Problem

Large number of files were created during the data collection process because ATTOM API returns a maximum of 10,000 records per call. Hence hundreds of API calls were made to collect non-truncated housing sales data for all counties of California between 1/1/2019 and 1/31/2021. This resulting in 322 files containing over 1 million rows. These files need to be processed and combined into a single dataframe for analysis. Further more, there needs to be a **provision** to process more data if we decide to pull more data from 2018, 2017, 2016 and prior years. We want to avoid running 'for' loops due to speed, efficiency and scalability reasons.

Solution

1. We solve this by **PARALLELIZING the Python processing of 322 text files using a DISTRIBUTED CLUSTER with DASK framework.** We use two macbook machines (called A and B) with 2 cores each and 8 GB RAM in each. 3rd or 4th machine can be easily added to the cluster.

2. We create a basic **PIPELINE** that automatically processes any new incoming JSON containing text file and immediately processes it and appends it to the main dataframe. This is required for scalability should we pull additional data after 2-3 weeks

3. Create HTTP server via Python so that all workers in the cluster have access to it via HTTP. This is a requirement for DASK distributed setup.

Implementation

Pandas has 2 bottlenecks - It is not easily scalable over a distributed cluster of machines and uses only 1 core at a time, which makes overall processing slow especially with a dataset with over a million rows. Also, Pandas was not designed for building scalable data pipelines. Therefore, we use DASK framework which consists of 3 main object classes - dataframe, array and bag. A DASK dataframe is different from a Pandas dataframe. A DASK scheduler process is initiated on 'A' and 2 'DASK worker' processes are set up (1 each on A and B).

In [1]:
```
import pandas as pd
import numpy as np

import dask.array as da
import dask.dataframe as dd
import dask.bag as bag
import json, time, aiohttp

from dask.distributed import LocalCluster, Client

pd.set_option('display.max_columns', 500)
```

In [62]:
```
cluster = LocalCluster()
client = Client('tcp://192.168.0.6:8786')
client
```

```
/opt/anaconda3/lib/python3.8/site-packages/distributed/node.py:151: UserWarning: Port 8787 is already in
use.
Perhaps you already have a cluster running?
```

```
Hosting the HTTP server on port 55699 instead
  warnings.warn(
```

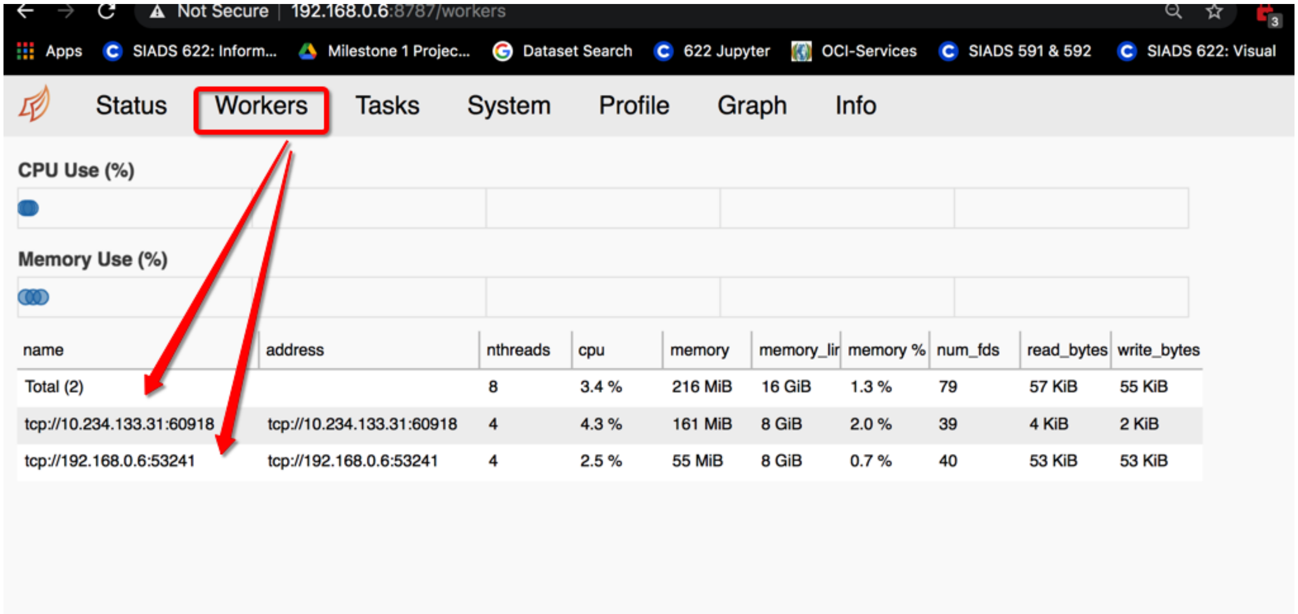
Out[62]:

Client

Scheduler: tcp://192.168.0.6:8786
Dashboard: http://192.168.0.6:8787/status

Cluster

Workers: 2
Cores: 8
Memory: 17.18 GB



In [63]:

```python
client.scheduler_info()
```

Out[63]:


```
{'type': 'Scheduler',
 'id': 'Scheduler-b1c052ff-2aa9-486c-acc5-f33e59a73563',
 'address': 'tcp://192.168.0.6:8786',
 'services': {'dashboard': 8787},
 'workers': {'tcp://10.234.133.31:60918': {'type': 'Worker',
   'id': 'tcp://10.234.133.31:60918',
   'host': '10.234.133.31',
   'resources': {},
   'local_directory': '/Users/namita/dask-worker-space/dask-worker-space/worker-7pc7oe0j',
   'name': 'tcp://10.234.133.31:60918',
   'nthreads': 4,
   'memory_limit': 8589934592,
   'last_seen': 1618541682.979007,
   'services': {'dashboard': 60919},
   'metrics': {'cpu': 3.5,
    'memory': 97914880,
    'time': 1618541682.882505,
    'read_bytes': 0.0,
    'write_bytes': 0.0,
    'num_fds': 47,
    'executing': 0,
    'in_memory': 0,
    'ready': 0,
    'in_flight': 0,
    'bandwidth': {'total': 100000000, 'workers': {}, 'types': {}}},
   'nanny': 'tcp://10.234.133.31:60917'},
  'tcp://192.168.0.6:53241': {'type': 'Worker',
   'id': 'tcp://192.168.0.6:53241',
   'host': '192.168.0.6',
   'resources': {},
   'local_directory': '/Users/adityahpatel/dask-worker-space/dask-worker-space/worker-_dt5l6zv',
   'name': 'tcp://192.168.0.6:53241',
   'nthreads': 4,
   'memory_limit': 8589934592,
   'last_seen': 1618541683.090251,
   'services': {'dashboard': 53242},
   'metrics': {'cpu': 2.5,
    'memory': 53854208,
    'time': 1618541682.5895412,
    'read_bytes': 52480.01330262567,
    'write_bytes': 51600.214253126505,
    'num_fds': 39,
```

```
    'executing': 0,
    'in_memory': 4,
    'ready': 0,
    'in_flight': 0,
    'bandwidth': {'total': 100000000, 'workers': {}, 'types': {}}},
   'nanny': 'tcp://192.168.0.6:53240'}}}
```

Conventional Pandas approach

Lets open 1 file. This has 136 rows and 43 columns. We need only 6-8 columns, we'll drop the rest

with open('Housing Full Dataset/CO04012 2019-01-01') as project_file:
data = json.load(project_file)

df_1 = pd.json_normalize(data) print(df_1.shape) df_1.columns cols_of_interest = ['lot.lotSize1','address.postal1', 'summary.propsubtype', 'summary.proptype', 'summary.yearbuilt', 'sale.saleTransDate', 'sale.amount.saleamt', 'building.size.universalsize','building.rooms.bathstotal', 'building.rooms.beds'] df_1 = df_1[cols_of_interest] df_1.head(5) df_1.head()

DASK approach

DASK has 3 main objects - Dataframe, array and bag. DASK dataframe is NOT the same as Pandas dataframe. Dask dataframe is parallelizable, scalable and fast. It has partitions, Pandas dataframe does not have that. Bag is kind of like a python list but it is not iterable. It stores collection of objects.

