time computing the average of couple of slices 0.64 s
```

Therefore, dumping large `data` array ahead of calling *joblib.Parallel* can speed up the processing by removing some overhead.

Writable memmap for shared memory `joblib.Parallel`

`slow_mean_write_output` will compute the mean for some given slices as in the previous example. However, the resulting mean will be directly written on the output array.

```
def slow_mean_write_output(data, sl, output, idx):
    """Simulate a time consuming processing."""
    time.sleep(0.005)
    res_ = data[sl].mean()
    print("[Worker %d] Mean for slice %d is %f" % (os.getpid(), idx, res_))
    output[idx] = res_
```

Prepare the folder where the memmap will be dumped.

```
output_filename_memmap = os.path.join(folder, 'output_memmap')
```

Pre-allocate a writable shared memory map as a container for the results of the parallel computation.

```
output = np.memmap(output_filename_memmap, dtype=data.dtype,
                   shape=len(slices), mode='w+')
```

`data` is replaced by its memory mapped version. Note that the buffer as already been dumped in the previous section.

```
data = load(data_filename_memmap, mmap_mode='r')
```

Fork the worker processes to perform computation concurrently

```
Parallel(n_jobs=2)(delayed(slow_mean_write_output)(data, sl, output, idx)
                   for idx, sl in enumerate(slices))
```

Compare the results from the output buffer with the expected results

```
print("\nExpected means computed in the parent process:\n {}"
      .format(np.array(results)))
print("\nActual means computed by the worker processes:\n {}"
      .format(output))
```

Out:

```
Expected means computed in the parent process:
 [0.49997861 0.50010424 0.49984722 0.50001905 0.50008059 0.50015487
 0.49989739 0.5002575  0.49975901 0.4989692  0.4993385  0.499383
 0.49948768 0.49972963 0.50026418 0.50015428 0.50039551 0.50011117
 0.50019554 0.50028272 0.50033161 0.50016569 0.50053333 0.50077934
 0.50097251 0.50081053 0.50084263 0.50125409 0.50096326 0.50059204
 0.50023474 0.50014827 0.49949279 0.49949027 0.49939413 0.49929631
 0.49949142 0.49949558 0.4996401  0.50000973 0.50064814 0.50055214
 0.50077792 0.50113339 0.50079294 0.50064855 0.5004424  0.50006844
 0.49971982 0.49977264 0.49960345 0.4996904  0.49966811 0.49948051
 0.49963273 0.49957282 0.49966268 0.49992882 0.49995213 0.49997251
 0.50019519 0.49954346 0.49947302 0.49962123 0.4993881  0.49920285
 0.49957388 0.49926641 0.49958534 0.49948026 0.49958056 0.49937326
 0.49973235 0.4992276  0.49950517 0.4997761  0.49975752 0.50002806
 0.50025216 0.50049629 0.50033086 0.50051157 0.50007051 0.50023099
 0.49997941 0.49962123 0.50023238 0.50013114 0.49989831 0.49983386
 0.50010692 0.49948908 0.49975941 0.49992882 0.49991322]

Actual means computed by the worker processes:
 [0.49997861 0.50010424 0.49984722 0.50001905 0.50008059 0.50015487
 0.49989739 0.5002575  0.49975901 0.4989692  0.4993385  0.499383
 0.49948768 0.49972963 0.50026418 0.50015428 0.50039551 0.50011117
 0.50019554 0.50028272 0.50033161 0.50016569 0.50053333 0.50077934
 0.50097251 0.50081053 0.50084263 0.50125409 0.50096326 0.50059204
 0.50023474 0.50014827 0.49949279 0.49949027 0.49939413 0.49929631
 0.49949142 0.49949558 0.4996401  0.50000973 0.50064814 0.50055214
 0.50077792 0.50113339 0.50079294 0.50064855 0.5004424  0.50006844
 0.49971982 0.49977264 0.49960345 0.4996904  0.49966811 0.49948051
 0.49963273 0.49957282 0.49966268 0.49992882 0.49995213 0.49997251
 0.50019519 0.49954346 0.49947302 0.49962123 0.4993881  0.49920285
 0.49957388 0.49926641 0.49958534 0.49948026 0.49958056 0.49937326
 0.49973235 0.4992276  0.49950517 0.4997761  0.49975752 0.50002806
 0.50025216 0.50049629 0.50033086 0.50051157 0.50007051 0.50023099
 0.49997941 0.49962123 0.50023238 0.50013114 0.49989831 0.49983386
 0.50010692 0.49948908 0.49975941 0.49992882 0.49991322]
```

Clean-up the memmap

Remove the different memmap that we created. It might fail in Windows due to file permissions.

```
import shutil

try:
    shutil.rmtree(folder)
except:  # noqa
    print('Could not clean-up automatically.')
```

Total running time of the script: (0 minutes 2.884 seconds)

Note: Click *here* to download the full example code

Improving I/O using compressors

This example compares the compressors available in Joblib. In the example, Zlib, LZMA and LZ4 compression only are used but Joblib also supports BZ2 and GZip compression methods. For each compared compression method, this example dumps and reloads a dataset fetched from an online machine-learning database. This gives 3 informations: the size on disk of the compressed data, the time spent to dump and the time spent to reload the data from disk.

```
import os
import os.path
import time
```

Get some data from real-world use cases

First fetch the benchmark dataset from an online machine-learning database and load it in a pandas dataframe.

```
import pandas as pd

url = ("https://archive.ics.uci.edu/ml/machine-learning-databases/"
       "kddcup99-mld/kddcup.data.gz")
names = ("duration, protocol_type, service, flag, src_bytes, "
         "dst_bytes, land, wrong_fragment, urgent, hot, "
         "num_failed_logins, logged_in, num_compromised, "
         "root_shell, su_attempted, num_root, "
         "num_file_creations, ").split(', ')

data = pd.read_csv(url, names=names, nrows=1e6)
```

Dump and load the dataset without compression

This gives reference values for later comparison.

```
from joblib import dump, load

pickle_file = './pickle_data.joblib'
```

Start by measuring the time spent for dumping the raw data:

```
start = time.time()
with open(pickle_file, 'wb') as f:
    dump(data, f)
raw_dump_duration = time.time() - start
print("Raw dump duration: %0.3fs" % raw_dump_duration)
```

Out:

```
Raw dump duration: 0.396s
```

Then measure the size of the raw dumped data on disk:

```
raw_file_size = os.stat(pickle_file).st_size / 1e6
print("Raw dump file size: %0.3fMB" % raw_file_size)
```

Out:

```
Raw dump file size: 305.223MB
```

Finally measure the time spent for loading the raw data:

```
start = time.time()
with open(pickle_file, 'rb') as f:
    load(f)
raw_load_duration = time.time() - start
print("Raw load duration: %0.3fs" % raw_load_duration)
```

Out:

```
Raw load duration: 0.457s
```

Dump and load the dataset using the Zlib compression method

The compression level is using the default value, 3, which is, in general, a good compromise between compression and speed.

Start by measuring the time spent for dumping of the zlib data:

```
start = time.time()
with open(pickle_file, 'wb') as f:
    dump(data, f, compress='zlib')
zlib_dump_duration = time.time() - start
print("Zlib dump duration: %0.3fs" % zlib_dump_duration)
```

Out:

```
Zlib dump duration: 1.528s
```

Then measure the size of the zlib dump data on disk:

