Erica Zhou (*ezhou*) & Katharina Gschwind (*gschwind*) 13 November 2019
Repo: *https://github.com/ericazhou7/6.s080-lab6*
Commit Hash: *c2433b7b1b27e00aac15d2b83d32e128381a4284*

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We can see that our computation gets faster as we have more workers who contribute to the task, while the actual predicted amount stays the same across trials.

Number of Cores	**Runtime (ms)**
1	2035.855200
2	1840.903200
4	1787.134400

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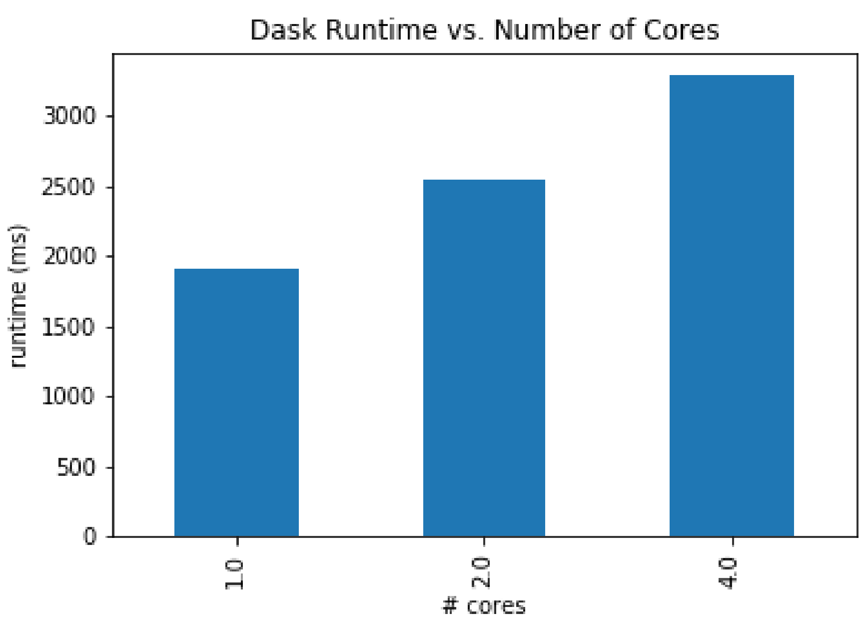
The rolling 5m 'y' average for the timeseries data looks like:

```
timestamp
2018-01-01 00:00:00   -0.263514
2018-01-01 00:00:01    0.215313
2018-01-01 00:00:02    0.120395
2018-01-01 00:00:03    0.289408
2018-01-01 00:00:04    0.314059
                          ...
2018-01-31 23:59:55   -0.027162
2018-01-31 23:59:56   -0.028964
2018-01-31 23:59:57   -0.026947
2018-01-31 23:59:58   -0.020739
2018-01-31 23:59:59   -0.017693
Freq: S, Name: y, Length: 2678400, dtype: float64
```

The entire series can be found in `part2.ipynb`.

The pandas runtime is faster than the fastest dask runtime by about 300ms. This suggests that the dataset isn't big enough for multiprocessing to make a difference. Additionally, the overhead of multiprocessing seems to outweigh the benefit because 2 & 4 cores take longer than 1 to run, and using dask even with 1 core takes more time than just using pandas. The runtime of using pandas including converting the table from dask, however, is longer than just using dask.



Operator	Runtime (ms)
dask (1 core)	1910.443300002953
dask (2 cores)	2538.1376999939675
dask (4 cores)	3287.3079999990296
pandas (with dask conversion)	5711.919199995464
pandas (computation only)	1247.863899996446

dask code:

```
n_workers = 1
runtime_df = pd.DataFrame(columns=['n_cores','runtime (ms)'])

while n_workers <= n_cores:
    # rescale cluster
    print('Resizing cluster to %s worker(s)...' % n_workers)
    cluster.scale(n_workers)
    time.sleep(1)

    # run calculation
    t_start = perf_counter()
    dd_df.y.rolling('5min').mean().loc['2018-01-01':'2018-01-31'].compute()
    t_stop = perf_counter()

    # save runtime to dataframe
    runtime = (t_stop - t_start)*1000
    runtime_df = runtime_df.append({'n_cores': n_workers,'runtime (ms)': runtime},
        ignore_index=True)
    print('dask time (ms): ', runtime)

    # double desired # workers
    n_workers *= 2;

# plot results
runtime_df.plot(x='n_cores',y='runtime (ms)',kind='bar',legend=False)
plt.title('Dask Runtime vs. Number of Cores')
plt.xlabel('# cores')
plt.ylabel('runtime (ms)')
plt.savefig('images/q2.png')
```

pandas code:

```
t_1 = perf_counter()
df = dd_df.compute()
t_2 = perf_counter()
df.y.rolling('5min').mean().loc['2018-01-01':'2018-01-31']
t_3 = perf_counter()
print('Pandas time for computation only(ms): %s' % ((t_3 - t_2)*1000))
print('Pandas time with table conversion (ms): %s' % ((t_3 - t_1)*1000))
```