`https://docs.dask.org/en/latest/bag.html`
`https://docs.dask.org/en/latest/bag-api.html`

In [64]:
```
# json.loads function converts JSON string into a python dictionary
def work_read():
    b = bag.read_text('http://192.168.0.6:8000/*').map(json.loads)
    b = b.flatten()    # without flattening the bag, the results in the bag will be useless due to excess
    return b
```

In [65]:
```
future = client.submit(work_read)
#y.result()
future
```

Out[65]: **Future: work_read** status: pending, key: work_read-c58dbbe25c30fa180b687a6f529de674

In [69]:
```
future
```

Out[69]: **Future: work_read** status: finished, type: dask.Bag, key: work_read-c58dbbe25c30fa180b687a6f529de674

In [67]:
```
#b.take(1)    # .take() is kind of like Pyspark RDD method. It shows the FIRST n number of records.
             #  There are 136 records. This is showing just 1 record of 136.
```

In [70]:
```
# We define a mapper function which pulls out the useful columns and their values in form of a dictionar
# using above format

def aditya(record):
    return {
        'transaction_date': record['sale']['saleTransDate'],
        'zipcode': record['address']['postal1'],
        'sale_price':record['sale']['amount']['saleamt'],
        'lot_size': record['lot']['lotSize1'],
        'size': record['building']['size']['universalsize'],
        'latitude': record ['location']['latitude'],
        'longitude': record['location']['longitude'],
        'type': record['summary']['proptype'],
        'year_built': record['summary']['yearbuilt']
    }
```

In [71]:
```
def work_map(future):
```

```
    dask_df = future.map(aditya).to_dataframe()
    return dask_df
#print(type(dask_df))
#dask_df.head(20)
```

In [41]:
```
big_df = client.submit(work_map,future)
big_df
```

Out[41]: **Future: work_map** status: pending, key: work_map-456bf0ead292d38ac67c2b88c642e8a0

In [77]:
```
navu_future = client.submit(work_map,future)    # passing aaglu future
navu_future
```

Out[77]: **Future: work_map** status: finished, type: dask.DataFrame, key: work_map-aef6189f6162f6cbbb4b17450d0be654

In [78]:
```
navu_future
```

Out[78]: **Future: work_map** status: finished, type: dask.DataFrame, key: work_map-aef6189f6162f6cbbb4b17450d0be654

In [79]:
```
# CALLING .result() converts future object i.e. remotely stored result into concrete form.
navu_future.result()
```

Out[79]: **Dask DataFrame Structure:**

	transaction_date	zipcode	sale_price	lot_size	size	latitude	longitude	type	year_built
npartitions=85									
	object	object	int64	float64	int64	object	object	object	int64
	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
	...	...	...	...	...	...	...	...	...
	...	...	...	...	...	...	...	...	...

Dask Name: to_dataframe, 255 tasks

: ABOVE is lazy dataframe. It is perfect and to be expected as it looks. Note Dask dataframe is diffrent from pandas df. Dask df has partitions, 1 for each file so total 85 files we have in uploaded on HTTP server. Above dask dataframe called navu_future.result().

MUST NOTE I have uploaded only 2021 folder to HTTP server. This has 85 files.

I checked that if i do **navu_future.result( ).head(3)** it will pull 1st few rows of 1st file which is CO04012 2021-01-01 and if i do **future.result( ).tail(3)** it will give last few rows of LAST file is CO41035 2021-01-01. This is super cool

Check head( ), both are same! Great!

