Parallelization in Python — Dask

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Custom Graphs: Intricate job.

Schedulers: Take the above specs, and run as efficiently as possible.

Chunked Algorithms

```
# Try chunked matrix operations
import dask.array as da
import numpy as np
baseArray = np.random.rand(10000,10000)
# Make positive-definite
baseArray = np.dot(baseArray,baseArray.transpose())
smallChunks = da.from_array(baseArray,chunks=(100))
largeChunks = da.from_array(baseArray,chunks=(1000))
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```
In [2]: %time np.linalg.cholesky(baseArray)
        %time da.linalg.cholesky(smallChunks)
        %time da.linalg.cholesky(largeChunks)

CPU times: user 21.5 s, sys: 849 ms, total: 22.4 s
Wall time: 6.43 s
CPU times: user 385 ms, sys: 26.4 ms, total: 412 ms
Wall time: 440 ms
CPU times: user 444 µs, sys: 1 µs, total: 445 µs
Wall time: 449 µs
```

Lazy Evaluation

```
npOnes = np.ones((10000,10000))
%time np.exp(npOnes)[1:100,1:100]

daskOnes = da.ones((10000,10000), chunks=(100))
%time da.exp(daskOnes)[1:100,1:100]
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Result: 10× speedup. (970ms → 90ms)

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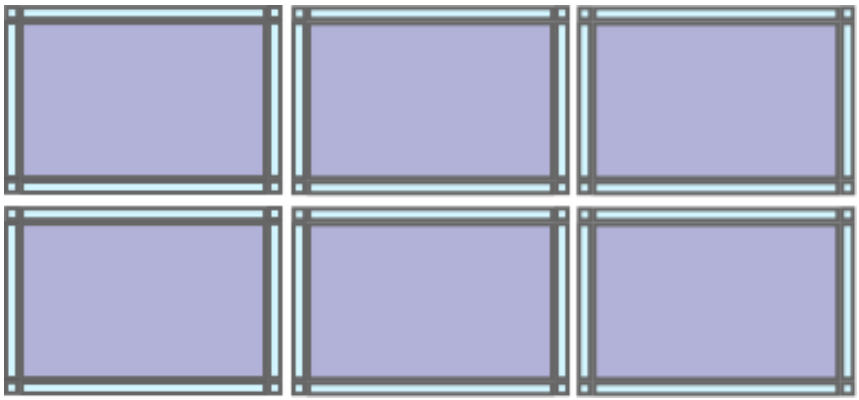
Solution: Ghosting. Expands each blocks by neighbor's borders.



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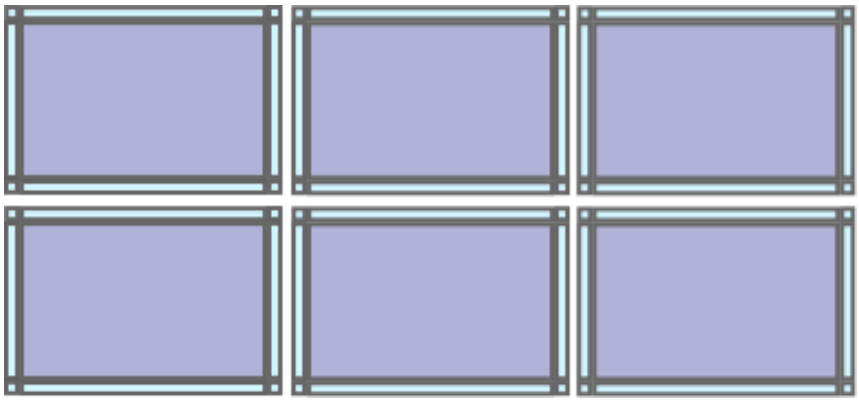

Can specify boundary conditions in {periodic, reflect, length}.
More on this in notebook.

Internals: Dictionary

```
import itertools slice =
itertools.islice(smallChunks.dask.items(), 0, 1) for
key, value in slice:  print(key,value)
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Result:

Key: (from-array-8c463a3b962efd2e81b47e1832acfb81', 83, 94)
Value: (<function getarray at 0x1083260d0>,
'from-array-8c463a3b962efd2e81b47e1832acfb81', (slice(8300, 8400, None), slice(9400, 9500, None))

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Data retrieved when needed.
Syntax: `cache = Chest()`, `cache=Chest(path,memBound)`

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Takeaway: Use if you can.

Reference: dir(dask.array)

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Dask Graph: {'y':(add,2,x),'x':(2,3)}
Note: Constructor doesn't reference Dask.

