# Serverless Parallel Computing

*CS 4740: Cloud Computing*

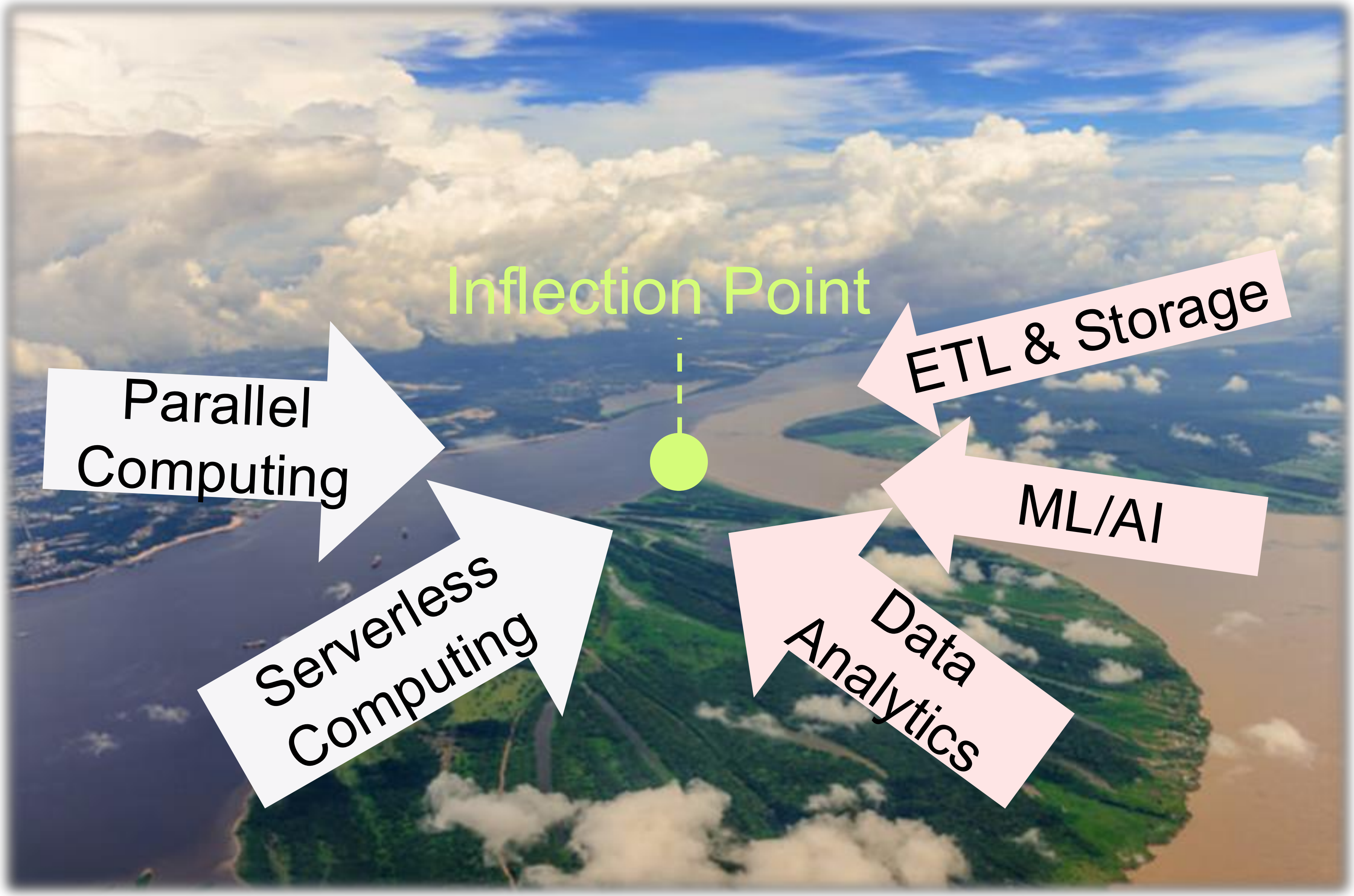
*Fall 2024*

Lecture 14b

Yue Cheng

University of Virginia

# Confluence: When stateful apps meet serverless



# Today’s data analytics landscape

**Libraries efficient for O(1MB)**

NumPy pandas

SciPy scikit learn

matplotlib

# Today's data analytics landscape

## Libraries efficient for O(1MB)

NumPy pandas

SciPy scikit learn

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## Frameworks for O(100s GB)

APACHE Spark DASK

hadoop

MPI

# Today's data analytics landscape

## Libraries efficient for O(1MB)

NumPy
pandas
SciPy
scikit learn
matplotlib

## Frameworks for O(100s GB)

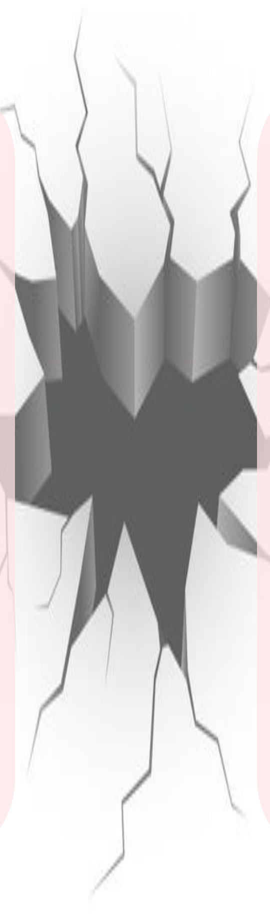
APACHE Spark
DASK
hadoop
MPI

# Today's data analytics landscape

## Libraries efficient for O(1MB)

- Easy to program (writing centralized code)
- Low barrier for environment setup (just installing libs)
- Well understood

- No scalability / elasticity
- Not able to efficiently handle large data



## Frameworks for O(100s GB)

- Scale to 100s GB data

- Difficult to program and debug
  - Requires distributed systems knowledge
- No elasticity
- High barrier for environment setup
  - Requires low-level administration skills

# Today’s data analytics landscape

**Libraries efficient for O(1MB)**

- **Easy-to-use**
- **Not scalable**
- **Not elastic**

**Frameworks for O(100s GB)**

- **Scalable**
- **Not easy-to-use**
- **Not elastic**

# Can we achieve all these desirable properties with **Serverless?**

Libraries efficient for O(1MB)

Frameworks for O(100s GB)

Easy-to-use

Elastic

Pay-per-use

Scalable

# Recap: What is serverless computing?

Many people define it many ways

A **programming abstraction** that enables users to upload programs, run them at **virtually** any scale, and pay **only for the resources used**

