Project concept

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About lithops

Lithops is a Python multi-cloud distributed computing framework. It allows you to run unmodified local python code at massive scale in the main serverless computing platforms. Lithops delivers the user's code into the cloud without requiring knowledge of how it is deployed and run. Moreover, its multicloud-agnostic architecture ensures portability across cloud providers. Lithops is specially suited for highly-parallel programs with little or no need for communication between processes, but it also supports parallel applications that need to share state among processes. Examples of applications that run with Lithops include Monte Carlo simulations, deep learning and machine learning processes, metabolomics computations, and geospatial analytics, to name a few.

Topic

- AWS deployment automation
- App management and scaling

The main purpose of the project is to test how well lithops performs with large and parallel data analysis using map-reduce concept.

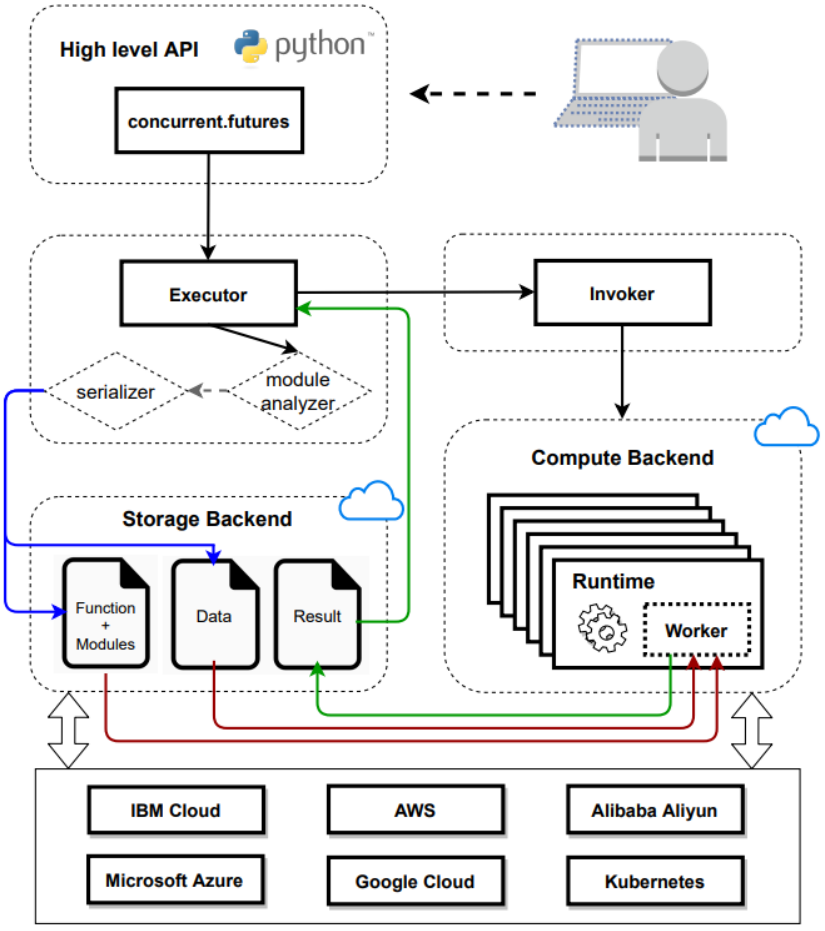
Challenges

- Large dataset processing

Main problems to solve

- Setting up the whole infrastructure
- Find and download large amount of appropriate data to analyze
- Decide what analysis to perform
- Measuring how well the system performs under various conditions

Architecture scheme



Planned tests

Infrastructure:

Compute backend: AWS Lambda

- 2048 MB memory
- cpu type: `Intel(R) Xeon(R) Processor @ 2.50GHz model 63`
- timeout: 900s
- vCPUs: 2 (scaled to 1.15)*
- lithops invokes lambdas asynchronously by design

Storage: S3

Dataset:

- World air pollution data. Source: https://registry.opendata.aws/openaq/
- Around 50 GB of data, divided into files ~ 25 MB each and uploaded to S3 storage

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5000 rows × 13 columns

Analysis:

- Computing average day values of the pollutants, grouping by every station.

```
[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_json()
```

```
[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(['count', '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_json()
```