Some Lingo

Graph: Such a dictionary.
Key: Hashable values, that aren't tasks. (i.e., pieces of data).
Tasks: Tuple, with a callable first element (something which needs to be computed).
Arguments: Non-function elements of a task. Could be other keys, literals, tasks, or lists thereof.

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LISP users will (apparently) recognize this as an s-expression.
Quick aside: Functional programming. `https://xkcd.com/297/`.

Graph Methods

`get`: Like Julian `fetch`. Has the scheduler go in and actually retrieve the value — the backend can be arbtrarily complex (i.e, parallel).
Actually a scheduler method (i.e. `dask.threaded.get`)
`compute`: For a collection, outputs the result of a computation (i.e., bypasses scheduler `get`:)

```
timeSum = timeData.sum().compute()
```

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Two general kinds of optimization:

- Simplify computation.
- Improve parallelism.

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Goal: `results = get(dsk,['print1','print2'])`

What shape makes a graph optimal?

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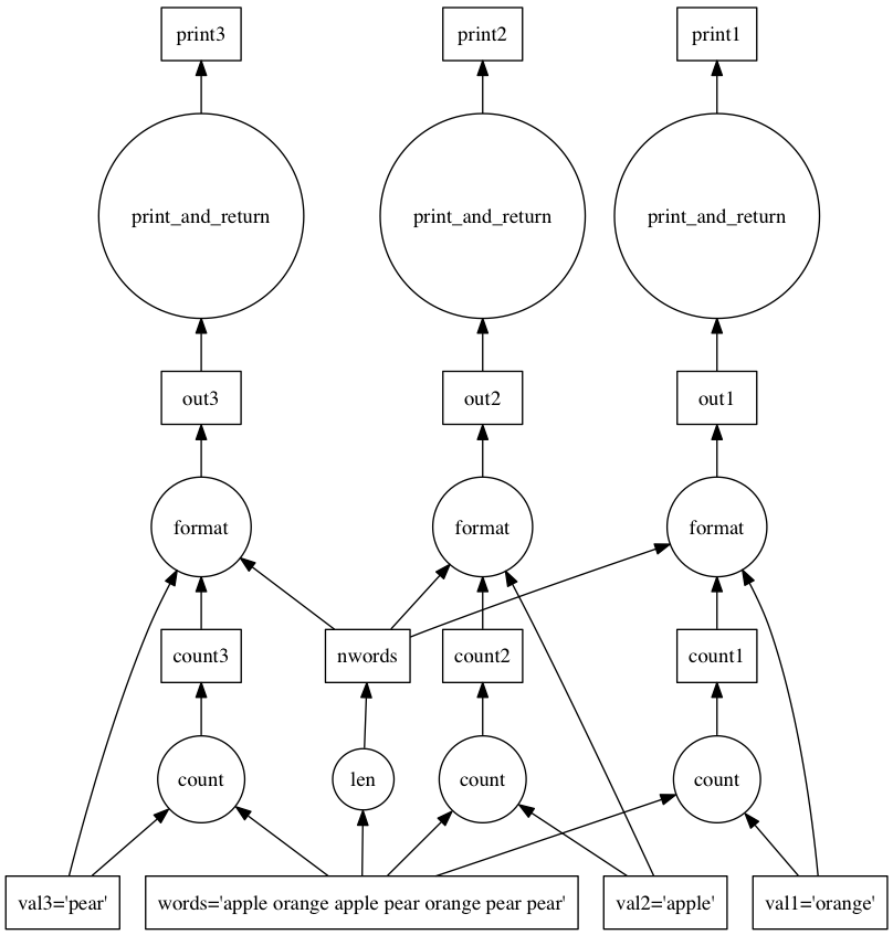