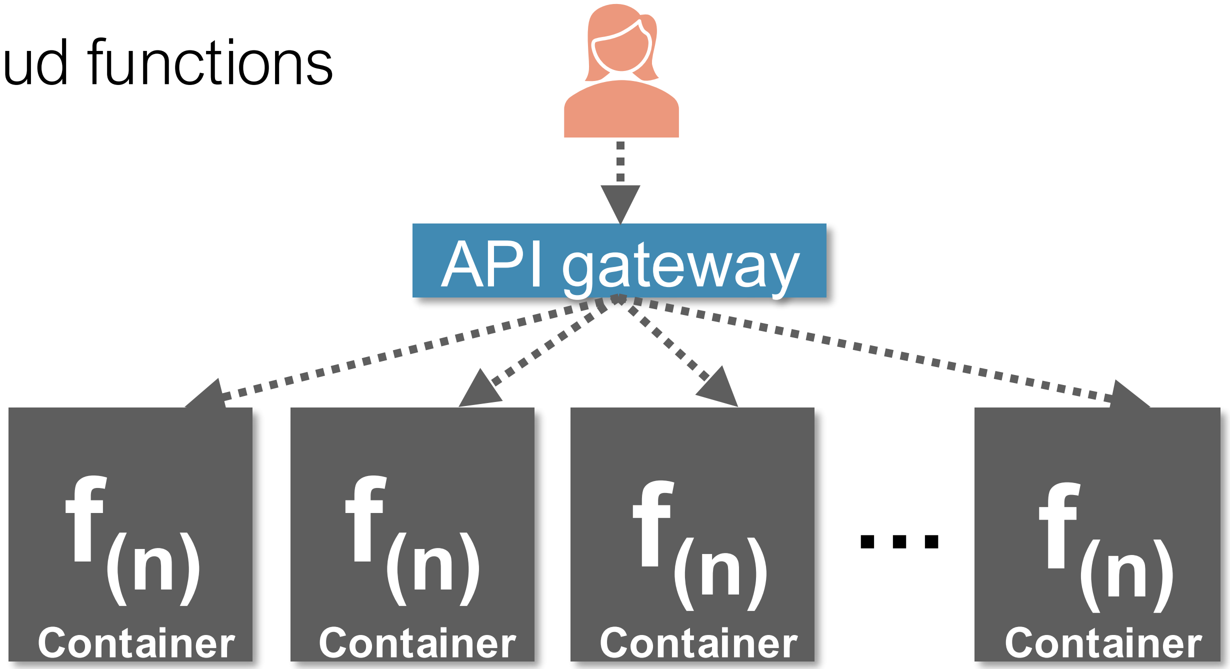
- **Function-as-a-Service (FaaS):** Cloud functions as a basic deployment unit

AWS Lambda

Azure Functions

Google Cloud Functions

Alibaba Function Compute

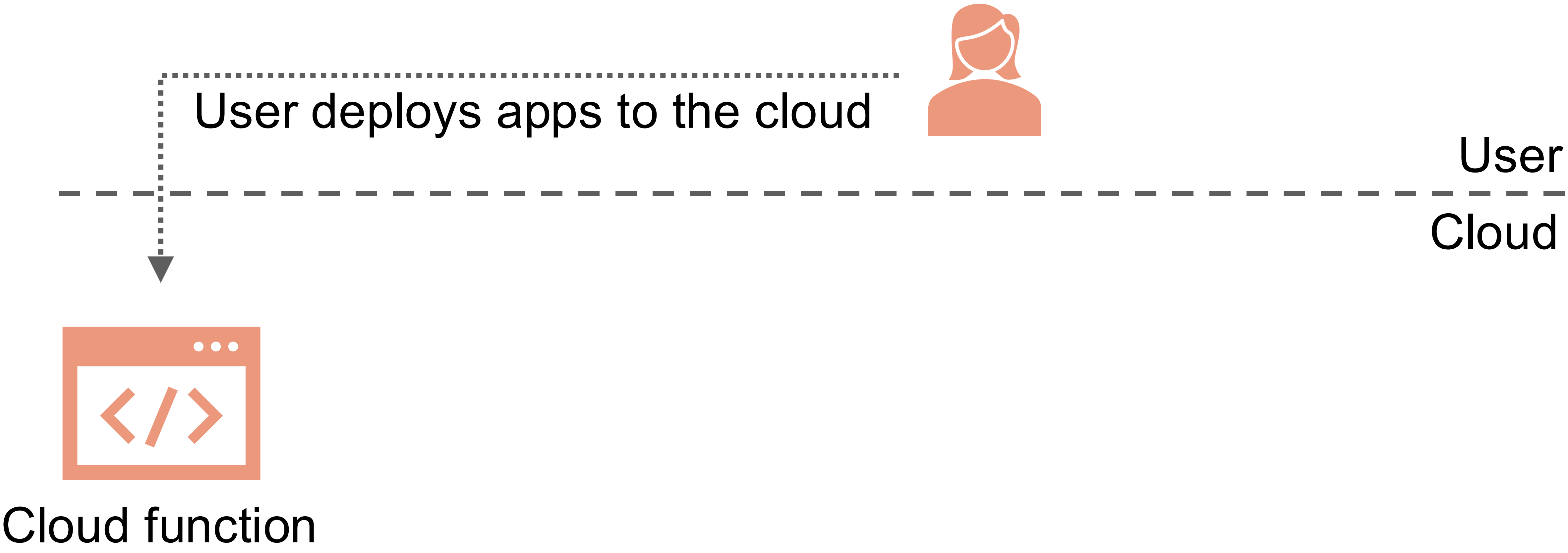


# Function-as-a-Service (FaaS)

User

Cloud

# Function-as-a-Service (FaaS)



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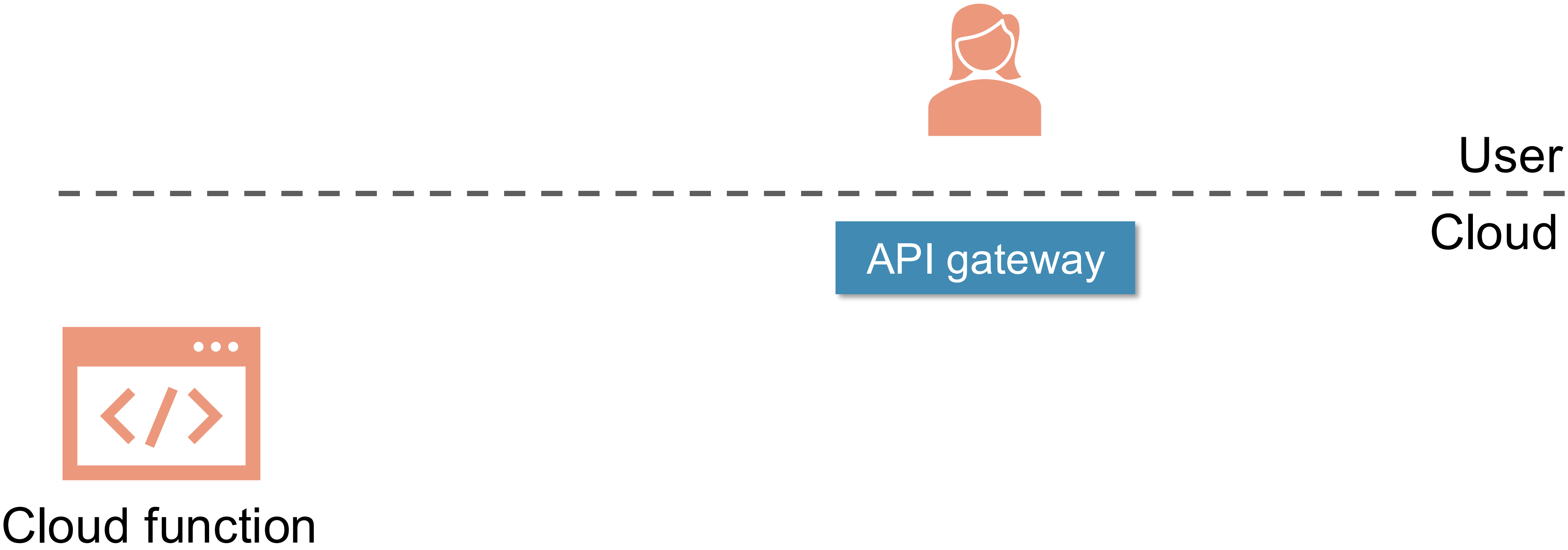

