# Data analysis using Lithops

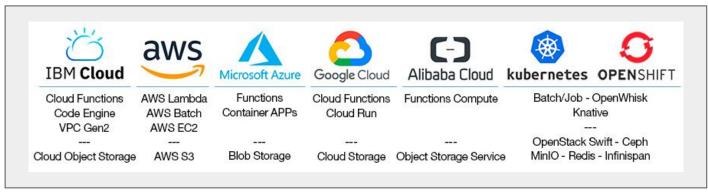
Dawid Białka, Kamil Burkiewicz

### What is Lithops



#### Main features:

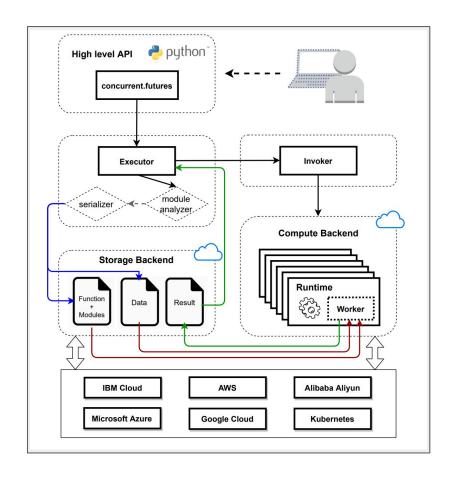
- distributed computing framework
- cloud-agnostic
- suited for highly-parallel jobs



### Lithops Architecture

#### Components:

- Storage:
  - provides abstraction for storage
- Compute:
  - allows running distributed computations
  - Various kinds of Executors:
    - Localhost
    - Serverless
    - Standalone



### **Dataset**

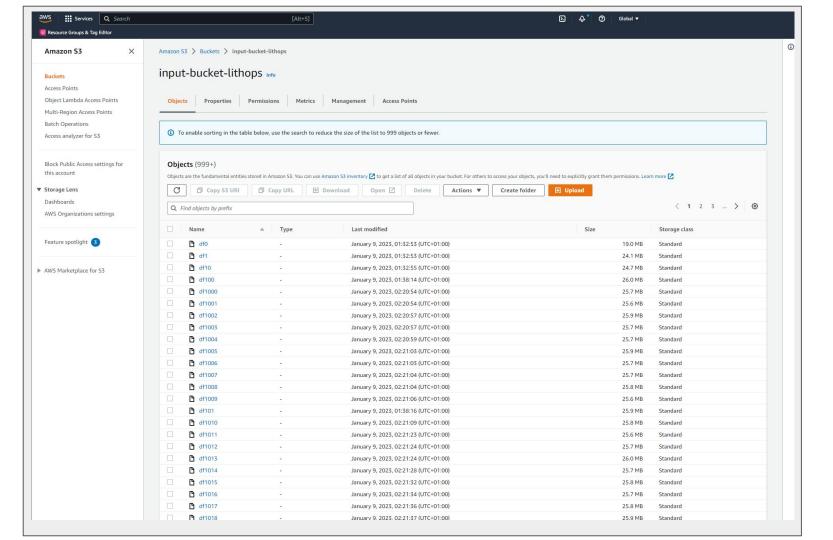
#### AWS OpenAQ

Global, aggregated physical air quality data from public data sources provided by government, research-grade and other sources.

Source: <a href="https://registry.opendata.aws/openag/">https://registry.opendata.aws/openag/</a>

- ~ 50 GB
- uploaded to s3 in the region where computations were performed for data locality
- divided into files ~ 25 MB each