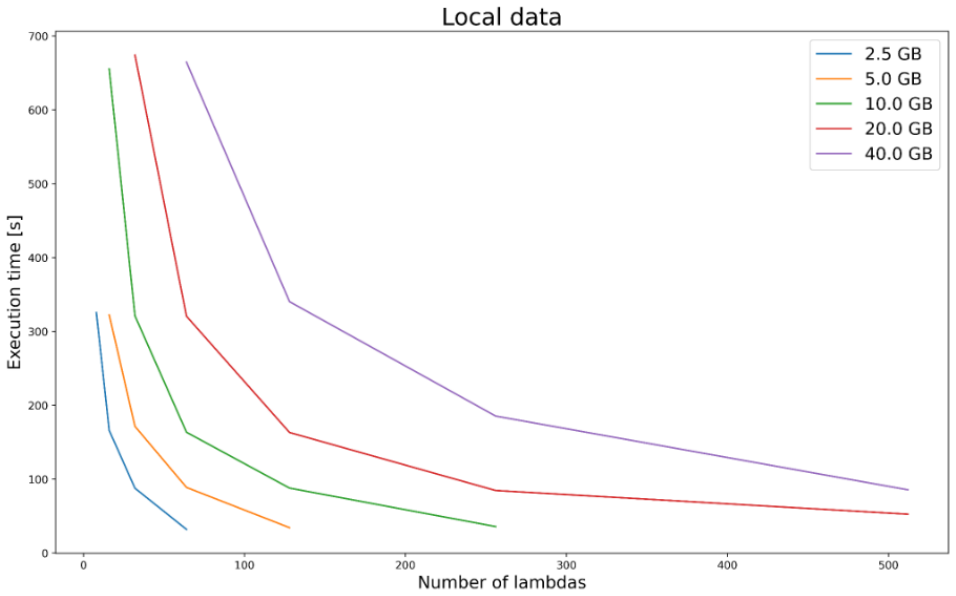
Metrics:

- Scalability
- Utilization
- Network usage
- Time from running analysis to task distribution
- Influence of data locality on system efficiency - S3 bucket located on the same region as the computations and on other one

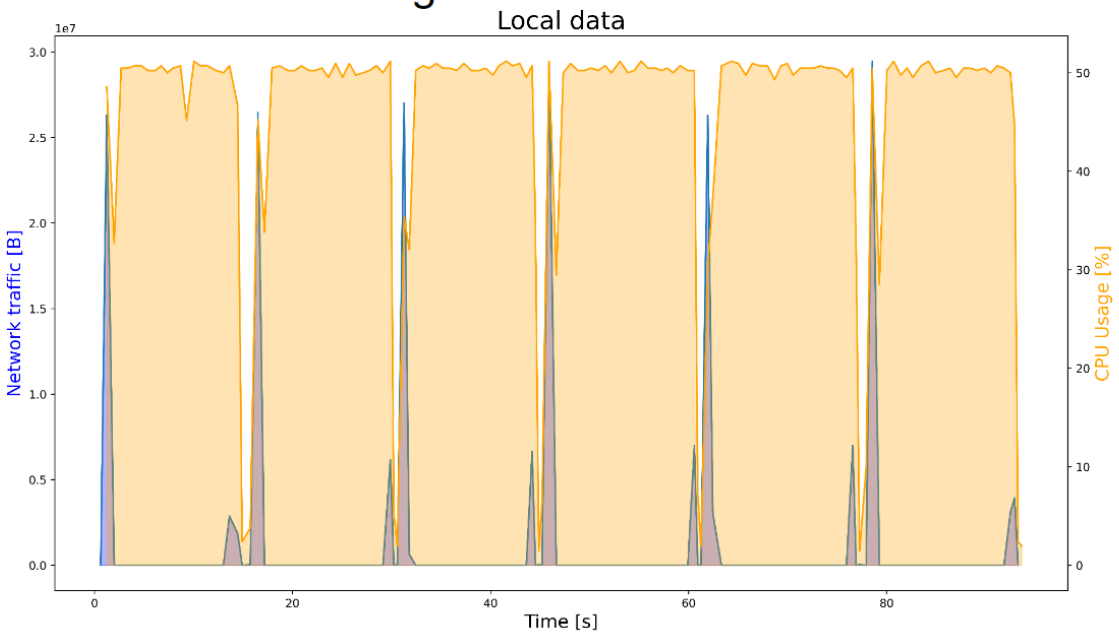
Performed tests:

8, 16, 32, 64, 128, 256, 512 lambdas calculating pollutant averages on 2.5, 5, 10, 20, 40 GB of data.