```
zlib_file_size = os.stat(pickle_file).st_size / 1e6
print("Zlib file size: %0.3fMB" % zlib_file_size)
```

Out:

```
Zlib file size: 5.956MB
```

Finally measure the time spent for loading the compressed dataset:

```
start = time.time()
with open(pickle_file, 'rb') as f:
    load(f)
zlib_load_duration = time.time() - start
print("Zlib load duration: %0.3fs" % zlib_load_duration)
```

Out:

```
Zlib load duration: 0.801s
```

Note: The compression format is detected automatically by Joblib. The compression format is identified by the standard magic number present at the beginning of the file. Joblib uses this information to determine the compression method used. This is the case for all compression methods supported by Joblib.

Dump and load the dataset using the LZMA compression method

LZMA compression method has a very good compression rate but at the cost of being very slow. In this example, a light compression level, e.g. 3, is used to speed up a bit the dump/load cycle.

Start by measuring the time spent for dumping the lzma data:

```
start = time.time()
with open(pickle_file, 'wb') as f:
    dump(data, f, compress=('lzma', 3))
lzma_dump_duration = time.time() - start
print("LZMA dump duration: %0.3fs" % lzma_dump_duration)
```

Out:

```
LZMA dump duration: 4.500s
```

Then measure the size of the lzma dump data on disk:

```
lzma_file_size = os.stat(pickle_file).st_size / 1e6
print("LZMA file size: %0.3fMB" % lzma_file_size)
```

Out:

```
LZMA file size: 2.873MB
```

Finally measure the time spent for loading the lzma data:

```
start = time.time()
with open(pickle_file, 'rb') as f:
    load(f)
```

```
lzma_load_duration = time.time() - start
print("LZMA load duration: %0.3fs" % lzma_load_duration)
```

Out:

```
LZMA load duration: 0.990s
```

Dump and load the dataset using the LZ4 compression method

LZ4 compression method is known to be one of the fastest available compression method but with a compression rate a bit lower than Zlib. In most of the cases, this method is a good choice.

Note: In order to use LZ4 compression with Joblib, the lz4 package must be installed on the system.

Start by measuring the time spent for dumping the lz4 data:

```
start = time.time()
with open(pickle_file, 'wb') as f:
    dump(data, f, compress='lz4')
lz4_dump_duration = time.time() - start
print("LZ4 dump duration: %0.3fs" % lz4_dump_duration)
```

Out:

```
LZ4 dump duration: 0.248s
```

Then measure the size of the lz4 dump data on disk:

```
lz4_file_size = os.stat(pickle_file).st_size / 1e6
print("LZ4 file size: %0.3fMB" % lz4_file_size)
```

Out:

```
LZ4 file size: 9.766MB
```

Finally measure the time spent for loading the lz4 data:

```
start = time.time()
with open(pickle_file, 'rb') as f:
    load(f)
lz4_load_duration = time.time() - start
print("LZ4 load duration: %0.3fs" % lz4_load_duration)
```

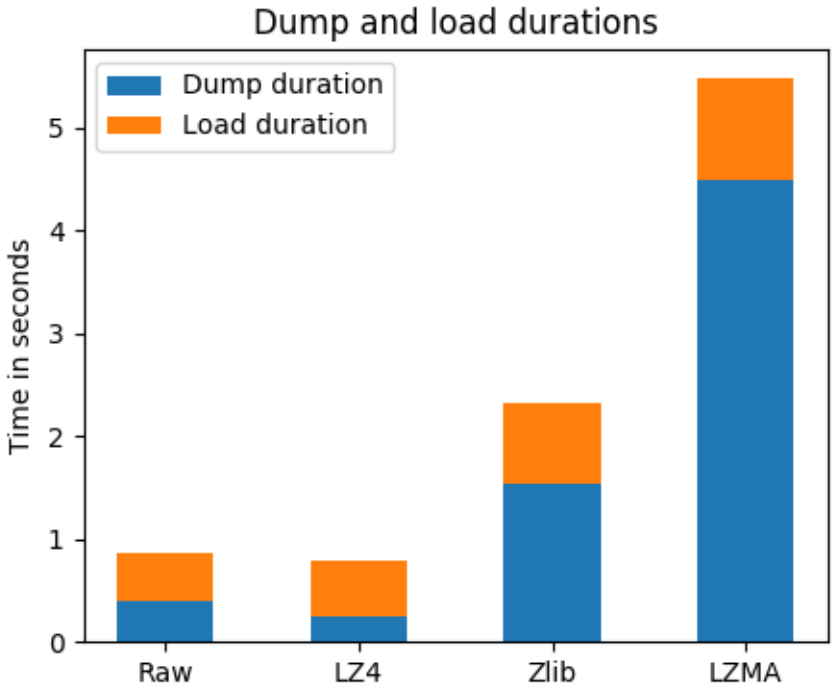
Out:

```
LZ4 load duration: 0.533s
```

Comparing the results

```
import numpy as np
import matplotlib.pyplot as plt
```

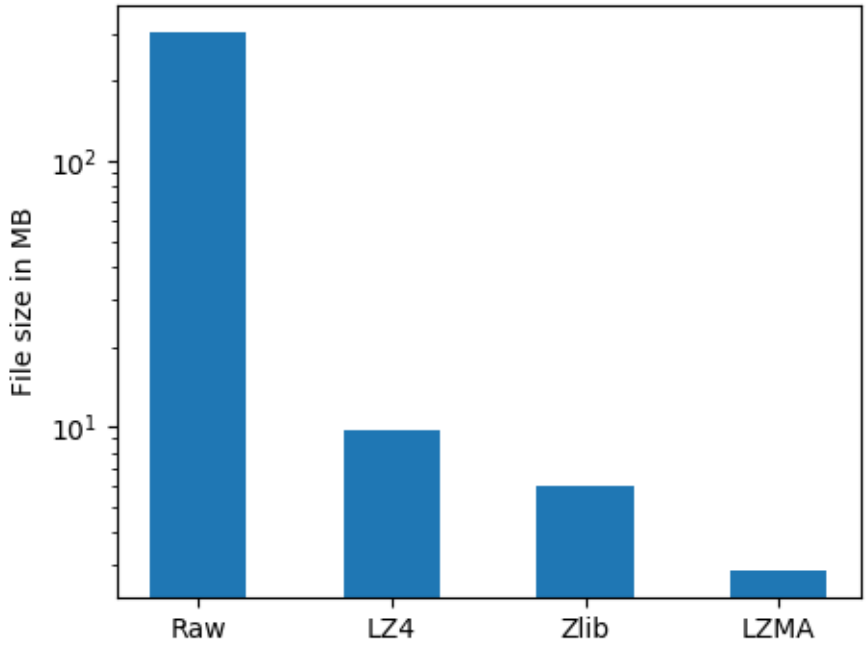
```
N = 4
load_durations = (raw_load_duration, lz4_load_duration, zlib_load_duration,
                  lzma_load_duration)
dump_durations = (raw_dump_duration, lz4_dump_duration, zlib_dump_duration,
                  lzma_dump_duration)
file_sizes = (raw_file_size, lz4_file_size, zlib_file_size, lzma_file_size)
ind = np.arange(N)
width = 0.5

plt.figure(1, figsize=(5, 4))
p1 = plt.bar(ind, dump_durations, width)
p2 = plt.bar(ind, load_durations, width, bottom=dump_durations)
plt.ylabel('Time in seconds')
plt.title('Dump and load durations')
plt.xticks(ind, ('Raw', 'LZ4', 'Zlib', 'LZMA'))
plt.yticks(np.arange(0, lzma_load_duration + lzma_dump_duration))
plt.legend((p1[0], p2[0]), ('Dump duration', 'Load duration'))
```



Compared with other compressors, LZ4 is clearly the fastest, especially for dumping compressed data on disk. In this particular case, it can even be faster than the raw dump. Also note that dump and load durations depend on the I/O speed of the underlying storage: for example, with SSD hard drives the LZ4 compression will be slightly slower than raw dump/load, whereas with spinning hard disk drives (HDD) or remote storage (NFS), LZ4 is faster in general.

LZMA and Zlib, even if always slower for dumping data, are quite fast when re-loading compressed data from disk.