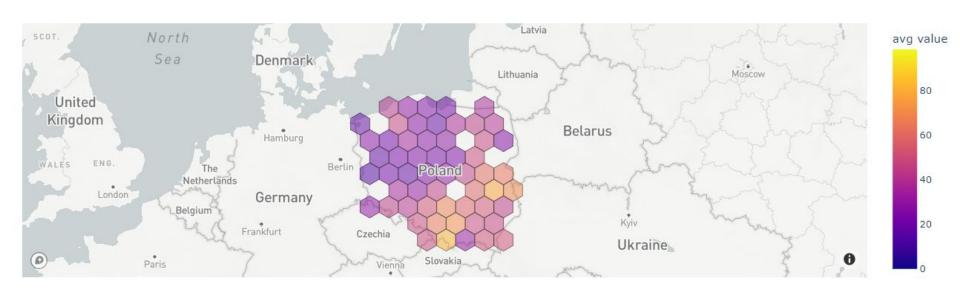
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2:	date	parameter	value	unit	averagingPeriod	location	city cou	untry	coordinates	attribution	sourceName	sourceType	mobile
0	('utc': '2020-10-31T06:30:00.000Z', 'local': '	pm25	100.000000	μg/m³	{'value': 1, 'unit': 'hours'}	US Diplomatic Post: Kabul	Kabul	AF	{'latitude': 34.535812, 'longitude': 69.190514}	[{'name': 'EPA AirNow DOS', 'url': 'http://air	StateAir_Kabul	government	False
1	{'utc': '2020-10-31T07:30:00.000Z', 'local': '	pm25	45.000000	µg/m³	{'value': 1, 'unit': 'hours'}	US Diplomatic Post: Kabul	Kabul	AF	{'latitude': 34.535812, 'longitude': 69.190514}	[{'name': 'EPA AirNow DOS', 'url': 'http://air	StateAir_Kabul	government	False
2	$ \hbox{\it ('utc': '2020-10-31T08:30:00.000Z', 'local': '} \\$	pm25	46.000000	µg/m³	{'value': 1, 'unit': 'hours'}	US Diplomatic Post: Kabul	Kabul	AF	{'latitude': 34.535812, 'longitude': 69.190514}	[{'name': 'EPA AirNow DOS', 'url': 'http://air	StateAir_Kabul	government	False
3	('utc': '2020-10-31T09:30:00.000Z', 'local': '	pm25	48.000000	µg/m³	{'value': 1, 'unit': 'hours'}	US Diplomatic Post: Kabul	Kabul	AF	{'latitude': 34.535812, 'longitude': 69.190514}	[{'name': 'EPA AirNow DOS', 'url': 'http://air	StateAir_Kabul	government	False
4	{'utc': '2020-10-31T10:30:00.000Z', 'local': '	pm25	39.000000	μg/m³	{'value': 1, 'unit': 'hours'}	US Diplomatic Post: Kabul	Kabul	AF	{'latitude': 34.535812, 'longitude': 69.190514}	[{'name': 'EPA AirNow DOS', 'url': 'http://air	StateAir_Kabul	government	False
	200	***	***		***		***	***			***	***	***
4995	{'utc': '2020-10-31T12:00:00.000Z', 'local': '	so2	6.000000	µg/m³	{'unit': 'hours', 'value': 1}	GR0020A	ΚΕΝΤΡΙΚΗ ΜΑΚΕΔΟΝΙΑ	GR	{'latitude': 40.67354965, 'longitude': 22.8934	[{'name': 'EEA', 'url': 'http://www.eea.europa	EEA Greece	government	False
4996	{'utc': '2020-11-01T04:00:00.000Z', 'local': '	pm10	12.500000	µg/m³	{'unit': 'hours', 'value': 1}	FR05090	Seine-Maritime	FR	{'latitude': 49.5146953797856, 'longitude': 0	[{'name': 'EEA', 'url': 'http://www.eea.europa	EEA France	government	False
4997	{'utc': '2020-11-01T04:00:00.000Z', 'local': '	03	44.113987	µg/m³	{'unit': 'hours', 'value': 1}	FI00357	Lapland	FI	{'latitude': 68.477009999634, 'longitude': 28	[{'name': 'EEA', 'url': 'http://www.eea.europa	EEA Finland	government	False
4998	{'utc': '2020-11-01T06:00:00.000Z', 'local': '	pm25	2.137920	µg/m³	{'value': 24, 'unit': 'hours'}	Heerlen-Jamboreepad	Heerlen	NL	('latitude': 50.9003, 'longitude': 5.986850000	[{'name': 'RIVM', 'url': 'http://www.lml.rivm	Netherlands	government	False
4999	{'utc': '2020-11-01T06:00:00.000Z', 'local': '	no2	0.005300	ppm	{'unit': 'hours', 'value': 1}	Renwu	高雄市	TW	{'latitude': 22.689056, 'longitude': 120.332631}	[{'name': 'http://opendata.epa.gov.tw/', 'url'	Taiwan	government	False
5000 ro	ows × 13 columns												

