Building Dask Bags & Globbing

PARALLEL COMPUTING WITH DASK



Dhavide Aruliah
Director of Training, Anaconda



Sequences to bags

6

```
the_bag.any(), the_bag.all()
```

True, False

Reading text files

```
import dask.bag as db
zen = db.read_text('zen')
taken = zen.take(1)
type(taken)
```

tuple

Reading text files

```
taken
('The Zen of Python, by Tim Peters\n',)
zen.take(3)
('The Zen of Python, by Tim Peters\n',
 '\n',
 'Beautiful is better than ugly.\n')
```



Glob expressions

```
import dask.dataframe as dd
df = dd.read_csv('taxi/*.csv', assume_missing=True)
```

- taxi/*.csv is a glob expression
- taxi/*.csv matches:

```
taxi/yellow_tripdata_2015-01.csv
taxi/yellow_tripdata_2015-02.csv
taxi/yellow_tripdata_2015-03.csv
...
taxi/yellow_tripdata_2015-10.csv
taxi/yellow_tripdata_2015-11.csv
taxi/yellow_tripdata_2015-12.csv
```



Using Python's glob module

```
%ls
```

```
Alice Dave README a02.txt a04.txt b05.txt b07.txt b09.txt b11.t
Bob Lisa a01.txt a03.txt a05.txt b06.txt b08.txt b10.txt taxi
```

```
import glob

txt_files = glob.glob('*.txt')

txt_files
```



More glob patterns

```
glob.glob('b*.txt')
                                 glob.glob('?0[1-6].txt')
['b05.txt',
                                 ['a01.txt',
 'b06.txt',
                                  'a02.txt',
 'b07.txt',
                                  'a03.txt',
 'b08.txt',
                                  'a04.txt',
 'b09.txt',
                                  'a05.txt',
 'b10.txt',
                                  'b05.txt',
 'b11.txt']
                                  'b06.txt']
glob.glob('b?.txt')
```



More glob patterns

```
glob.glob('??[1-6].txt')
```



Permissible glob patterns

- Filename characters (e.g., file-02_tmp.txt)
- Wildcard character * : matches 0 or more
- Wildcard character ? : matches exactly 1
- Character ranges (e.g., [0-5], [a-m], [A-Z0-9])

Let's practice!

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Functional Approaches using Dask Bags

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Functional programming

- Functions: first-class data
- Higher-order functions:
 - functions as input or output to functions
- Functions replacing loops with:
 - map operations
 - filter operations
 - reduction operations (or aggregations)

Using map

```
def squared(x):
    return x ** 2
squares = map(squared, [1, 2, 3, 4, 5, 6])
squares
```

```
<map at 0x1037a1b70>
```

```
squares = list(squares)
squares
```

```
[1, 4, 9, 16, 25, 36]
```



Using filter

```
def is_even(x):
...:    return x % 2 == 0

evens = filter(is_even, [1, 2, 3, 4, 5, 6])
list(evens)
```

```
[2, 4, 6]
```

```
even_squares = filter(is_even, squares))
list(even_squares)
```

```
[4, 16, 36]
```



Using dask.bag.map

```
import dask.bag as db
numbers = db.from_sequence([1, 2, 3, 4, 5, 6])
squares = numbers.map(squared)
squares
```

dask.bag<map-squared, npartitions=6>

```
result = squares.compute() # Must fit in memory
result
```

[1, 4, 9, 16, 25, 36]



Using dask.bag.filter

```
numbers = db.from_sequence([1, 2, 3, 4, 5, 6])
evens = numbers.filter(is_even)
evens.compute()
```

[2, 4, 6]

```
even_squares = numbers.map(squared).filter(is_even)
even_squares.compute()
```

[4, 16, 36]



Using .str & string methods

```
zen = db.read_text('zen.txt')
uppercase = zen.str.upper()
uppercase.take(1)
```

```
('THE ZEN OF PYTHON, BY TIM PETERS\n',)
```

```
def my_upper(string):
...: return string.upper()
my_uppercase = zen.map(my_upper)
my_uppercase.take(1)
```

```
('THE ZEN OF PYTHON, BY TIM PETERS\n',)
```



A bigger example I

```
def load(k):
     template = 'yellow_tripdata_2015-{:02d}.csv'
     return pd.read_csv(template.format(k))
def average(df):
     return df['total_amount'].mean()
def total(df):
     return df['total_amount'].sum()
data = db.from_sequence(range(1, 13)).map(load)
data
```

```
dask.bag<map-loa..., npartitions=12>
```