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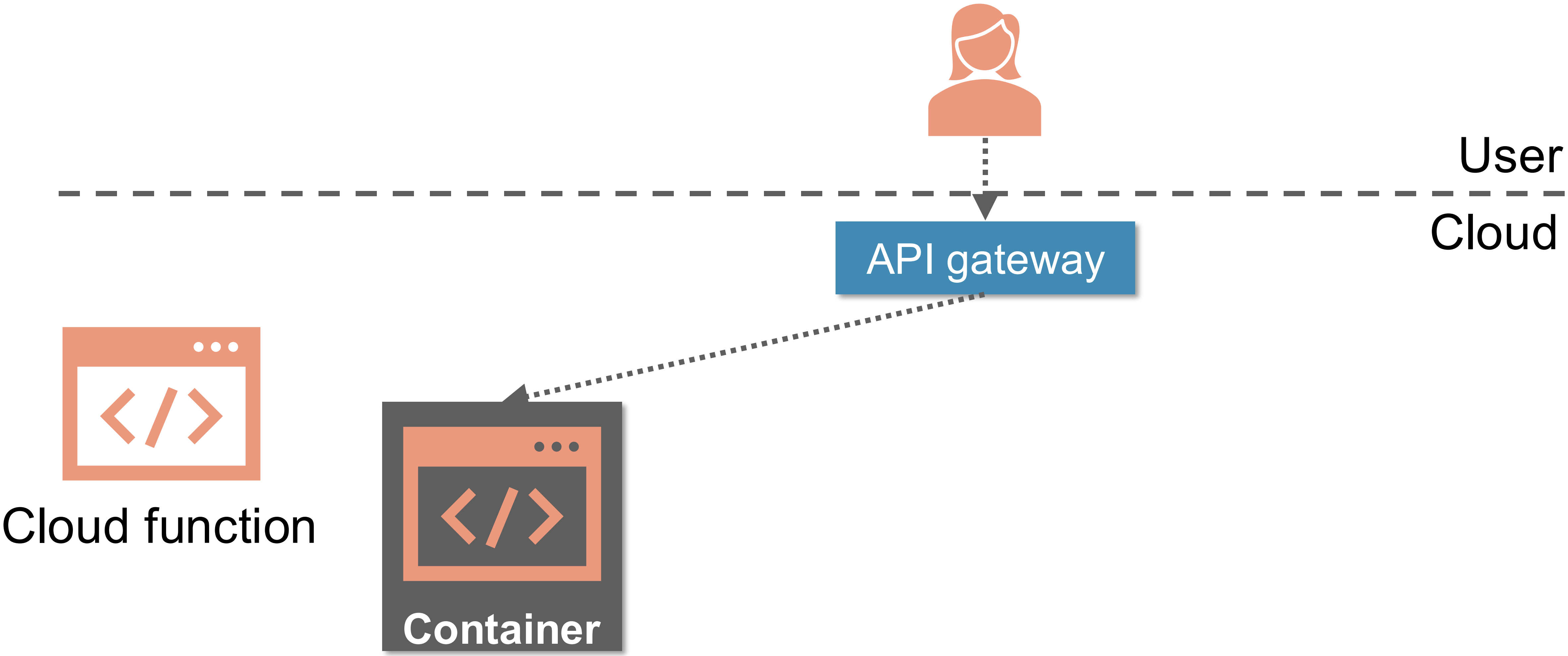

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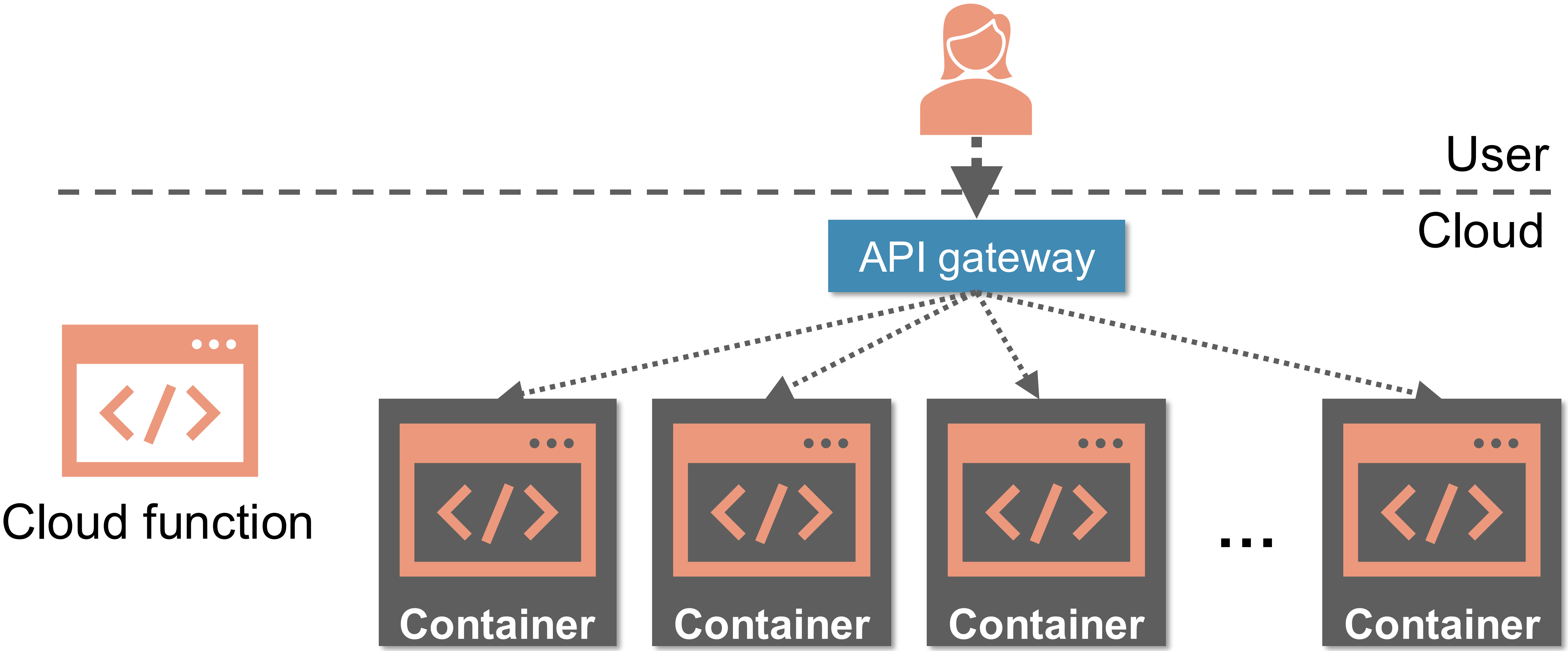