```
plt.figure(2, figsize=(5, 4))
plt.bar(ind, file_sizes, width, log=True)
plt.ylabel('File size in MB')
plt.xticks(ind, ('Raw', 'LZ4', 'Zlib', 'LZMA'))
```



Compressed data obviously takes a lot less space on disk than raw data. LZMA is the best compression method in terms of compression rate. Zlib also has a better compression rate than LZ4.

```
plt.show()
```

Clear the pickle file

```
import os
os.remove(pickle_file)
```

Total running time of the script: (0 minutes 16.874 seconds)

2.6.2 Parallel examples

Examples demoing more advanced parallel patterns.

Note: Click *here* to download the full example code

Using dask distributed for single-machine parallel computing

This example shows the simplest usage of the dask distributed backend, on the local computer.

This is useful for prototyping a solution, to later be run on a truly distributed cluster, as the only change to be made is the address of the scheduler.

Another realistic usage scenario: combining dask code with joblib code, for instance using dask for preprocessing data, and scikit-learn for machine learning. In such a setting, it may be interesting to use distributed as a backend scheduler for both dask and joblib, to orchestrate well the computation.

Setup the distributed client

```
from dask.distributed import Client

# If you have a remote cluster running Dask
# client = Client('tcp://scheduler-address:8786')

# If you want Dask to set itself up on your personal computer
client = Client(processes=False)
```

Run parallel computation using dask.distributed

```
import time
import joblib


def long_running_function(i):
    time.sleep(.1)
    return i
```

The verbose messages below show that the backend is indeed the dask.distributed one

```
with joblib.parallel_backend('dask'):
    joblib.Parallel(verbose=100)(
        joblib.delayed(long_running_function)(i)
        for i in range(10))
```

Out:

```
[Parallel(n_jobs=-1)]: Using backend DaskDistributedBackend with 4␣
↪concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done   3 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done   4 out of  10 | elapsed:    0.1s remaining:   ␣
↪0.2s
[Parallel(n_jobs=-1)]: Done   5 out of  10 | elapsed:    0.2s remaining:   ␣
↪0.2s
[Parallel(n_jobs=-1)]: Done   6 out of  10 | elapsed:    0.2s remaining:   ␣
↪0.1s
[Parallel(n_jobs=-1)]: Done   7 out of  10 | elapsed:    0.2s remaining:   ␣
↪0.1s
[Parallel(n_jobs=-1)]: Done   8 out of  10 | elapsed:    0.2s remaining:   ␣
↪0.1s
[Parallel(n_jobs=-1)]: Done  10 out of  10 | elapsed:    0.3s remaining:   ␣
↪0.0s
[Parallel(n_jobs=-1)]: Done  10 out of  10 | elapsed:    0.3s finished
```

Progress in computation can be followed on the distributed web interface, see http://dask.pydata.org/en/latest/diagnostics-distributed.html

Total running time of the script: (0 minutes 1.266 seconds)

2.7 Development

The homepage of joblib with user documentation is located on:

https://joblib.readthedocs.io

2.7.1 Getting the latest code

To get the latest code using git, simply type:

```
git clone git://github.com/joblib/joblib.git
```

If you don't have git installed, you can download a zip or tarball of the latest code: http://github.com/joblib/joblib/archives/master

2.7.2 Installing

You can use *pip* to install joblib:

```
pip install joblib
```

from any directory or:

```
python setup.py install
```

from the source directory.

2.7.3 Dependencies

- Joblib has no mandatory dependencies besides Python (supported versions are 2.7+ and 3.4+).
- Joblib has an optional dependency on Numpy (at least version 1.6.1) for array manipulation.
- Joblib includes its own vendored copy of loky for process management.
- Joblib can efficiently dump and load numpy arrays but does not require numpy to be installed.
- Joblib has an optional dependency on python-lz4 as a faster alternative to zlib and gzip for compressed serialization.
- Joblib has an optional dependency on psutil to mitigate memory leaks in parallel worker processes.
- Some examples require external dependencies such as pandas. See the instructions in the *Building the docs* section for details.

2.7.4 Workflow to contribute

To contribute to joblib, first create an account on github. Once this is done, fork the joblib repository to have your own repository, clone it using 'git clone' on the computers where you want to work. Make your changes in your clone, push them to your github account, test them on several computers, and when you are happy with them, send a pull request to the main repository.

2.7.5 Running the test suite

To run the test suite, you need the pytest (version >= 3) and coverage modules. Run the test suite using:

```
pytest joblib
```

from the root of the project.

2.7.6 Building the docs

To build the docs you need to have sphinx (>=1.4) and some dependencies installed:

```
pip install -U -r .readthedocs-requirements.txt
```

The docs can then be built with the following command:

```
make doc
```

The html docs are located in the `doc/_build/html` directory.

2.7.7 Making a source tarball

To create a source tarball, eg for packaging or distributing, run the following command:

```
python setup.py sdist
```

The tarball will be created in the *dist* directory. This command will compile the docs, and the resulting tarball can be installed with no extra dependencies than the Python standard library. You will need setuptool and sphinx.

2.7.8 Making a release and uploading it to PyPI

This command is only run by project manager, to make a release, and upload in to PyPI:

```
python setup.py sdist bdist_wheel upload_docs --upload-dir doc/_build/html
twine upload dist/*
```

2.7.9 Updating the changelog

Changes are listed in the CHANGES.rst file. They must be manually updated but, the following git command may be used to generate the lines:

```
git log --abbrev-commit --date=short --no-merges --sparse
```

Licensing

joblib is **BSD-licenced** (3 clause):

2.7.10 Latest changes

master

Thomas Moreau

Fix nested backend in SequentialBackend to avoid changing the default backend to Sequential. (#792)

Thomas Moreau, Olivier Grisel

Fix nested_backend behavior to avoid setting the default number of workers to -1 when the backend is not dask. (#784)

Release 0.12.5

Thomas Moreau, Olivier Grisel

Include loky 2.3.1 with better error reporting when a worker is abruptly terminated. Also fixes spurious debug output.

Pierre Glaser

Include cloudpickle 0.5.6. Fix a bug with the handling of global variables by locally defined functions.

Release 0.12.4

Thomas Moreau, Pierre Glaser, Olivier Grisel

Include loky 2.3.0 with many bugfixes, notably w.r.t. when setting non-default multiprocessing contexts. Also include improvement on memory management of long running worker processes and fixed issues when using the loky backend under PyPy.

Maxime Weyl

Raises a more explicit exception when a corrupted MemorizedResult is loaded.

Maxime Weyl

Loading a corrupted cached file with mmap mode enabled would recompute the results and return them without memmory mapping.

Release 0.12.3

Thomas Moreau

Fix joblib import setting the global start_method for multiprocessing.

Alexandre Abadie

Fix MemorizedResult not picklable (#747).

Loïc Estève

Fix Memory, MemorizedFunc and MemorizedResult round-trip pickling + unpickling (#746).

James Collins

Fixed a regression in Memory when positional arguments are called as kwargs several times with different values (#751).

Thomas Moreau and Olivier Grisel

Integration of loky 2.2.2 that fixes issues with the selection of the default start method and improve the reporting when calling functions with arguments that raise an exception when unpickling.

Maxime Weyl

Prevent MemorizedFunc.call_and_shelve from loading cached results to RAM when not necessary. Results in big performance improvements

Release 0.12.2

Olivier Grisel

Integrate loky 2.2.0 to fix regression with unpicklable arguments and functions reported by users (#723, #643).

Loky 2.2.0 also provides a protection against memory leaks long running applications when psutil is installed (reported as #721).

Joblib now includes the code for the dask backend which has been updated to properly handle nested parallelism and data scattering at the same time (#722).

Alexandre Abadie and Olivier Grisel

Restored some private API attribute and arguments (*MemorizedResult.argument_hash* and *BatchedCalls.__init__*'s *pickle_cache*) for backward compat. (#716, #732).

Joris Van den Bossche

Fix a deprecation warning message (for *Memory*'s *cachedir*) (#720).

Release 0.12.1

Thomas Moreau

Make sure that any exception triggered when serializing jobs in the queue will be wrapped as a PicklingError as in past versions of joblib.

Noam Hershtig

Fix kwonlydefaults key error in filter_args (#715)

Release 0.12

Thomas Moreau

Implement the `'loky'` backend with @ogrisel. This backend relies on a robust implementation of `concurrent.futures.ProcessPoolExecutor` with spawned processes that can be reused accross the `Parallel` calls. This fixes the bad interation with third paty libraries relying on thread pools, described in https://pythonhosted.org/joblib/parallel.html#bad-interaction-of-multiprocessing-and-third-party-libraries

Limit the number of threads used in worker processes by C-libraries that relies on threadpools. This functionality works for MKL, OpenBLAS, OpenMP and Accelerated.

Elizabeth Sander

Prevent numpy arrays with the same shape and data from hashing to the same memmap, to prevent jobs with preallocated arrays from writing over each other.

Olivier Grisel

Reduce overhead of automatic memmap by removing the need to hash the array.

Make `Memory.cache` robust to `PermissionError (errno 13)` under Windows when run in combination with `Parallel`.

The automatic array memory mapping feature of `Parallel` does no longer use `/dev/shm` if it is too small (less than 2 GB). In particular in docker containers `/dev/shm` is only 64 MB by default which would cause frequent failures when running joblib in Docker containers.

Make it possible to hint for thread-based parallelism with `prefer='threads'` or enforce shared-memory semantics with `require='sharedmem'`.

Rely on the built-in exception nesting system of Python 3 to preserve traceback information when an exception is raised on a remote worker process. This avoid verbose and redundant exception reports under Python 3.

Preserve exception type information when doing nested Parallel calls instead of mapping the exception to the generic `JoblibException` type.

Alexandre Abadie

Introduce the concept of 'store' and refactor the `Memory` internal storage implementation to make it accept extra store backends for caching results. `backend` and `backend_options` are the new options added to `Memory` to specify and configure a store backend.

Add the `register_store_backend` function to extend the store backend used by default with Memory. This default store backend is named 'local' and corresponds to the local filesystem.

The store backend API is experimental and thus is subject to change in the future without deprecation.

The `cachedir` parameter of `Memory` is now marked as deprecated, use `location` instead.

Add support for LZ4 compression if `lz4` package is installed.

Add `register_compressor` function for extending available compressors.

Allow passing a string to `compress` parameter in `dump` funtion. This string should correspond to the compressor used (e.g. zlib, gzip, lz4, etc). The default compression level is used in this case.

Matthew Rocklin

Allow `parallel_backend` to be used globally instead of only as a context manager. Support lazy registration of external parallel backends

Release 0.11

Alexandre Abadie

Remove support for python 2.6

Alexandre Abadie

Remove deprecated *format_signature*, *format_call* and *load_output* functions from Memory API.

Loïc Estève

Add initial implementation of LRU cache cleaning. You can specify the size limit of a `Memory` object via the `bytes_limit` parameter and then need to clean explicitly the cache via the `Memory.reduce_size` method.

Olivier Grisel

Make the multiprocessing backend work even when the name of the main thread is not the Python default. Thanks to Roman Yurchak for the suggestion.

Karan Desai

pytest is used to run the tests instead of nosetests. `python setup.py test` or `python setup.py nosetests` do not work anymore, run `pytest joblib` instead.

Loïc Estève

An instance of `joblib.ParallelBackendBase` can be passed into the `parallel` argument in `joblib.Parallel`.

Loïc Estève

Fix handling of memmap objects with offsets greater than mmap.ALLOCATIONGRANULARITY in `joblib.Parrallel`. See https://github.com/joblib/joblib/issues/451 for more details.

Loïc Estève

Fix performance regression in `joblib.Parallel` with n_jobs=1. See https://github.com/joblib/joblib/issues/483 for more details.

Loïc Estève

Fix race condition when a function cached with `joblib.Memory.cache` was used inside a `joblib.Parallel`. See https://github.com/joblib/joblib/issues/490 for more details.

Release 0.10.3

Loïc Estève

Fix tests when multiprocessing is disabled via the JOBLIB_MULTIPROCESSING environment variable.

harishmk

Remove warnings in nested Parallel objects when the inner Parallel has n_jobs=1. See https://github.com/joblib/joblib/pull/406 for more details.

Release 0.10.2

Loïc Estève

FIX a bug in stack formatting when the error happens in a compiled extension. See https://github.com/joblib/joblib/pull/382 for more details.

Vincent Latrouite

FIX a bug in the constructor of BinaryZlibFile that would throw an exception when passing unicode filename (Python 2 only). See https://github.com/joblib/joblib/pull/384 for more details.

Olivier Grisel

Expose `joblib.parallel.ParallelBackendBase` and `joblib.parallel.AutoBatchingMixin` in the public API to make them officially re-usable by backend implementers.

Release 0.10.0

Alexandre Abadie

ENH: joblib.dump/load now accept file-like objects besides filenames. https://github.com/joblib/joblib/pull/351 for more details.

Niels Zeilemaker and Olivier Grisel

Refactored joblib.Parallel to enable the registration of custom computational backends. https://github.com/joblib/joblib/pull/306 Note the API to register custom backends is considered experimental and subject to change without deprecation.

Alexandre Abadie

Joblib pickle format change: joblib.dump always create a single pickle file and joblib.dump/joblib.save never do any memory copy when writing/reading pickle files. Reading pickle files generated with joblib versions prior to 0.10 will be supported for a limited amount of time, we advise to regenerate them from scratch when convenient. joblib.dump

and joblib.load also support pickle files compressed using various strategies: zlib, gzip, bz2, lzma and xz. Note that lzma and xz are only available with python >= 3.3. https://github.com/joblib/joblib/pull/260 for more details.

Antony Lee

ENH: joblib.dump/load now accept pathlib.Path objects as filenames. https://github.com/joblib/joblib/pull/316 for more details.

Olivier Grisel

Workaround for "WindowsError: [Error 5] Access is denied" when trying to terminate a multiprocessing pool under Windows: https://github.com/joblib/joblib/issues/354

Release 0.9.4

Olivier Grisel

FIX a race condition that could cause a joblib.Parallel to hang when collecting the result of a job that triggers an exception. https://github.com/joblib/joblib/pull/296

Olivier Grisel

FIX a bug that caused joblib.Parallel to wrongly reuse previously memmapped arrays instead of creating new temporary files. https://github.com/joblib/joblib/pull/294 for more details.

Loïc Estève

FIX for raising non inheritable exceptions in a Parallel call. See https://github.com/joblib/joblib/issues/269 for more details.

Alexandre Abadie

FIX joblib.hash error with mixed types sets and dicts containing mixed types keys when using Python 3. see https://github.com/joblib/joblib/issues/254

Loïc Estève