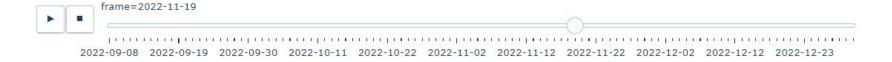


# Computation of average levels of air pollution with map-reduce model

```
✓ [25] def day_average_map(x):
         if isinstance(x, str):
           df = pd.DataFrame(loads recursive(json.loads(download bytes(os.path.basename(x), input bucket).decode(encoding='utf-8'))))
         else:
           df = x
         df to process = preprocess(df)
         df_sum = df_to_process.groupby(['country', 'city', 'date', 'parameter', 'latitude', 'longitude'])['value'].agg(['sum','count'])
         df to process = df to process.drop(columns=['value'], axis=1)
         df merged = pd.merge(df sum, df to process, on=['country', 'city', 'date', 'parameter', 'latitude', 'longitude']).drop duplicates()
         return df merged.to ison()
 [26] def day average reduce(results):
         dfs = [pd.read_json(result) for result in results]
         df concatenated = pd.concat(dfs)
         df concatenated.reset index(drop=True, inplace=True)
         df_avg = df_concatenated.groupby(['country', 'city', 'date', 'parameter', 'latitude', 'longitude']).sum(['country', 'sum'])
         df avg['average'] = df avg.apply(lambda row: row['sum'] / row['count'], axis=1)
         df avg = df avg.drop(columns=['count', 'sum'], axis=1).dropna()
         df concatenated = df concatenated.drop(columns=['count', 'sum'], axis=1).dropna()
         df merged = pd.merge(df avg, df concatenated, on=['country', 'city', 'date', 'parameter', 'latitude', 'longitude']).drop duplicates()
         return df merged.to ison()
```

## Map of average concentration of PM10 in Poland based on localization and time





# Computation of maximum levels of air pollution with map-reduce model

```
def day_max_map(x):
    df = pd.DataFrame(loads_recursive(json.loads(download_bytes(os.path.basename(x), input_bucket).decode(encoding='utf-8'))))
    df_to_process = preprocess(df)
    df_sum = df_to_process.groupby(['country', 'city', 'date', 'parameter', 'latitude', 'longitude'])['value'].agg(['max'])
    df_to_process = df_to_process.drop(columns=['value'], axis=1)

    df_merged = pd.merge(df_sum, df_to_process, on=['country', 'city', 'date', 'parameter', 'latitude', 'longitude']).drop_duplicates()
    return df_merged.to_json()

def day_max_reduce(results):
    dfs = [pd.read_json(result) for result in results]
    df_concatenated = pd.concat(dfs)
    df_concatenated.reset_index(drop=True, inplace=True)
    return df_concatenated.to_json()
```

# Map of maximum concentration of PM10 in Poland based on localization and time



### Warmup

To avoid cold start there was a warmup.

990 Lambdas processing whole dataset in about a minute

2023-01-16 02:11:22,127 [INFO] executors.py:609 -- ExecutorID cc0069-1 - Cleaning temporary data

Warmup

```
[21] fexec = lithops.ServerlessExecutor(config=config)
fexec.map(map_function=day_average_map, map_iterdata=objs, chunksize=2)
result = fexec.get_result()

2023-01-16 02:10:12,323 [INFO] config.py:131 -- Lithops v2.7.1
2023-01-16 02:10:12,339 [INFO] aws_s3.py:60 -- S3 client created - Region: us-east-1
2023-01-16 02:10:12,422 [INFO] aws_lambda.py:94 -- AWS Lambda client created - Region: us-east-1
2023-01-16 02:10:12,427 [INFO] invokers.py:108 -- ExecutorID cc0069-1 | JobID M000 - Selected Runtime: lithops-default-runtime-v38 - 1024MB
2023-01-16 02:10:12,711 [INFO] invokers.py:172 -- ExecutorID cc0069-1 | JobID M000 - Starting function invocation: day_average_map() - Total: 1979 activations
2023-01-16 02:10:14,648 [INFO] invokers.py:208 -- ExecutorID cc0069-1 | JobID M000 - View execution logs at /tmp/lithops/logs/cc0069-1-M000.log
2023-01-16 02:10:14,970 [INFO] wait.py:97 -- ExecutorID cc0069-1 - Getting results from 1979 function activations
```