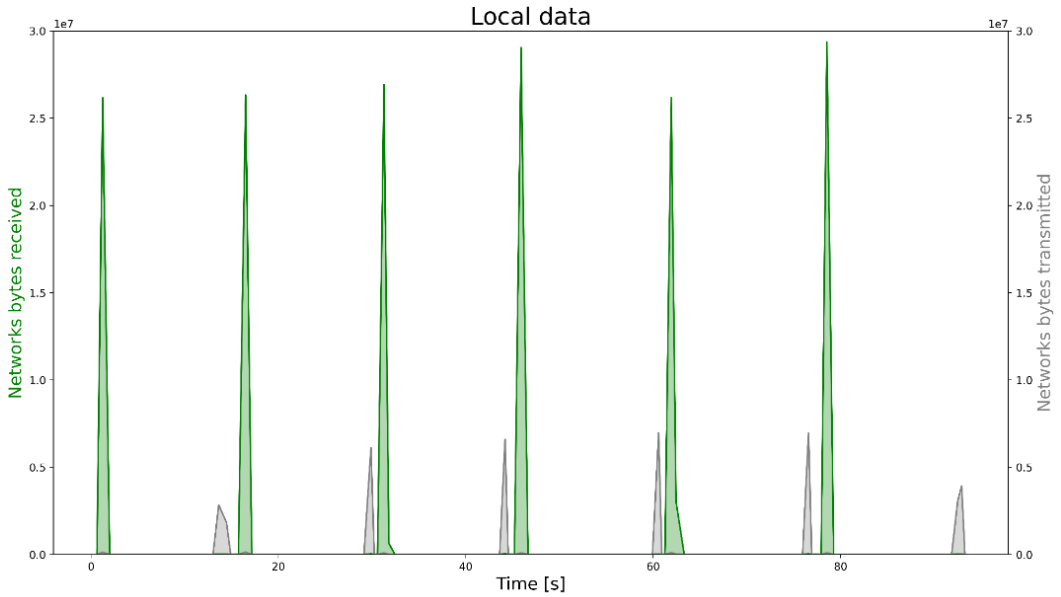
Scalability



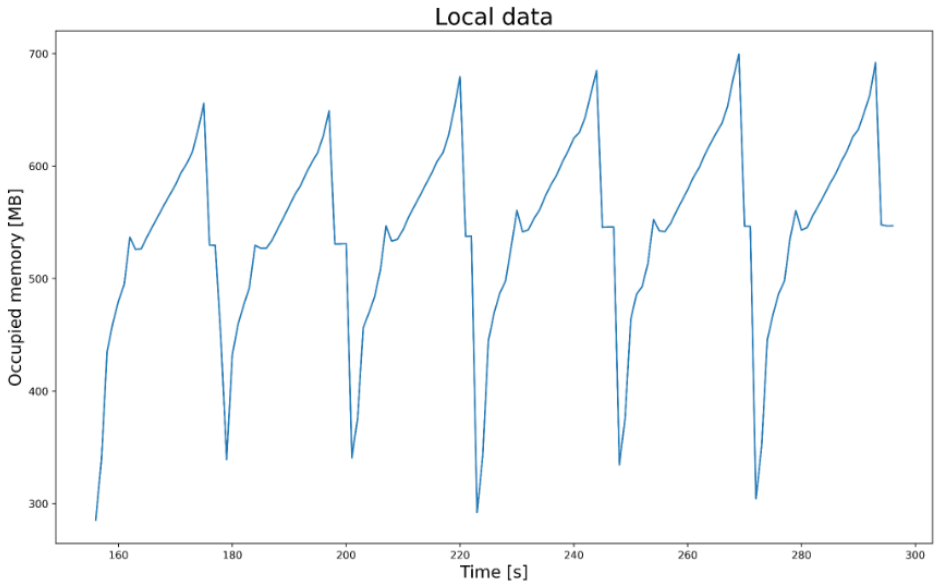
CPU and network usage