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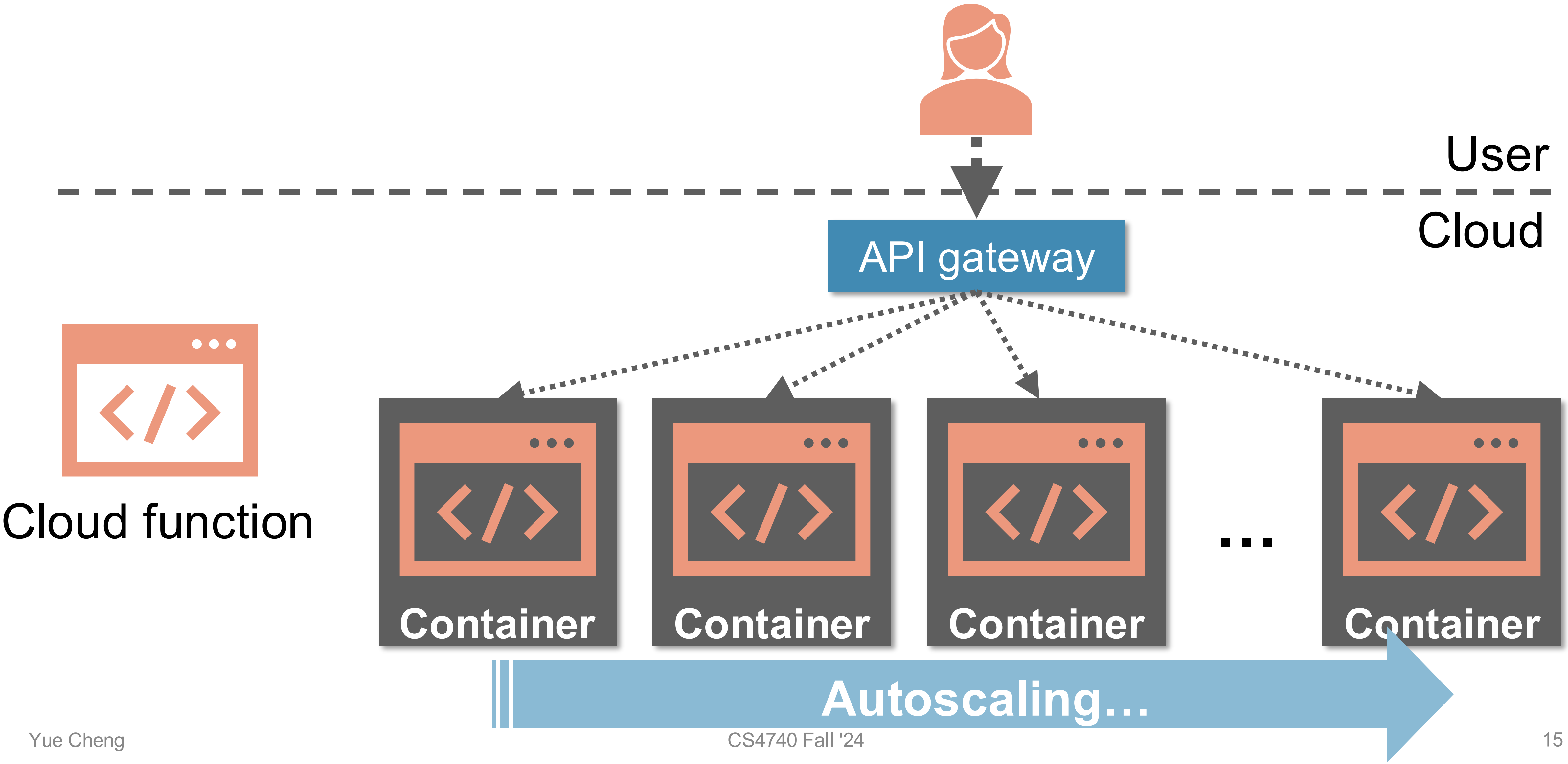
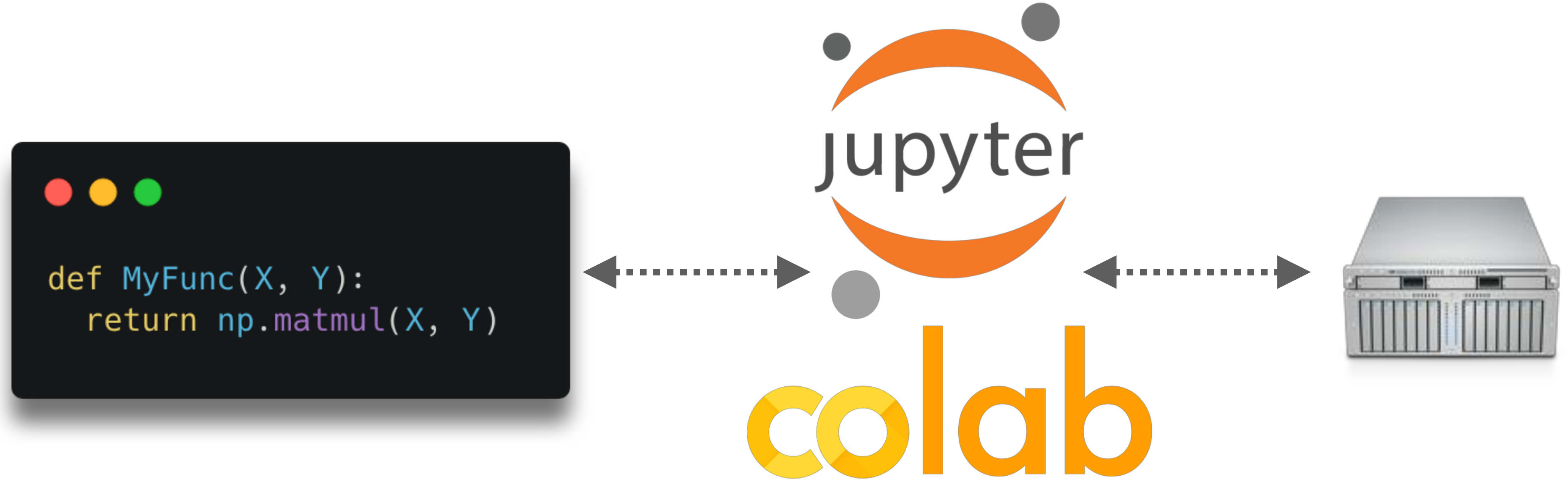


# Python analytics: What we have today



# Python analytics: What we have today

```
def MyFunc(X, Y):
  return np.matmul(X, Y)
```

jupyter

colab

Fixed resource

User writes interactive analytics and runs it on a notebook server

- No autoscaling for large computations
- Too slow? OOM? Need to scale out manually!
- Too expensive? Idled resources charge $$

# Python analytics: What we have today

```python
def MyFunc(X, Y):
  return np.matmul(X, Y)
```

jupyter

colab

Manually deployed distributed computing cluster

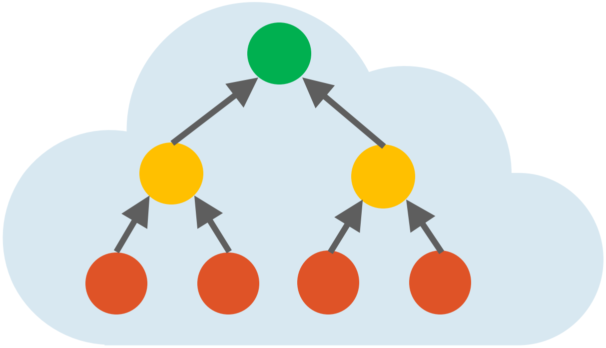
User writes interactive analytics and runs it on a notebook server

- No autoscaling for large computations
- Too slow? OOM? Need to scale out manually!
- Too expensive? Idled resources charge $$