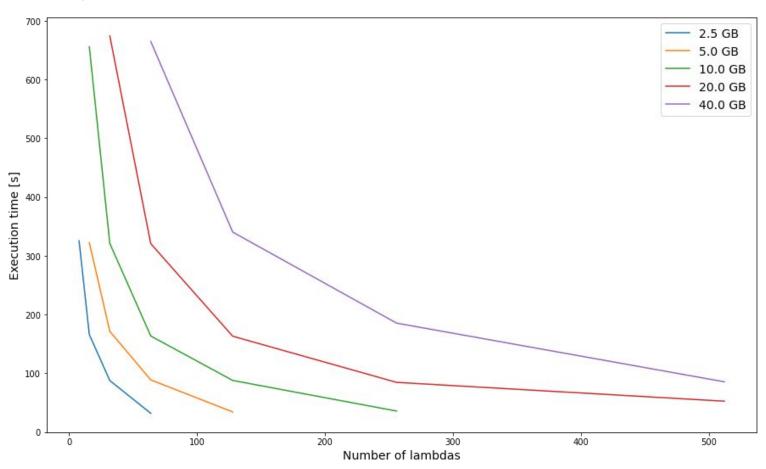
### Measurements

Compute backend: AWS Lambda

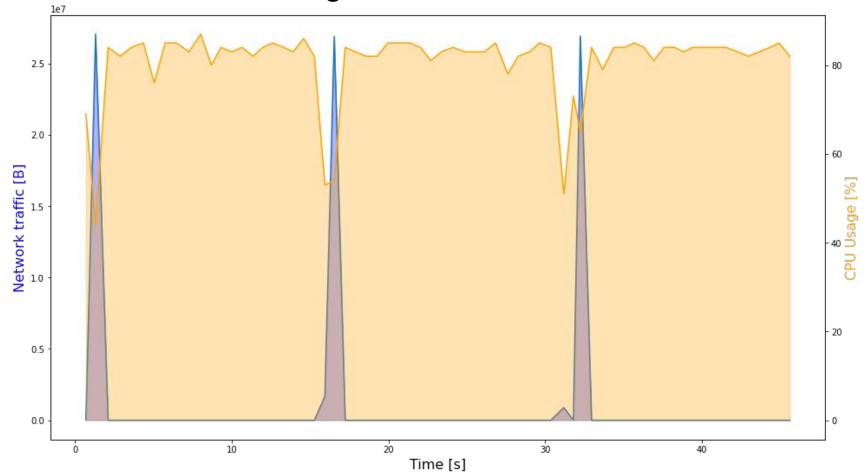
- 2048 MB memory
- CPU: Intel(R) Xeon(R) Processor @ 2.50GHz model 63
- timeout: 900s

Storage: S3

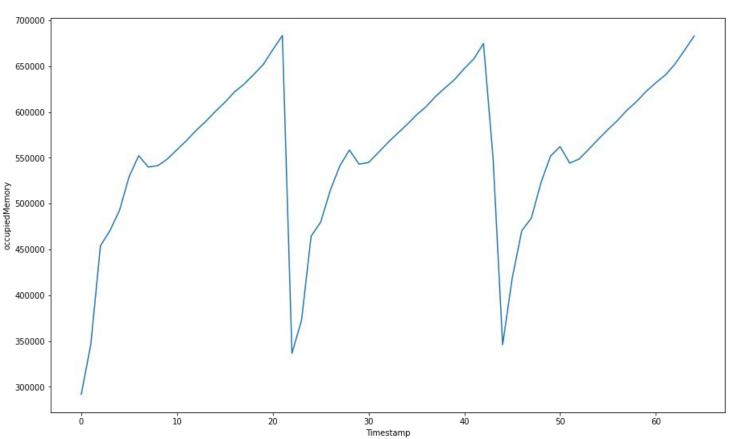
## Scalability



### CPU and network usage



### Occupied memory



### Sources

 J. Sampe, M. Sanchez-Artigas, G. Vernik, I. Yehekzel and P. Garcia-Lopez,
 "Outsourcing Data Processing Jobs with Lithops," in IEEE Transactions on Cloud Computing, doi: <u>10.1109/TCC.2021.3129000</u>