Graph Optimization - Cull

```
from dask.optimize import cull;
results=get(cull(dsk,args),args...)
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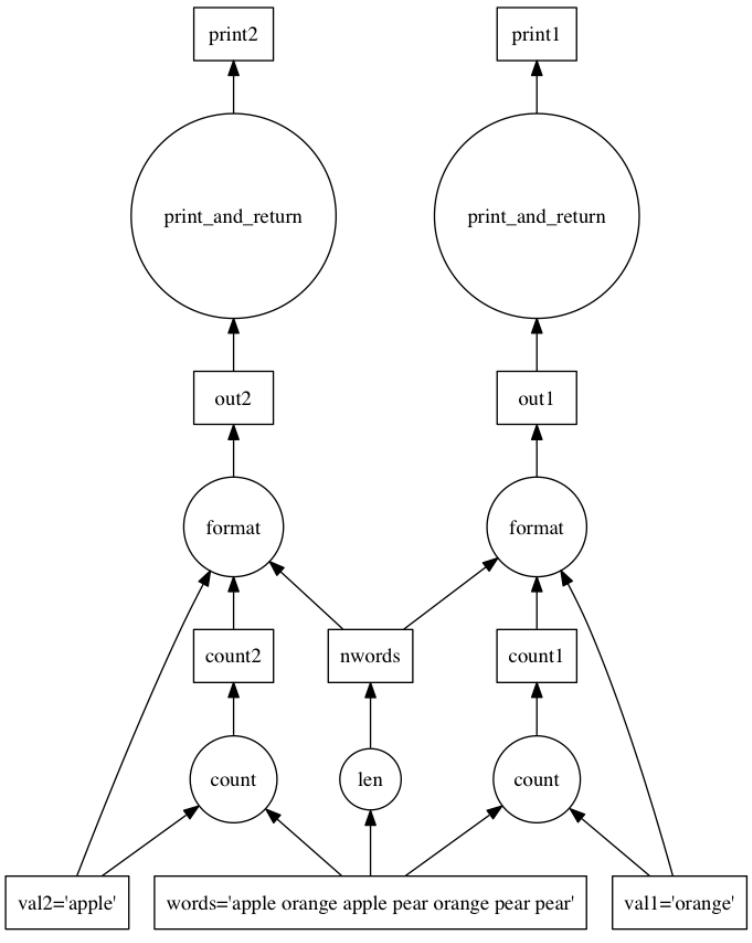

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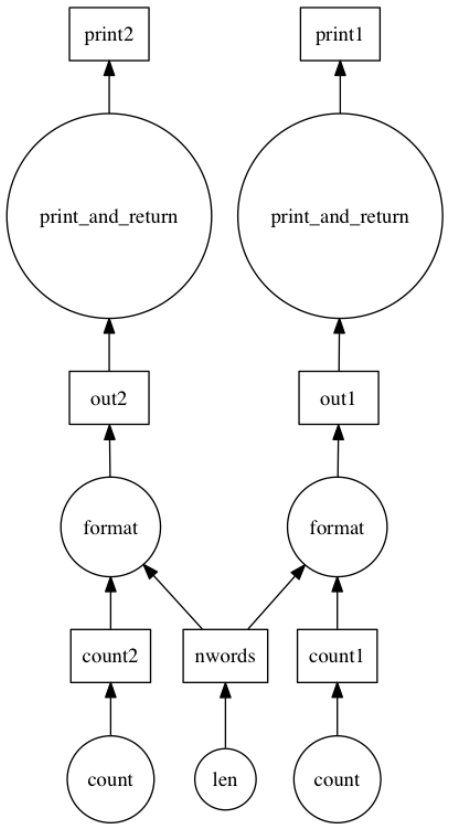

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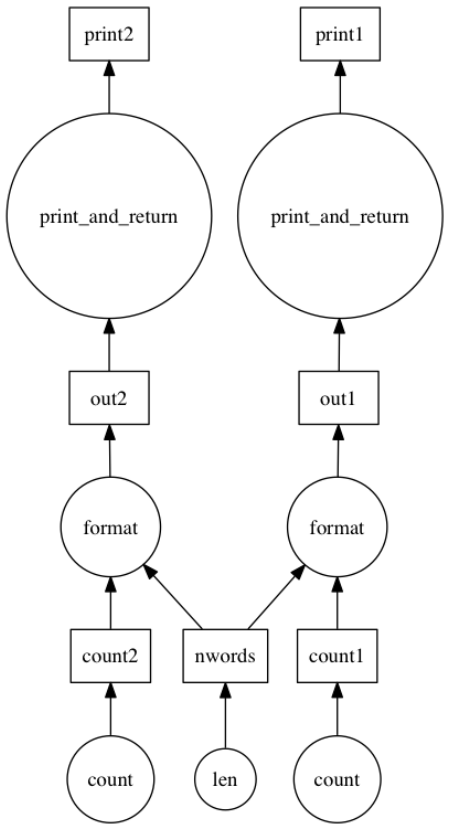

Code: dsk2 = inline(dsk1)

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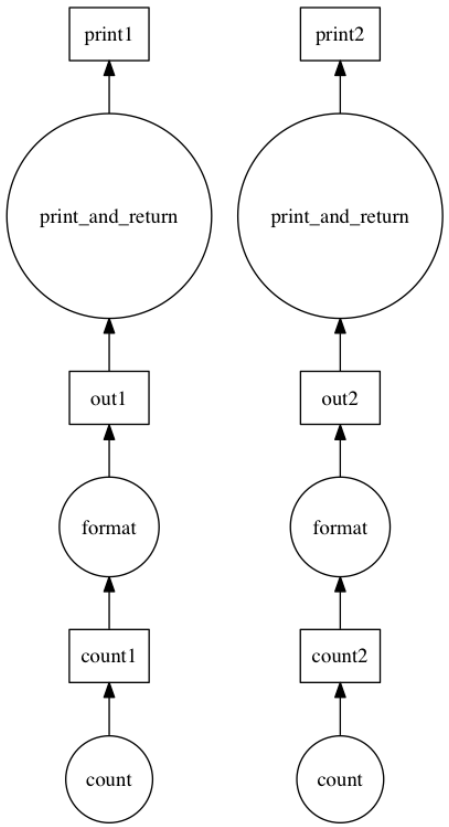

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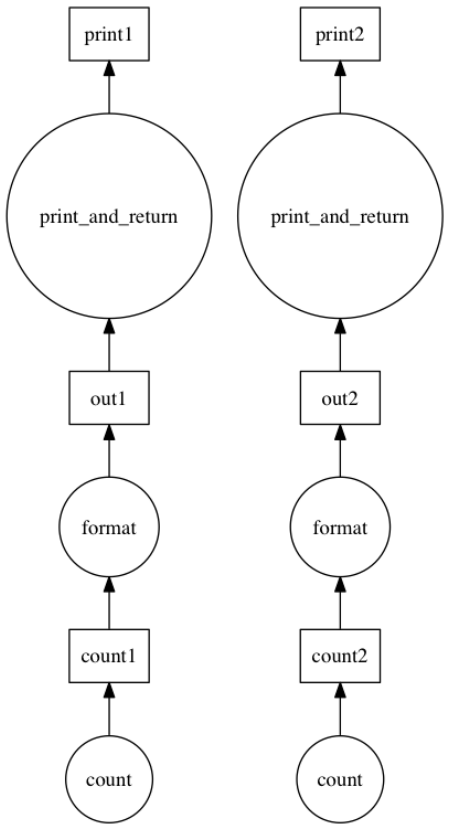

Code: $dsk3 = inline_functions(dsk2, [len, str.split])$

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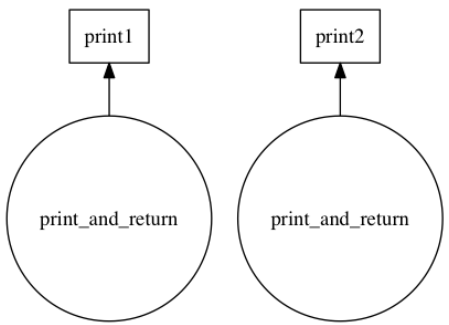

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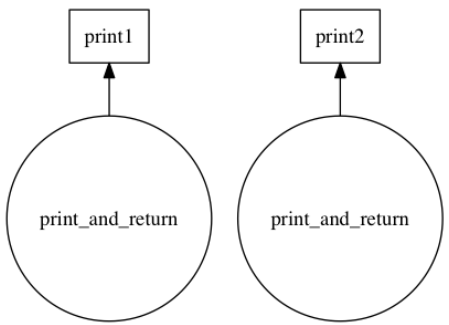

Code: `dsk4 = fuse(dsk3)`

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- *dask.multi_processing.get* — a scheduler which delegates tasks to a bunch of processes
- *dask.async.get_sync* — a synchronous scheduler, useful for debugging
- *distributed.Executor.get* — a scheduler for executing distributed projects (i.e., across multiple machines). This is a separate GitHub repo (distributed).

How Scheduling Works

I/O-bound code vs. CPU-bound code.

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- Tiebreaker 1: Tasks placed on a stack, so LIFO ordering.
- Tiebreaker 2 (deciding between tasks to place on stack): Use the ordering of tasks induced by a depth-first search on the graph.
- Tiebreaker 3 (how to choose between children): Prioritize those children upon whom the most data depends.

Overhead and Scaling — Message Passing

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Key performance takeaways for Dask (threaded):

- 1 ms overhead per task
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This should be surprising! Remember, number of edges grows as follows: $\binom{n}{2} p$

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Contrasts with:
`Set`: Unordered collection, no repeats.
`List`: Ordered collection, has repeats.

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Writable to text, to DataFrame.

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Other Functions: `topk`*, Cartesian product between two bags.

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Expensive. Recommended workflow is to clean using Bags, and then perform ordered operations using `DataFrame` or `Array`.
Dask Implementation: https://github.com/dask/partd

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Natural hierarchy of problems, in terms of parallelizability.

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Many operations require setting such an index.