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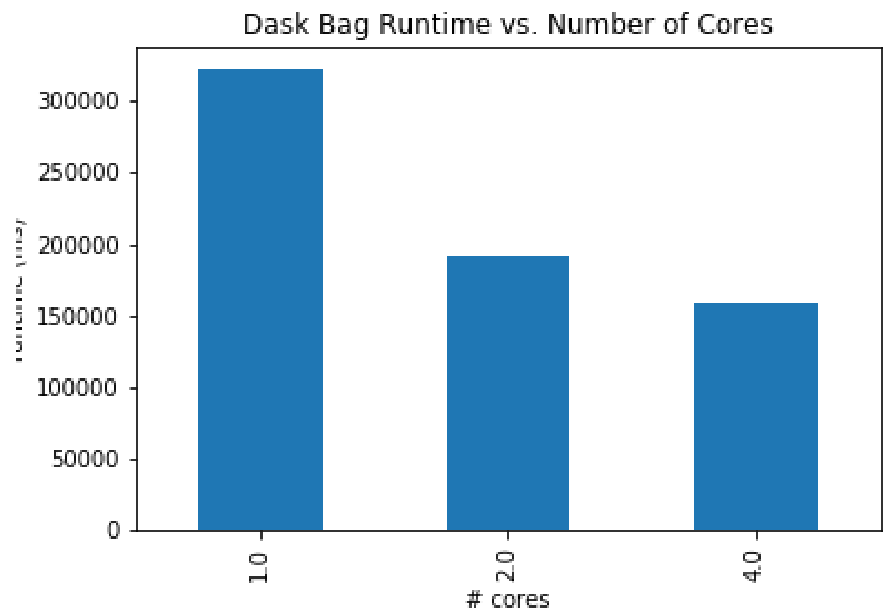
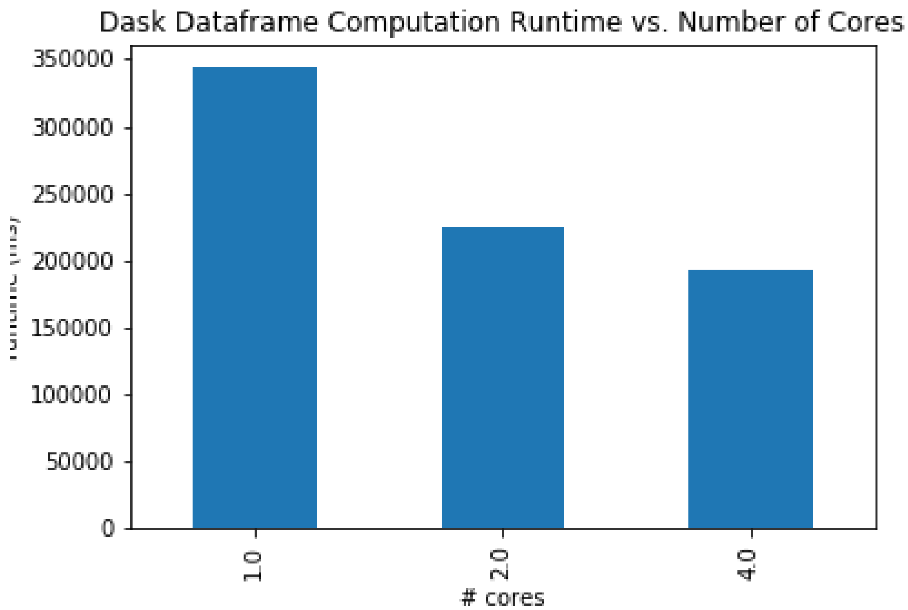
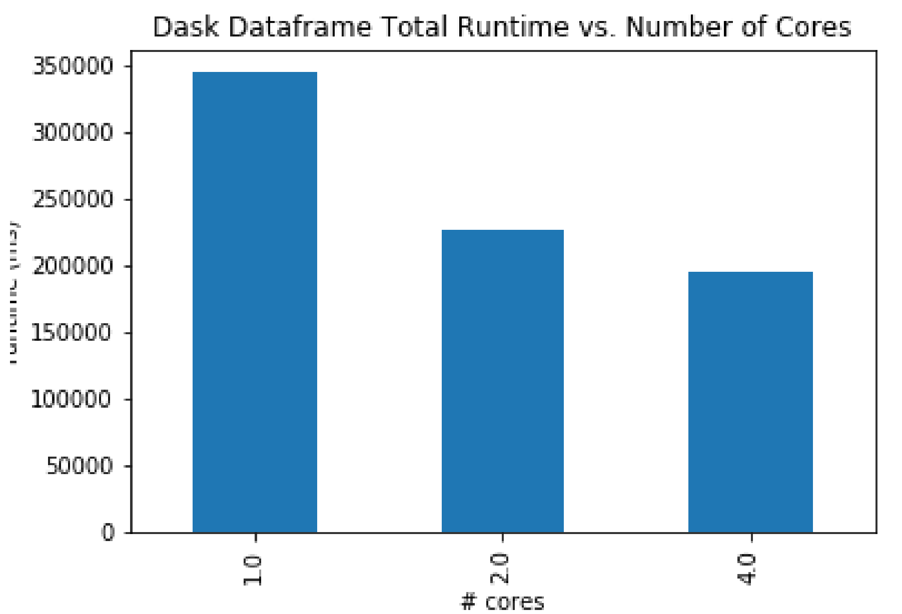
The top 2 notebook providers in August 2019 were **Github (374145 runs)** and **Gist (5894 runs)**. In this case, the dataset is large enough that multiprocessing does make a difference. Using 1 core takes significantly longer than 2 cores, which takes significantly more time than 4 cores. Overall, dask dataframe takes a little bit longer (20000-30000 ms more) on all tasks than dask bag, and only a very small minority (about 1000ms) of this is spent converting the dask representation to a dataframe.