**High barriers to enter for those who lack CS/systems background**

# Python analytics: What we would like to have

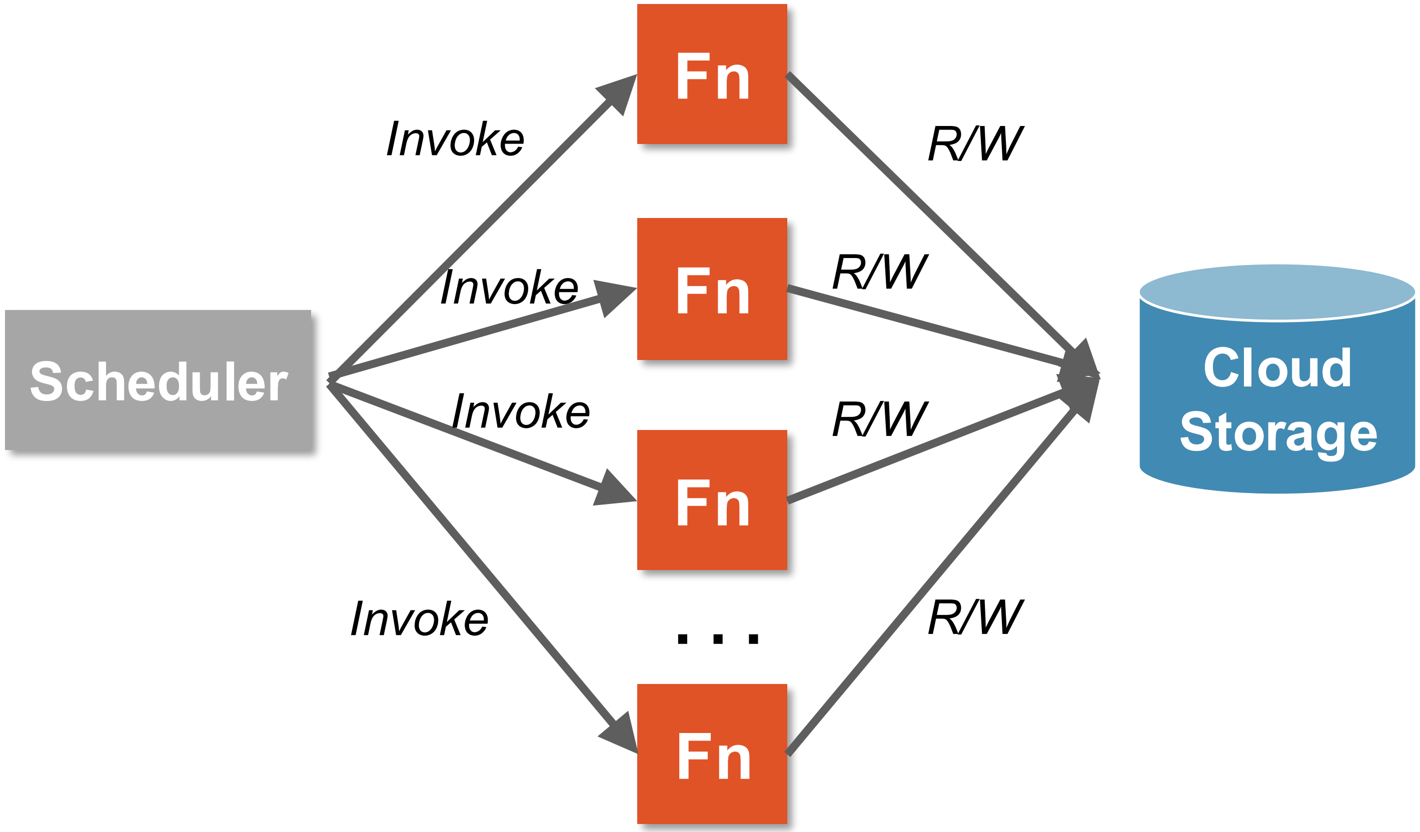
```python
def MyFunc(X, Y):
  return np.matmul(X, Y)
```



User writes interactive analytics and runs it **on FaaS**

- Elastically and automatically scales to the right size
- Pay-per-use with minimal $$ cost
- Expertise of writing parallel programs **NOT required**
- Manual cluster maintenance **NOT required**

# PyWren: Stateful computing over stateless serverless functions




pywren

wren

vs.

HTCondor

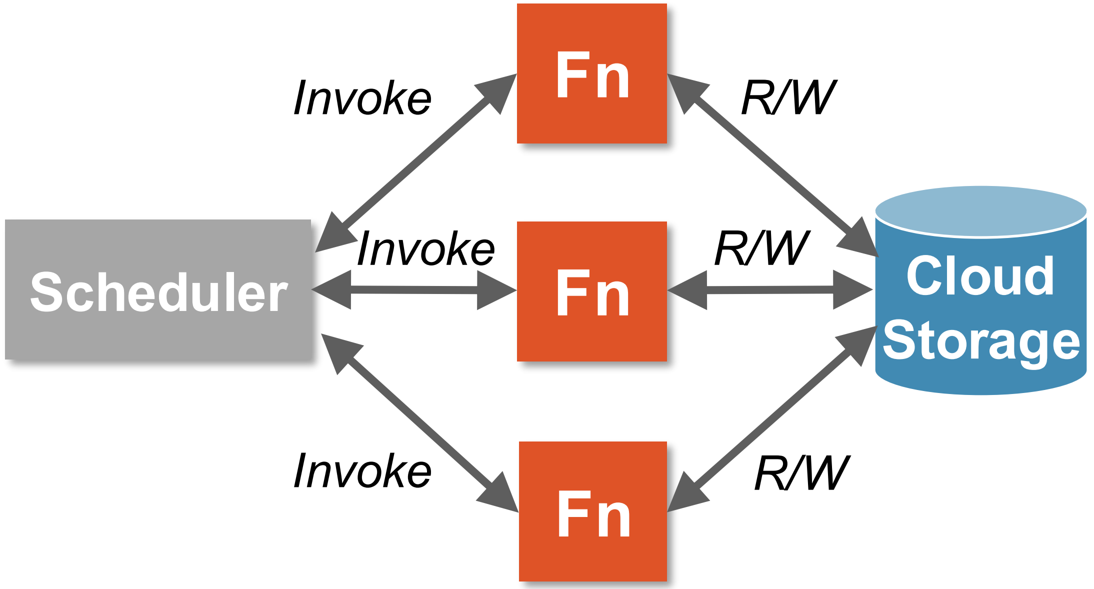
condor

* [PyWren] Occupy the Cloud: Distributed Computing for the 99%. In ACM SoCC'17.

# Quantifying the pain of FaaS

How FaaS adds huge amounts of **performance taxes**

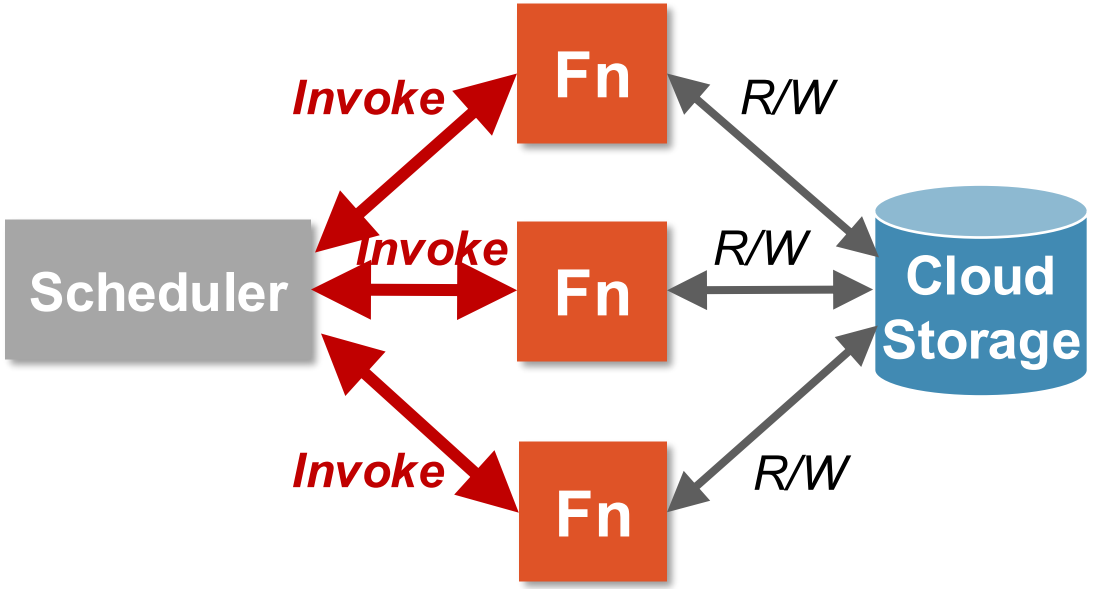
# Python analytics on FaaS is slow!