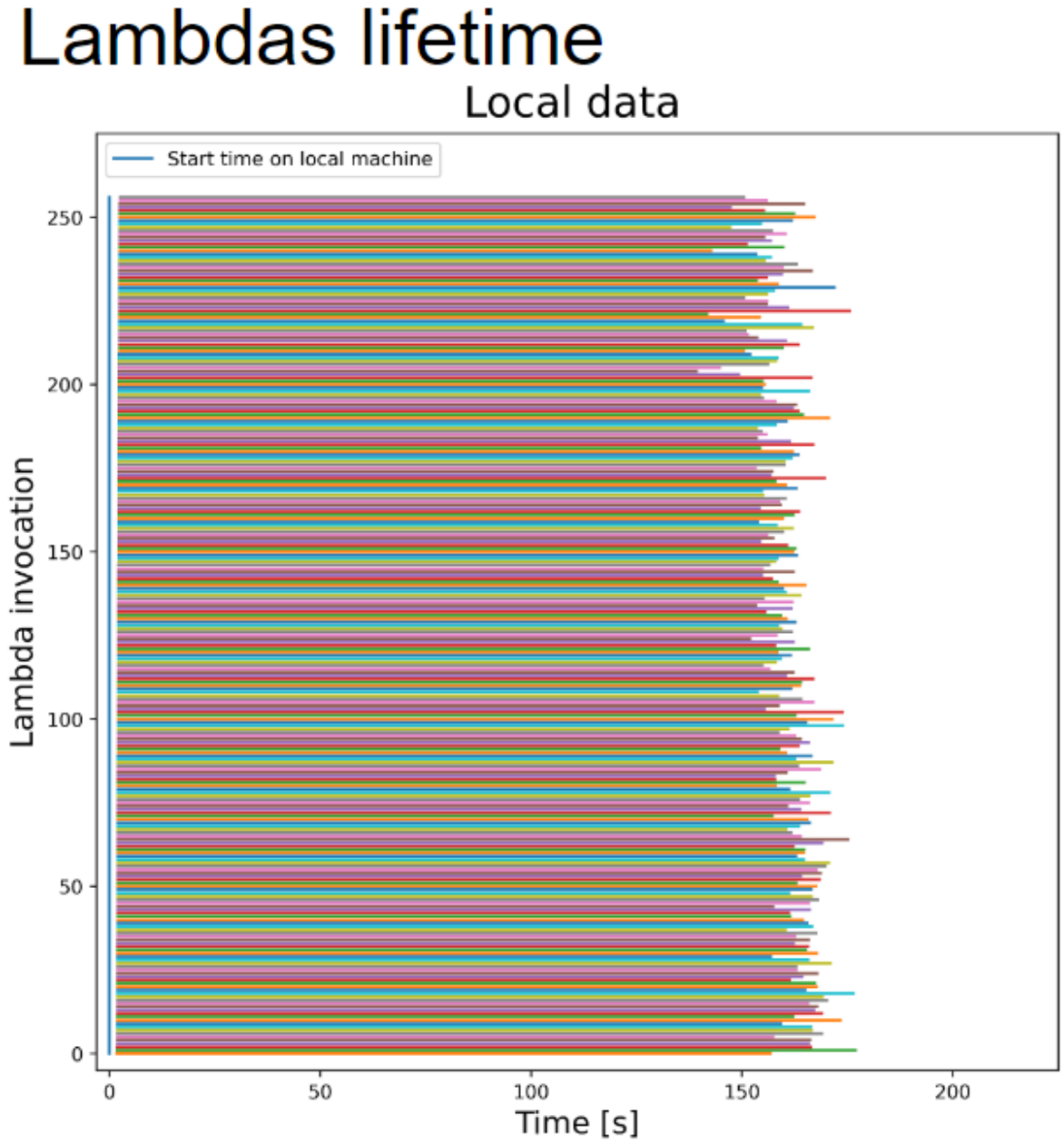


Network transmission



Occupied memory





The cumulative cost of the whole testing was about 150 $.