Operator	**Runtime (ms)**
dask bag (1 core)	322395.9199000019
dask bag (2 cores)	191198.12199999433
dask bag (4 cores)	158067.04860000173
dask dataframe (1 core - computation only)	344221.50160000456
dask dataframe (1 core - pipeline)	345122.7319000027
dask dataframe (2 cores - computation only)	225037.7512999985
dask dataframe (2 cores - pipeline)	226004.4448999979
dask dataframe (4 cores - computation only)	192420.03690000274
dask dataframe (4 cores - pipeline)	194219.77809999953

dask bag code:

```
# get data
urls = (db.read_text('https://archive.analytics.mybinder.org/index.jsonl')
                .map(json.loads)
                .pluck('name')
                .compute())
urls = ['https://archive.analytics.mybinder.org/' + u for u in urls]
notebook_runs = db.read_text(urls).map(json.loads)

runtime_df_q3 = pd.DataFrame(columns=['n_cores','runtime (ms)'])
n_workers = 1

while n_workers <= n_cores:
    # resize cluster
    print('Resizing cluster to %s worker(s)...' % n_workers)
    cluster.scale(n_workers)
    time.sleep(1)

    # run calculation
    t_start = perf_counter()
    (notebook_runs.filter(lambda record: record['timestamp'].startswith('2019-08'))
                  .pluck('provider').frequencies(sort=True).take(2))
    t_stop = perf_counter()

    # save runtime to dataframe
    runtime = (t_stop - t_start)*1000
    runtime_df_q3 = (runtime_df_q3.append({'n_cores': n_workers,'runtime (ms)':
                        runtime},ignore_index=True))
    print('dask time (ms): ', runtime)

    # double desired # workers
    n_workers *= 2
```

dask dataframe code:

```
runtime_df_q3 = pd.DataFrame(columns=['n_cores','runtime (ms)'])
n_workers = 1

while n_workers <= n_cores:
    # resize cluster
    print('Resizing cluster to %s worker(s)...' % n_workers)
    cluster.scale(n_workers)
    time.sleep(1)

    # run calculation
    t1 = perf_counter()
    runs_df = notebook_runs.to_dataframe()
    t2 = perf_counter()
    runs_df[runs_df['timestamp'].str.startswith('2019-08')].provider.value_counts().
            nlargest(2).compute()
    t3 = perf_counter()

    # save runtime to dataframe
```

```
total_runtime = (t3 - t1)*1000
comp_runtime = (t3 - t2)*1000
runtime_df_q3_2 = runtime_df_q3_2.append({'n_cores': n_workers,
                                          'pipeline runtime (ms)': total_runtime,
                                          'computation runtime (ms)': comp_runtime},
                                         ignore_index=True)
print('computation time (ms): ', comp_runtime)
print('pipeline runtime (ms): ', total_runtime)

# double desired # workers
n_workers *= 2
```

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Our code can be found in `filter.py` and filters out urls based on whether their `status` has the value `success`, which ends up being **all urls**. Using different amounts of workers outputs the same result, but allows for speedup.

Workers	**Time**	**Status**
1	4274	success = 144000
2	4046	success = 144000
4	2385	success = 144000

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N/A

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We use the dataset of crimes on London streets found at: *https://data.police.uk/api/crimes-street-dates*. In `crime.py`, we calculate how often streets are mentioned in these monthly aggregates of crime at this url, and what the worst street by that metric is. We use multiprocessing to answer this question. We identify that (one of) the worst street(s, since many streets end up tying) is **Bedfordshire** with 36 many stop-and-searches (where stop-and-searches are the type of crimes reported within this specific data set).