A bigger example II

```
totals = data.map(total)
averages = data.map(average)
totals.compute()
```

```
[1175217.5200009614,
947282.0900005419,
956752.3400005258,
1304602.4800011297,
1354966.290001166,
1251511.6500010253,
1167936.1000008786,
915174.880000469,
994643.300000564,
1273267.4800010026,
1158279.990000822,
1166242.130000856]
```

averages.compute()

```
[14.75051171665384,

15.463557844570461,

15.790076907851297,

15.971334410669527,

16.477159899324676,

16.250654434978838,

16.163639508987067,

16.164026987891997,

16.364647910506154,

16.544750841370114,

16.385807916489675,

16.28056690958003]
```



Reductions (aggregations)

```
t_sum, t_min, t_max, = totals.sum(), totals.min(), totals.max()
t_mean, t_std, = totals.mean(), totals.std()
stats = [t_sum, t_min, t_max, t_mean, t_std]
%time [s.compute() for s in stats]
```

```
CPU times: user 142 ms, sys: 101 ms, total: 243 ms
Wall time: 4.57 s
[13665876.250009943,
915174.880000469,
1354966.290001166,
1138823.0208341617,
144025.81874405374]
```



Reductions (aggregations)

```
import dask
%time dask.compute(t_sum, t_min, t_max, t_mean, t_std)
```

```
CPU times: user 63.7 ms, sys: 29.1 ms, total: 92.7 ms
Wall time: 852 ms
(13665876.250009943,
915174.880000469,
1354966.290001166,
1138823.0208341617,
144025.81874405374)
```



Let's practice!

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Analyzing Congressional Legislation

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Director of Training, Anaconda





JSON data files

- JavaScript Object Notation:
 - stored as plain text
 - common web format
 - direct mapping to Python lists & dictionaries

Sample JSON FIle: items.json

items.json

```
"name": "item1",
  "content": ["a", "b", "c"]
},
  "name": "item2",
  "content": {"a": 0, "b": 1}
```

Using json module

```
import json
with open('items.json') as f:
   items = json.load(f)
type(items)
```

list

```
items[0]
items[1]
items[1]['content']['b']
```

```
{'content': ['a', 'b', 'c'], 'name': 'item1'}
{'content': {'a': 0, 'b': 1}, 'name': 'item2'}
1
```



JSON Files into Dask Bags

items-by-line.json

```
{"name": "item1", "content": ["a", "b", "c"]}
{"name": "item2", "content": {"a": 0, "b": 1}}
```

```
import dask.bag as db
items = db.read_text('items-by-line.json')
items.take(1) # Note: tuple containing a *string*
```

```
('{"name": "item1", "content": ["a", "b", "c"]}\n',)
```

JSON Files into Dask Bags

```
dict_items = items.map(json.loads) # converts strings -> other data
dict_items.take(2) # Note: tuple containing dicts
```

```
({'content': ['a', 'b', 'c'], 'name': 'item1'},
{'content': {'a': 0, 'b': 1}, 'name': 'item2'})
```

Plucking values

```
type(dict_items.take(2))
tuple
dict_items.take(2)[1]['content'] # Chained indexing
{'a': 0, 'b': 1}
dict_items.take(1)[0]['name'] # Chained indexing
'item1'
```



Plucking values

```
contents = dict_items.pluck('content')
names = dict_items.pluck('name')
contents
names
```

```
dask.bag<pluck-5..., npartitions=1>
dask.bag<pluck-3..., npartitions=1>
```

```
contents.compute()
names.compute()
```

```
[['a', 'b', 'c'], {'a': 0, 'b': 1}]
['item1', 'item2']
```

Congressional legislation metadata

- 23 JSON files
 - metadata about congressional bills
 - up to 1500 pieces of legislation per congress.
- Load all into Dask Bag
 - use current_status to count vetoed bills
 - use date info to compute average times

Metadata keys

Selected dictionary keys

```
'bill_type'
'title_without_number'
'related_bills'
'id'
'titles'
'display_number'
'major_actions'
'current_status_description'
'link'
'current_status_date'
committee_reports
'current_status_label'
'introduced_date'
'sponsor'
'current_status'
'title'
```

Warning: Not all available for every bill

Let's practice!

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