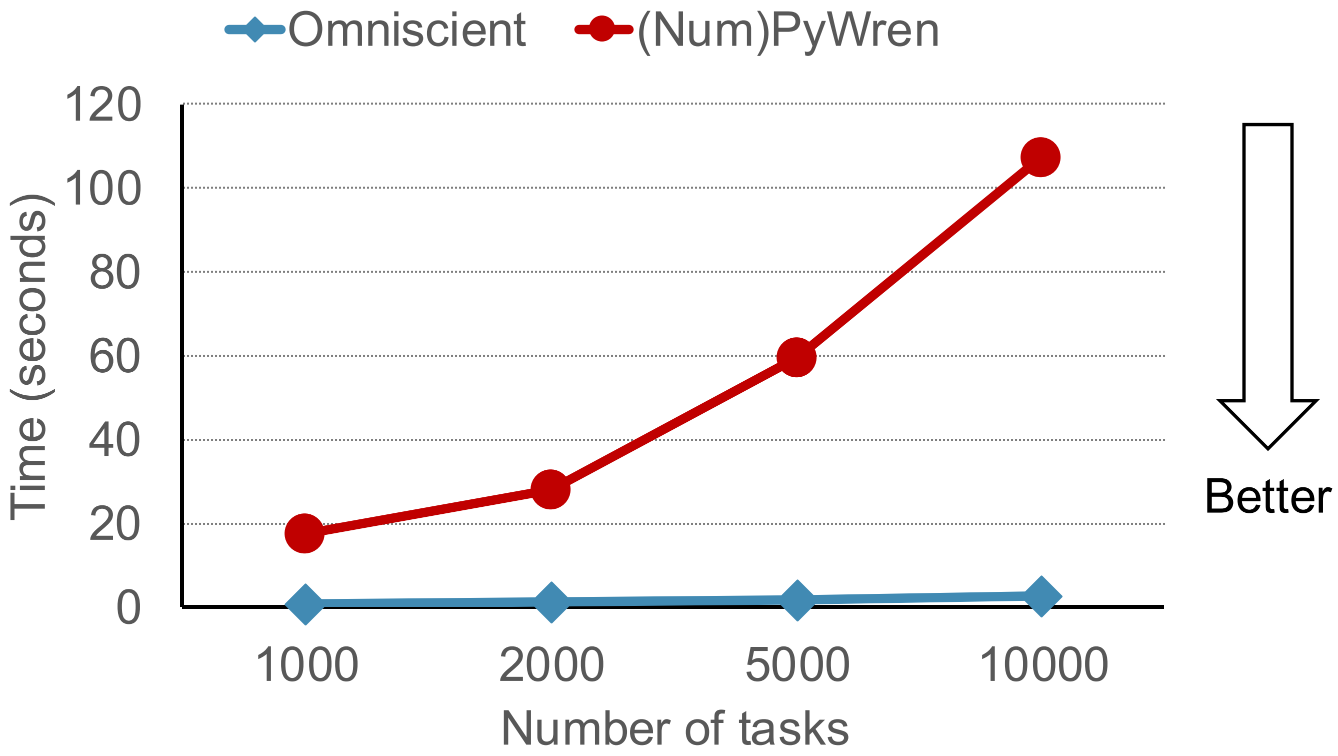



PyWren and numpywren

* [PyWren] Occupy the Cloud: Distributed Computing for the 99%. In ACM SoCC'17.
* [numpywren] Serverless linear algebra. In ACM SoCC'20.