FIX joblib.dump/load for big numpy arrays with dtype=object. See https://github.com/joblib/joblib/issues/220 for more details.

Loïc Estève

FIX joblib.Parallel hanging when used with an exhausted iterator. See https://github.com/joblib/joblib/issues/292 for more details.

Release 0.9.3

Olivier Grisel

Revert back to the `fork` start method (instead of `forkserver`) as the latter was found to cause crashes in interactive Python sessions.

Release 0.9.2

Loïc Estève

Joblib hashing now uses the default pickle protocol (2 for Python 2 and 3 for Python 3). This makes it very unlikely to get the same hash for a given object under Python 2 and Python 3.

In particular, for Python 3 users, this means that the output of joblib.hash changes when switching from joblib 0.8.4 to 0.9.2 . We strive to ensure that the output of joblib.hash does not change needlessly in future versions of joblib but this is not officially guaranteed.

Loïc Estève

Joblib pickles generated with Python 2 can not be loaded with Python 3 and the same applies for joblib pickles generated with Python 3 and loaded with Python 2.

During the beta period 0.9.0b2 to 0.9.0b4, we experimented with a joblib serialization that aimed to make pickles serialized with Python 3 loadable under Python 2. Unfortunately this serialization strategy proved to be too fragile as far as the long-term maintenance was concerned (For example see https://github.com/joblib/joblib/pull/243). That means that joblib pickles generated with joblib 0.9.0bN can not be loaded under joblib 0.9.2. Joblib beta testers, who are the only ones likely to be affected by this, are advised to delete their joblib cache when they upgrade from 0.9.0bN to 0.9.2.

Arthur Mensch

Fixed a bug with `joblib.hash` that used to return unstable values for strings and numpy.dtype instances depending on interning states.

Olivier Grisel

Make joblib use the 'forkserver' start method by default under Python 3.4+ to avoid causing crash with 3rd party libraries (such as Apple vecLib / Accelerate or the GCC OpenMP runtime) that use an internal thread pool that is not not reinitialized when a `fork` system call happens.

Olivier Grisel

New context manager based API (`with` block) to re-use the same pool of workers across consecutive parallel calls.

Vlad Niculae and Olivier Grisel

Automated batching of fast tasks into longer running jobs to hide multiprocessing dispatching overhead when possible.

Olivier Grisel

FIX make it possible to call `joblib.load(filename, mmap_mode='r')` on pickled objects that include a mix of arrays of both memory memmapable dtypes and object dtype.

Release 0.8.4

2014-11-20 Olivier Grisel

OPTIM use the C-optimized pickler under Python 3

This makes it possible to efficiently process parallel jobs that deal with numerous Python objects such as large dictionaries.

Release 0.8.3

2014-08-19 Olivier Grisel

FIX disable memmapping for object arrays

2014-08-07 Lars Buitinck

MAINT NumPy 1.10-safe version comparisons

2014-07-11 Olivier Grisel

FIX #146: Heisen test failure caused by thread-unsafe Python lists

This fix uses a queue.Queue datastructure in the failing test. This datastructure is thread-safe thanks to an internal Lock. This Lock instance not picklable hence cause the picklability check of delayed to check fail.

When using the threading backend, picklability is no longer required, hence this PRs give the user the ability to disable it on a case by case basis.

Release 0.8.2

2014-06-30 Olivier Grisel

BUG: use mmap_mode='r' by default in Parallel and MemmappingPool

The former default of mmap_mode='c' (copy-on-write) caused problematic use of the paging file under Windows.

2014-06-27 Olivier Grisel

BUG: fix usage of the /dev/shm folder under Linux

Release 0.8.1

2014-05-29 Gael Varoquaux

BUG: fix crash with high verbosity

Release 0.8.0

2014-05-14 Olivier Grisel

Fix a bug in exception reporting under Python 3

2014-05-10 Olivier Grisel

Fixed a potential segfault when passing non-contiguous memmap instances.

2014-04-22 Gael Varoquaux

ENH: Make memory robust to modification of source files while the interpreter is running. Should lead to less spurious cache flushes and recomputations.

2014-02-24 Philippe Gervais

New `Memory.call_and_shelve` API to handle memoized results by reference instead of by value.

Release 0.8.0a3

2014-01-10 Olivier Grisel & Gael Varoquaux

FIX #105: Race condition in task iterable consumption when pre_dispatch != 'all' that could cause crash with error messages "Pools seems closed" and "ValueError: generator already executing".

2014-01-12 Olivier Grisel

FIX #72: joblib cannot persist "output_dir" keyword argument.

Release 0.8.0a2

2013-12-23 Olivier Grisel

ENH: set default value of Parallel's max_nbytes to 100MB

Motivation: avoid introducing disk latency on medium sized parallel workload where memory usage is not an issue.

FIX: properly handle the JOBLIB_MULTIPROCESSING env variable

FIX: timeout test failures under windows

Release 0.8.0a

2013-12-19 Olivier Grisel

FIX: support the new Python 3.4 multiprocessing API

2013-12-05 Olivier Grisel

ENH: make Memory respect mmap_mode at first call too

ENH: add a threading based backend to Parallel

This is low overhead alternative backend to the default multiprocessing backend that is suitable when calling compiled extensions that release the GIL.

Author: Dan Stahlke <dan@stahlke.org> Date: 2013-11-08

FIX: use safe_repr to print arg vals in trace

This fixes a problem in which extremely long (and slow) stack traces would be produced when function parameters are large numpy arrays.

2013-09-10 Olivier Grisel

ENH: limit memory copy with Parallel by leveraging numpy.memmap when possible

Release 0.7.1

2013-07-25 Gael Varoquaux

MISC: capture meaningless argument (n_jobs=0) in Parallel

2013-07-09 Lars Buitinck

ENH Handles tuples, sets and Python 3's dict_keys type the same as lists. in pre_dispatch

2013-05-23 Martin Luessi

ENH: fix function caching for IPython

Release 0.7.0

This release drops support for Python 2.5 in favor of support for Python 3.0

2013-02-13 Gael Varoquaux

BUG: fix nasty hash collisions

2012-11-19 Gael Varoquaux

ENH: Parallel: Turn of pre-dispatch for already expanded lists

Gael Varoquaux 2012-11-19

ENH: detect recursive sub-process spawning, as when people do not protect the __main__ in scripts under Windows, and raise a useful error.

Gael Varoquaux 2012-11-16

ENH: Full python 3 support

Release 0.6.5

2012-09-15 Yannick Schwartz

BUG: make sure that sets and dictionnaries give reproducible hashes

2012-07-18 Marek Rudnicki

BUG: make sure that object-dtype numpy array hash correctly

2012-07-12 GaelVaroquaux

BUG: Bad default n_jobs for Parallel

Release 0.6.4

2012-05-07 Vlad Niculae

ENH: controlled randomness in tests and doctest fix

2012-02-21 GaelVaroquaux

ENH: add verbosity in memory

2012-02-21 GaelVaroquaux

BUG: non-reproducible hashing: order of kwargs

The ordering of a dictionnary is random. As a result the function hashing was not reproducible. Pretty hard to test

Release 0.6.3

2012-02-14 GaelVaroquaux

BUG: fix joblib Memory pickling

2012-02-11 GaelVaroquaux

BUG: fix hasher with Python 3

2012-02-09 GaelVaroquaux

API: filter_args: **args, **kwargs -> args, kwargs*

Release 0.6.2

2012-02-06 Gael Varoquaux

BUG: make sure Memory pickles even if cachedir=None

Release 0.6.1

Bugfix release because of a merge error in release 0.6.0

Release 0.6.0

Beta 3

2012-01-11 Gael Varoquaux

BUG: ensure compatibility with old numpy

DOC: update installation instructions

BUG: file semantic to work under Windows

2012-01-10 Yaroslav Halchenko

BUG: a fix toward 2.5 compatibility

Beta 2

2012-01-07 Gael Varoquaux

ENH: hash: bugware to be able to hash objects defined interactively in IPython

2012-01-07 Gael Varoquaux

ENH: Parallel: warn and not fail for nested loops

ENH: Parallel: n_jobs=-2 now uses all CPUs but one

2012-01-01 Juan Manuel Caicedo Carvajal and Gael Varoquaux

ENH: add verbosity levels in Parallel

Release 0.5.7

2011-12-28 Gael varoquaux

API: zipped -> compress

2011-12-26 Gael varoquaux

ENH: Add a zipped option to Memory

API: Memory no longer accepts save_npy

2011-12-22 Kenneth C. Arnold and Gael varoquaux

BUG: fix numpy_pickle for array subclasses

2011-12-21 Gael varoquaux

ENH: add zip-based pickling

2011-12-19 Fabian Pedregosa

Py3k: compatibility fixes. This makes run fine the tests test_disk and test_parallel

Release 0.5.6

2011-12-11 Lars Buitinck

ENH: Replace os.path.exists before makedirs with exception check New disk.mkdirp will fail with other errnos than EEXIST.

2011-12-10 Bala Subrahmanyam Varanasi

MISC: pep8 compliant

Release 0.5.5

2011-19-10 Fabian Pedregosa

ENH: Make joblib installable under Python 3.X

Release 0.5.4

2011-09-29 Jon Olav Vik

BUG: Make mangling path to filename work on Windows

2011-09-25 Olivier Grisel

FIX: doctest heisenfailure on execution time

2011-08-24 Ralf Gommers

STY: PEP8 cleanup.

Release 0.5.3

2011-06-25 Gael varoquaux

API: All the usefull symbols in the __init__

Release 0.5.2

2011-06-25 Gael varoquaux

ENH: Add cpu_count

2011-06-06 Gael varoquaux

ENH: Make sure memory hash in a reproducible way

Release 0.5.1

2011-04-12 Gael varoquaux

TEST: Better testing of parallel and pre_dispatch

Yaroslav Halchenko 2011-04-12

DOC: quick pass over docs – trailing spaces/spelling

Yaroslav Halchenko 2011-04-11

ENH: JOBLIB_MULTIPROCESSING env var to disable multiprocessing from the environment

Alexandre Gramfort 2011-04-08

ENH : adding log message to know how long it takes to load from disk the cache

Release 0.5.0

2011-04-01 Gael varoquaux

BUG: pickling MemoizeFunc does not store timestamp

2011-03-31 Nicolas Pinto

TEST: expose hashing bug with cached method

2011-03-26. . . 2011-03-27 Pietro Berkes

BUG: fix error management in rm_subdirs BUG: fix for race condition during tests in mem.clear()

Gael varoquaux 2011-03-22. . . 2011-03-26

TEST: Improve test coverage and robustness

Gael varoquaux 2011-03-19

BUG: hashing functions with only *var **kwargs

Gael varoquaux 2011-02-01. . . 2011-03-22

BUG: Many fixes to capture interprocess race condition when mem.cache is used by several processes on the same cache.

Fabian Pedregosa 2011-02-28

First work on Py3K compatibility