In [111…
```
navu_future.result().head(3)
```

```
distributed.client - WARNING - Couldn't gather 1 keys, rescheduling {"('head-1-3-to_dataframe-a33a8b2c36
0c97f0bee25b2a5d7f932f', 0)": ('tcp://10.234.133.31:60918',)}
```

Out[111…

	transaction_date	zipcode	sale_price	lot_size	size	latitude	longitude	type	year_built
0	2021-1-1	85344	265000	0.1148	1624	34.191529	-114.220966	SFR	1995
1	2021-1-2	85346	500000	1.9968	5168	33.664570	-114.228435	STORE BUILDING	2006
2	2021-1-4	85344	459250	0.0579	2391	34.205912	-114.216127	CONDOMINIUM	0

In [113…
```
df_firstfile.head(3)    # same as future nu....this is JUST TO CHECK
```

Out[113…

	lot.lotSize1	address.postal1	summary.propsubtype	summary.proptype	summary.yearbuilt	sale.saleTransDate	sale.amount.

	lot.lotSize1	address.postal1	summary.propsubtype	summary.proptype	summary.yearbuilt	sale.saleTransDate	sale.amount.
0	0.1148	85344	HOUSE	SFR	1995	2021-1-1	
1	1.9968	85346	COMMERCIAL	STORE BUILDING	2006	2021-1-2	
2	0.0579	85344	RESIDENTIAL	CONDOMINIUM	0	2021-1-4	

Check tail( ) ...both are same BELOW...great!

In [118…

```
navu_future.result().tail(3)
```

```
distributed.client - WARNING - Couldn't gather 1 keys, rescheduling {"('tail-3-to_dataframe-a33a8b2c360c
97f0bee25b2a5d7f932f', 0)": ('tcp://10.234.133.31:60918',)}
```

Out[118…

	transaction_date	zipcode	sale_price	lot_size	size	latitude	longitude	type	year_built
100	2021-2-26	97603	275000	0.36	0	42.198855	-121.701953	COMMON AREA	0
101	2021-2-26	97633	650000	42.66	1428	42.023983	-121.560540	FARMS	0
102	2021-2-26	97603	3200000	3.30	51906	42.189070	-121.733425	MULTI FAMILY DWELLING	0

In [119…

```
df_lastfile.tail(3)
```

Out[119…

	lot.lotSize1	address.postal1	summary.propsubtype	summary.proptype	summary.yearbuilt	sale.saleTransDate	sale.amou
100	0.36	97603	COMMERCIAL	COMMON AREA	0	2021-2-26	
101	42.66	97633	HOUSE	FARMS	0	2021-2-26	
102	3.30	97603	COMMERCIAL	MULTI FAMILY DWELLING	0	2021-2-26	

END OF WORKBOOK...1 million rows!! 1,017,244 rows 2019 to today!

Goal achieved: We combined approx 330 files into 1 single dataframe...please note its DASK df and NOT Pandas df! You can't see whole dataframe at once. This is specifically to facilitate parallel and fast processing. More data can be added and this code won't change a bit!

THIS CODE CELL IS JUST TO CHECK...###UNCOMMENT IF NEEDED

with open('/Users/adityahpatel/Desktop/PYTHON PROGRAMS/2021 California housing sales transactions upto 31 march/CO41035 2021-01-01') as project_file:
data = json.load(project_file)

df_lastfile = pd.json_normalize(data)

print(df_1astfile.shape)

cols_of_interest = ['lot.lotSize1','address.postal1', 'summary.propsubtype', 'summary.proptype', 'summary.yearbuilt', 'sale.saleTransDate', 'sale.amount.saleamt', 'building.size.universalsize','building.rooms.bathstotal', 'building.rooms.beds']
df_lastfile = df_lastfile[cols_of_interest] df_lastfile.head(3)

THIS CODE CELL IS JUST TO CHECK...### UNCOMMENT IF NEEDED

with open('/Users/adityahpatel/Desktop/PYTHON PROGRAMS/2021 California housing sales transactions upto 31 march/CO04012 2021-01-01') as project_file:
data = json.load(project_file)

df_firstfile = pd.json_normalize(data) print(df_firstfile.shape) df_firstfile.columns cols_of_interest = ['lot.lotSize1','address.postal1', 'summary.propsubtype', 'summary.proptype', 'summary.yearbuilt', 'sale.saleTransDate', 'sale.amount.saleamt', 'building.size.universalsize','building.rooms.bathstotal', 'building.rooms.beds'] df_firstfile = df_firstfile[cols_of_interest] df_firstfile.head(3)

In [ ]:

```

```