# Python analytics on FaaS is slow!




State-of-the-art FaaS frameworks pay huge amounts of FaaS taxes

- **Task scheduling bottleneck:** Too slow to scale to thousands of functions

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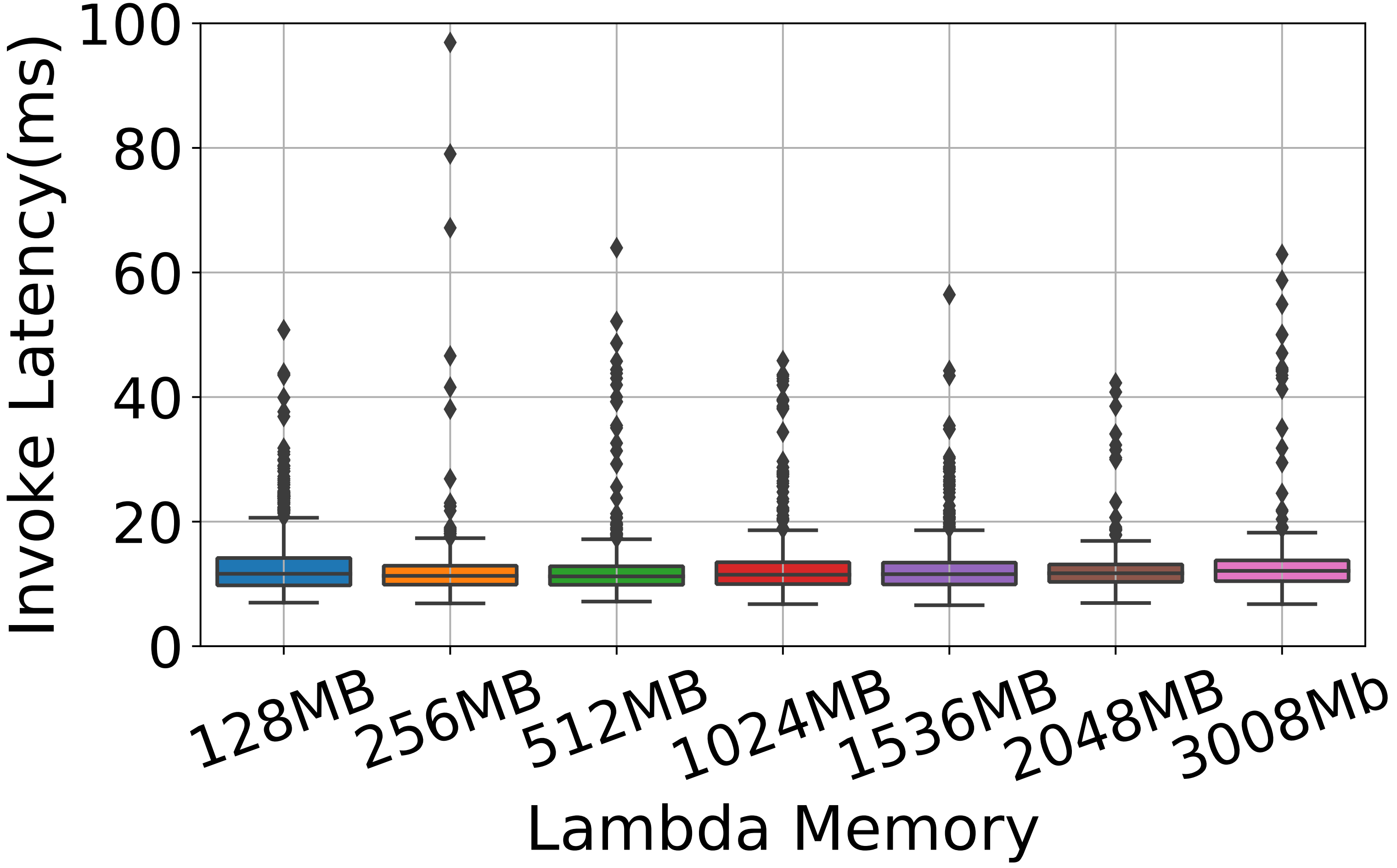
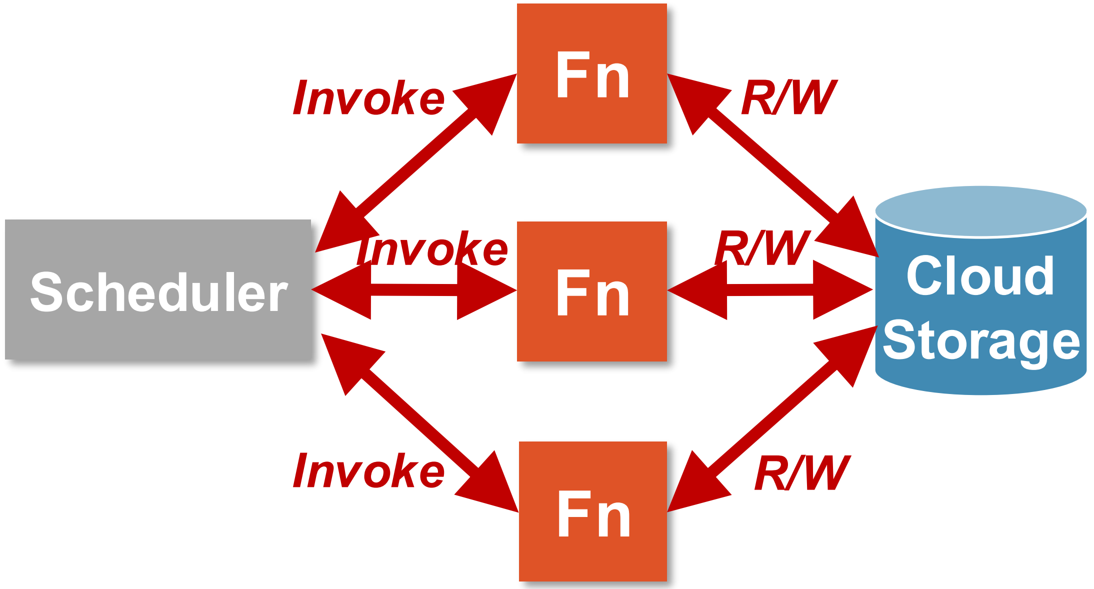
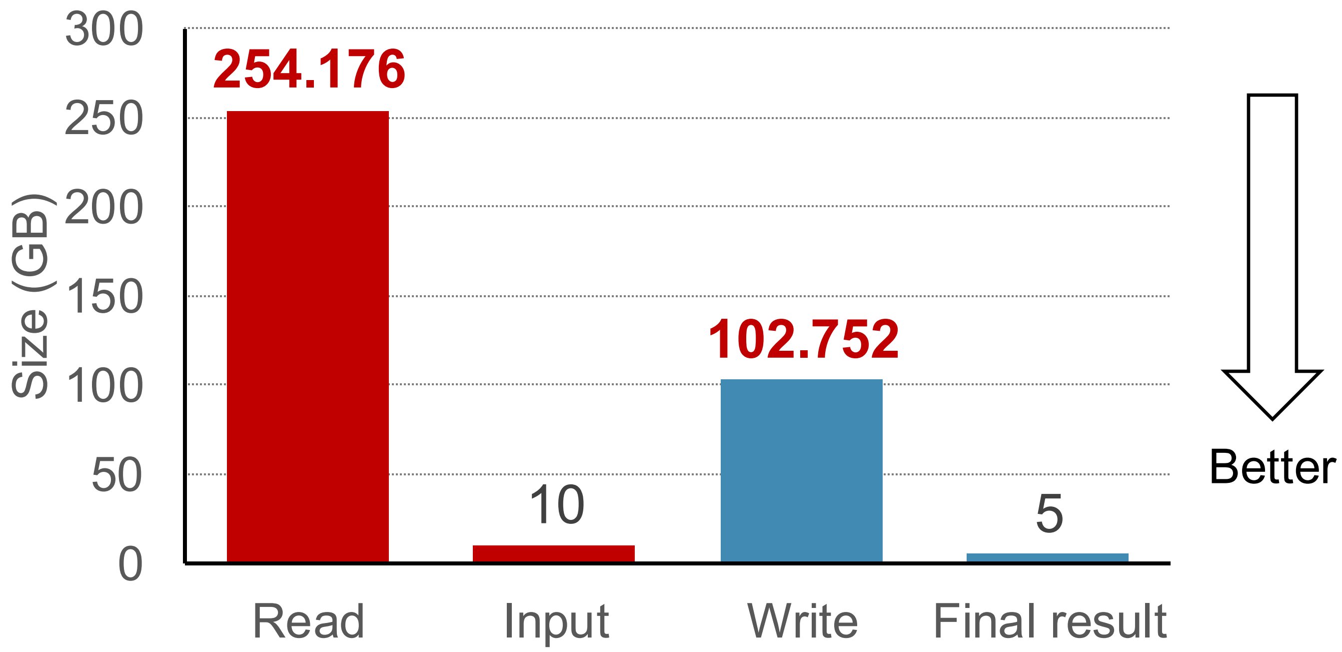
# High HTTP invocation cost for AWS Lambda



# Python analytics on FaaS is slow!




numpywren GEMM read & write amplification

State-of-the-art FaaS frameworks pay huge amounts of FaaS taxes

- **Task scheduling bottleneck:** Too slow to scale to thousands of functions
- **I/O bottleneck:** Excessive data movement cost due to FaaS constraint

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# Naively porting a stateful cluster computing application to FaaS won't work!