Gael varoquaux 2011-02-27

ENH: pre_dispatch in parallel: lazy generation of jobs in parallel for to avoid drowning memory.

GaelVaroquaux 2011-02-24

ENH: Add the option of overloading the arguments of the mother 'Memory' object in the cache method that is doing the decoration.

Gael varoquaux 2010-11-21

ENH: Add a verbosity level for more verbosity

Release 0.4.6

Gael varoquaux 2010-11-15

ENH: Deal with interruption in parallel

Gael varoquaux 2010-11-13

BUG: Exceptions raised by Parallel when n_job=1 are no longer captured.

Gael varoquaux 2010-11-13

BUG: Capture wrong arguments properly (better error message)

Release 0.4.5

Pietro Berkes 2010-09-04

BUG: Fix Windows peculiarities with path separators and file names BUG: Fix more windows locking bugs

Gael varoquaux 2010-09-03

ENH: Make sure that exceptions raised in Parallel also inherit from the original exception class ENH: Add a shadow set of exceptions

Fabian Pedregosa 2010-09-01

ENH: Clean up the code for parallel. Thanks to Fabian Pedregosa for the patch.

Release 0.4.4

Gael varoquaux 2010-08-23

BUG: Fix Parallel on computers with only one CPU, for n_jobs=-1.

Gael varoquaux 2010-08-02

BUG: Fix setup.py for extra setuptools args.

Gael varoquaux 2010-07-29

MISC: Silence tests (and hopefuly Yaroslav :P)

Release 0.4.3

Gael Varoquaux 2010-07-22

BUG: Fix hashing for function with a side effect modifying their input argument. Thanks to Pietro Berkes for reporting the bug and proving the patch.

Release 0.4.2

Gael Varoquaux 2010-07-16

BUG: Make sure that joblib still works with Python2.5. => release 0.4.2

Release 0.4.1

CHAPTER 3

Module reference

Memory([location, backend, cachedir, ...])	A context object for caching a function's return value each time it is called with the same input arguments.
Parallel([n_jobs, backend, verbose, ...])	Helper class for readable parallel mapping.

3.1 joblib.Memory

class joblib.**Memory**(*location=None*, *backend='local'*, *cachedir=None*, *mmap_mode=None*, *compress=False*, *verbose=1*, *bytes_limit=None*, *backend_options=None*)

A context object for caching a function's return value each time it is called with the same input arguments.

All values are cached on the filesystem, in a deep directory structure.

Read more in the *User Guide*.

Parameters

location: str or None The path of the base directory to use as a data store or None. If None is given, no caching is done and the Memory object is completely transparent. This option replaces cachedir since version 0.12.

backend: str, optional Type of store backend for reading/writing cache files. Default: 'local'. The 'local' backend is using regular filesystem operations to manipulate data (open, mv, etc) in the backend.

cachedir: str or None, optional

mmap_mode: {None, 'r+', 'r', 'w+', 'c'}, optional The memmapping mode used when loading from cache numpy arrays. See numpy.load for the meaning of the arguments.

compress: boolean, or integer, optional Whether to zip the stored data on disk. If an integer is given, it should be between 1 and 9, and sets the amount of compression. Note that compressed arrays cannot be read by memmapping.

verbose: int, optional Verbosity flag, controls the debug messages that are issued as functions are evaluated.

bytes_limit: int, optional Limit in bytes of the size of the cache.

backend_options: dict, optional Contains a dictionnary of named parameters used to configure the store backend.

__init__(*location=None*, *backend='local'*, *cachedir=None*, *mmap_mode=None*, *compress=False*, *verbose=1*, *bytes_limit=None*, *backend_options=None*)

Methods

__init__([location, backend, cachedir, ...])	
cache([func, ignore, verbose, mmap_mode])	Decorates the given function func to only compute its return value for input arguments not cached on disk.
clear([warn])	Erase the complete cache directory.
debug(msg)	
eval(func, *args, **kwargs)	Eval function func with arguments **args* and ***kwargs*, in the context of the memory.
format(obj[, indent])	Return the formatted representation of the object.
reduce_size()	Remove cache elements to make cache size fit in bytes_limit.
warn(msg)	

3.1.1 Examples using joblib.Memory

- *Checkpoint using joblib.Memory and joblib.Parallel*
- *How to use joblib.Memory*

3.2 joblib.Parallel

class joblib.**Parallel**(*n_jobs=None*, *backend=None*, *verbose=0*, *timeout=None*, *pre_dispatch='2 * n_jobs'*, *batch_size='auto'*, *temp_folder=None*, *max_nbytes='1M'*, *mmap_mode='r'*, *prefer=None*, *require=None*)

Helper class for readable parallel mapping.

Read more in the *User Guide*.

Parameters

n_jobs: int, default: None The maximum number of concurrently running jobs, such as the number of Python worker processes when backend="multiprocessing" or the size of the thread-pool when backend="threading". If -1 all CPUs are used. If 1 is given, no parallel computing code is used at all, which is useful for debugging. For n_jobs below -1, (n_cpus + 1 + n_jobs) are used. Thus for n_jobs = -2, all CPUs but one are used. None is a marker for 'unset' that will be interpreted as n_jobs=1 (sequential execution) unless the call is performed under a parallel_backend context manager that sets another value for n_jobs.

backend: str, ParallelBackendBase instance or None, default: 'loky' Specify the parallelization backend implementation. Supported backends are:

- "loky" used by default, can induce some communication and memory overhead when exchanging input and output data with the worker Python processes.

- "multiprocessing" previous process-based backend based on *multiprocessing.Pool*. Less robust than *loky*.
- "threading" is a very low-overhead backend but it suffers from the Python Global Interpreter Lock if the called function relies a lot on Python objects. "threading" is mostly useful when the execution bottleneck is a compiled extension that explicitly releases the GIL (for instance a Cython loop wrapped in a "with nogil" block or an expensive call to a library such as NumPy).
- finally, you can register backends by calling register_parallel_backend. This will allow you to implement a backend of your liking.

It is not recommended to hard-code the backend name in a call to Parallel in a library. Instead it is recommended to set soft hints (prefer) or hard constraints (require) so as to make it possible for library users to change the backend from the outside using the parallel_backend context manager.

prefer: str in {'processes', 'threads'} or None, default: None Soft hint to choose the default backend if no specific backend was selected with the parallel_backend context manager. The default process-based backend is 'loky' and the default thread-based backend is 'threading'.

require: 'sharedmem' or None, default None Hard constraint to select the backend. If set to 'sharedmem', the selected backend will be single-host and thread-based even if the user asked for a non-thread based backend with parallel_backend.

verbose: int, optional The verbosity level: if non zero, progress messages are printed. Above 50, the output is sent to stdout. The frequency of the messages increases with the verbosity level. If it more than 10, all iterations are reported.

timeout: float, optional Timeout limit for each task to complete. If any task takes longer a TimeOutError will be raised. Only applied when n_jobs != 1

pre_dispatch: {'all', integer, or expression, as in '3*n_jobs'} The number of batches (of tasks) to be pre-dispatched. Default is '2*n_jobs'. When batch_size="auto" this is reasonable default and the workers should never starve.

batch_size: int or 'auto', default: 'auto' The number of atomic tasks to dispatch at once to each worker. When individual evaluations are very fast, dispatching calls to workers can be slower than sequential computation because of the overhead. Batching fast computations together can mitigate this. The `'auto'` strategy keeps track of the time it takes for a batch to complete, and dynamically adjusts the batch size to keep the time on the order of half a second, using a heuristic. The initial batch size is 1. `batch_size="auto"` with `backend="threading"` will dispatch batches of a single task at a time as the threading backend has very little overhead and using larger batch size has not proved to bring any gain in that case.

temp_folder: str, optional Folder to be used by the pool for memmapping large arrays for sharing memory with worker processes. If None, this will try in order:

- a folder pointed by the JOBLIB_TEMP_FOLDER environment variable,
- /dev/shm if the folder exists and is writable: this is a RAM disk filesystem available by default on modern Linux distributions,
- the default system temporary folder that can be overridden with TMP, TMPDIR or TEMP environment variables, typically /tmp under Unix operating systems.

Only active when backend="loky" or "multiprocessing".

max_nbytes int, str, or None, optional, 1M by default Threshold on the size of arrays passed to the workers that triggers automated memory mapping in temp_folder. Can be an int in

Bytes, or a human-readable string, e.g., '1M' for 1 megabyte. Use None to disable memmapping of large arrays. Only active when backend="loky" or "multiprocessing".

mmap_mode: {None, 'r+', 'r', 'w+', 'c'} Memmapping mode for numpy arrays passed to workers. See 'max_nbytes' parameter documentation for more details.

Notes

This object uses workers to compute in parallel the application of a function to many different arguments. The main functionality it brings in addition to using the raw multiprocessing or concurrent.futures API are (see examples for details):

- More readable code, in particular since it avoids constructing list of arguments.
- **Easier debugging:**
  - informative tracebacks even when the error happens on the client side
  - using 'n_jobs=1' enables to turn off parallel computing for debugging without changing the code-path
  - early capture of pickling errors
- An optional progress meter.
- Interruption of multiprocesses jobs with 'Ctrl-C'
- Flexible pickling control for the communication to and from the worker processes.
- Ability to use shared memory efficiently with worker processes for large numpy-based datastructures.

Examples

A simple example:

```
>>> from math import sqrt
>>> from joblib import Parallel, delayed
>>> Parallel(n_jobs=1)(delayed(sqrt)(i**2) for i in range(10))
[0.0, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]
```

Reshaping the output when the function has several return values:

```
>>> from math import modf
>>> from joblib import Parallel, delayed
>>> r = Parallel(n_jobs=1)(delayed(modf)(i/2.) for i in range(10))
>>> res, i = zip(*r)
>>> res
(0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5)
>>> i
(0.0, 0.0, 1.0, 1.0, 2.0, 2.0, 3.0, 3.0, 4.0, 4.0)
```

The progress meter: the higher the value of *verbose*, the more messages:

```
>>> from time import sleep
>>> from joblib import Parallel, delayed
>>> r = Parallel(n_jobs=2, verbose=10)(delayed(sleep)(.2) for _ in range(10))
[Parallel(n_jobs=2)]: Done   1 tasks      | elapsed:    0.6s
[Parallel(n_jobs=2)]: Done   4 tasks      | elapsed:    0.8s
[Parallel(n_jobs=2)]: Done  10 out of  10 | elapsed:    1.4s finished
```

Traceback example, note how the line of the error is indicated as well as the values of the parameter passed to the function that triggered the exception, even though the traceback happens in the child process:

```
>>> from heapq import nlargest
>>> from joblib import Parallel, delayed
>>> Parallel(n_jobs=2)(delayed(nlargest)(2, n) for n in (range(4), 'abcde', 3))
#...
---------------------------------------------------------------------------
Sub-process traceback:
---------------------------------------------------------------------------
TypeError                                          Mon Nov 12 11:37:46 2012
PID: 12934                                    Python 2.7.3: /usr/bin/python
...........................................................................
/usr/lib/python2.7/heapq.pyc in nlargest(n=2, iterable=3, key=None)
    419         if n >= size:
    420             return sorted(iterable, key=key, reverse=True)[:n]
    421
    422     # When key is none, use simpler decoration
    423     if key is None:
--> 424         it = izip(iterable, count(0,-1))                    # decorate
    425         result = _nlargest(n, it)
    426         return map(itemgetter(0), result)                   # undecorate
    427
    428     # General case, slowest method
 TypeError: izip argument #1 must support iteration
___________________________________________________________________________
```

Using pre_dispatch in a producer/consumer situation, where the data is generated on the fly. Note how the producer is first called 3 times before the parallel loop is initiated, and then called to generate new data on the fly:

```
>>> from math import sqrt
>>> from joblib import Parallel, delayed
>>> def producer():
...     for i in range(6):
...         print('Produced %s' % i)
...         yield i
>>> out = Parallel(n_jobs=2, verbose=100, pre_dispatch='1.5*n_jobs')(
...                delayed(sqrt)(i) for i in producer())
Produced 0
Produced 1
Produced 2
[Parallel(n_jobs=2)]: Done 1 jobs     | elapsed:  0.0s
Produced 3
[Parallel(n_jobs=2)]: Done 2 jobs     | elapsed:  0.0s
Produced 4
[Parallel(n_jobs=2)]: Done 3 jobs     | elapsed:  0.0s
Produced 5
[Parallel(n_jobs=2)]: Done 4 jobs     | elapsed:  0.0s
[Parallel(n_jobs=2)]: Done 6 out of 6 | elapsed:  0.0s remaining: 0.0s
[Parallel(n_jobs=2)]: Done 6 out of 6 | elapsed:  0.0s finished
```

__init__(*n_jobs=None*, *backend=None*, *verbose=0*, *timeout=None*, *pre_dispatch='2 * n_jobs'*, *batch_size='auto'*, *temp_folder=None*, *max_nbytes='1M'*, *mmap_mode='r'*, *prefer=None*, *require=None*)

Methods

`__init__`([n_jobs, backend, verbose, ...])	
`debug`(msg)	
`dispatch_next`()	Dispatch more data for parallel processing
`dispatch_one_batch`(iterator)	Prefetch the tasks for the next batch and dispatch them.
`format`(obj[, indent])	Return the formatted representation of the object.
`print_progress`()	Display the process of the parallel execution only a fraction of time, controlled by self.verbose.
`retrieve`()	
`warn`(msg)	

3.2.1 Examples using `joblib.Parallel`

- *Random state within joblib.Parallel*
- *Checkpoint using joblib.Memory and joblib.Parallel*
- *NumPy memmap in joblib.Parallel*
- *Using dask distributed for single-machine parallel computing*

`dump`(value, filename[, compress, protocol, ...])	Persist an arbitrary Python object into one file.
`load`(filename[, mmap_mode])	Reconstruct a Python object from a file persisted with joblib.dump.
`hash`(obj[, hash_name, coerce_mmap])	Quick calculation of a hash to identify uniquely Python objects containing numpy arrays.
`register_compressor`(compressor_name, compressor)	Register a new compressor.

3.3 `joblib`.dump

joblib.**dump**(*value*, *filename*, *compress=0*, *protocol=None*, *cache_size=None*)

Persist an arbitrary Python object into one file.

Read more in the *User Guide*.

Parameters

value: any Python object The object to store to disk.

filename: str, pathlib.Path, or file object. The file object or path of the file in which it is to be stored. The compression method corresponding to one of the supported filename extensions ('.z', '.gz', '.bz2', '.xz' or '.lzma') will be used automatically.

compress: int from 0 to 9 or bool or 2-tuple, optional Optional compression level for the data. 0 or False is no compression. Higher value means more compression, but also slower read and write times. Using a value of 3 is often a good compromise. See the notes for more details. If compress is True, the compression level used is 3. If compress is a 2-tuple, the first element must correspond to a string between supported compressors (e.g 'zlib', 'gzip', 'bz2', 'lzma' 'xz'), the second element must be an integer from 0 to 9, corresponding to the compression level.

protocol: int, optional Pickle protocol, see pickle.dump documentation for more details.

cache_size: positive int, optional This option is deprecated in 0.10 and has no effect.

Returns

filenames: list of strings The list of file names in which the data is stored. If compress is false, each array is stored in a different file.

See also:

joblib.load corresponding loader

Notes

Memmapping on load cannot be used for compressed files. Thus using compression can significantly slow down loading. In addition, compressed files take extra extra memory during dump and load.

3.3.1 Examples using `joblib.dump`

- *NumPy memmap in joblib.Parallel*
- *Improving I/O using compressors*

3.4 `joblib`.load

`joblib.load`(*filename*, *mmap_mode=None*)

Reconstruct a Python object from a file persisted with joblib.dump.

Read more in the *User Guide*.

Parameters

filename: str, pathlib.Path, or file object. The file object or path of the file from which to load the object

mmap_mode: {None, 'r+', 'r', 'w+', 'c'}, optional If not None, the arrays are memory-mapped from the disk. This mode has no effect for compressed files. Note that in this case the reconstructed object might no longer match exactly the originally pickled object.

Returns

result: any Python object The object stored in the file.

See also:

joblib.dump function to save an object

Notes

This function can load numpy array files saved separately during the dump. If the mmap_mode argument is given, it is passed to np.load and arrays are loaded as memmaps. As a consequence, the reconstructed object might not match the original pickled object. Note that if the file was saved with compression, the arrays cannot be memmapped.

3.4.1 Examples using `joblib.load`

- *NumPy memmap in joblib.Parallel*
- *Improving I/O using compressors*

3.5 `joblib`.hash

`joblib.`**`hash`**(*obj*, *hash_name='md5'*, *coerce_mmap=False*)
Quick calculation of a hash to identify uniquely Python objects containing numpy arrays.

Parameters

hash_name: 'md5' or 'sha1' Hashing algorithm used. sha1 is supposedly safer, but md5 is faster.

coerce_mmap: boolean Make no difference between np.memmap and np.ndarray

3.6 `joblib`.register_compressor

`joblib.`**`register_compressor`**(*compressor_name*, *compressor*, *force=False*)
Register a new compressor.

Parameters

compressor_name: str. The name of the compressor.

compressor: CompressorWrapper An instance of a 'CompressorWrapper'.

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