## Need a FaaS-centric approach

**Insight:** A FaaS framework may not care about traditional metrics (load balancing, cluster util.)

# Wukong

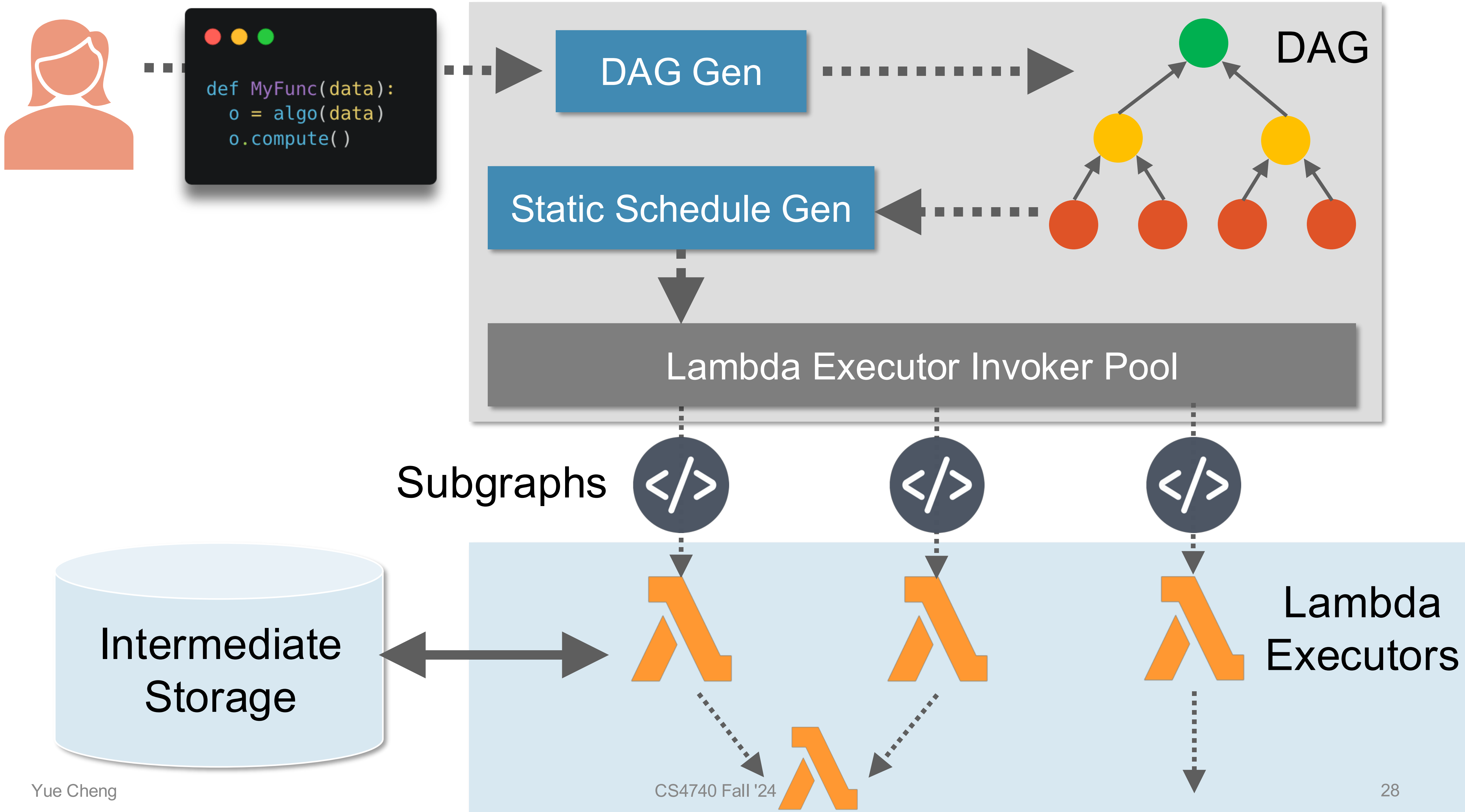
https://github.com/ds2-lab/Wukong

Wukong is a **FaaS-centric** parallel computing framework

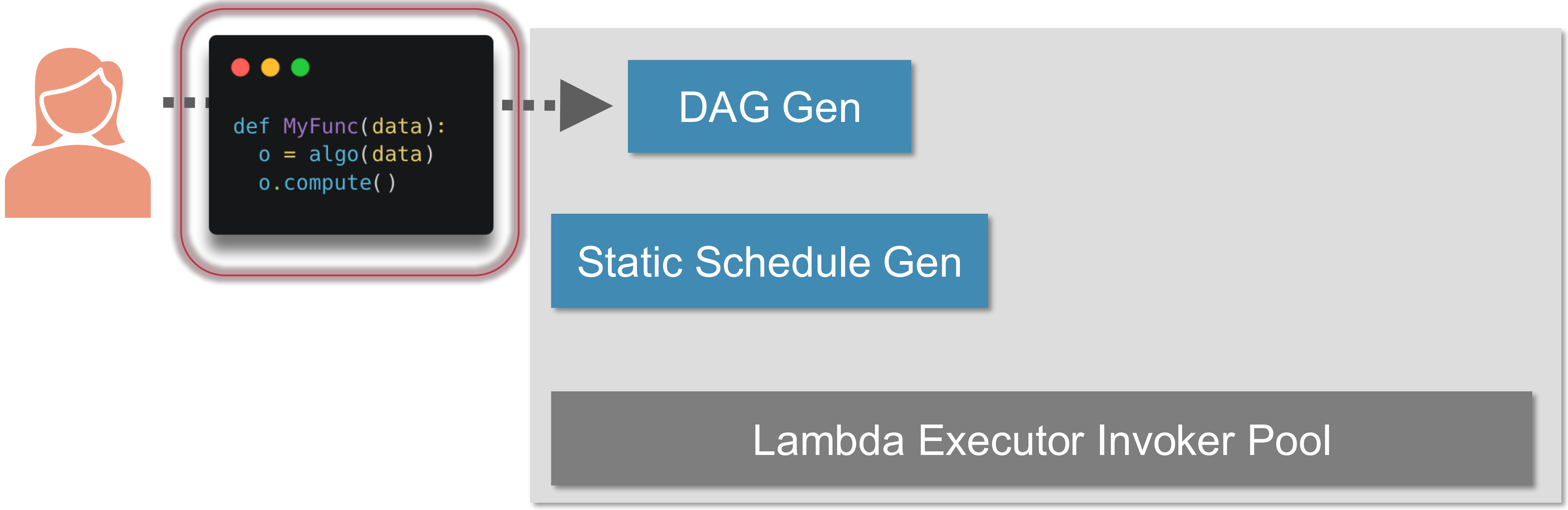
**Key idea:** Partitions the work of a centralized scheduler across many functions to take advantage of FaaS elasticity

**Naturally enables multiple benefits**

- Functions schedule tasks by invoking functions → **Exploits autoscaling for scalability**
- Functions execute multiple tasks to reduce data movement cost → **Improved data locality**
- Functions scale out / in autonomously → **No tedious cluster configuration**



def MyFunc(data):
o = algo(data)
o.compute()
DAG Gen
DAG
Static Schedule Gen
Lambda Executor Invoker Pool
Subgraphs
Intermediate Storage
Lambda Executors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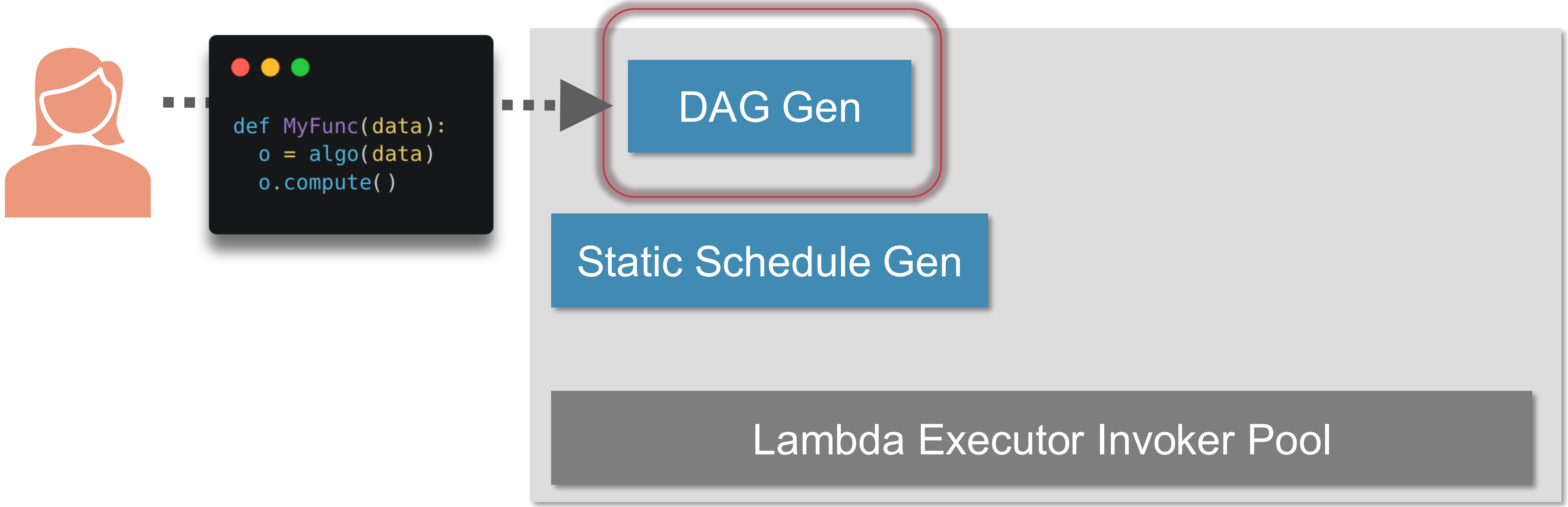
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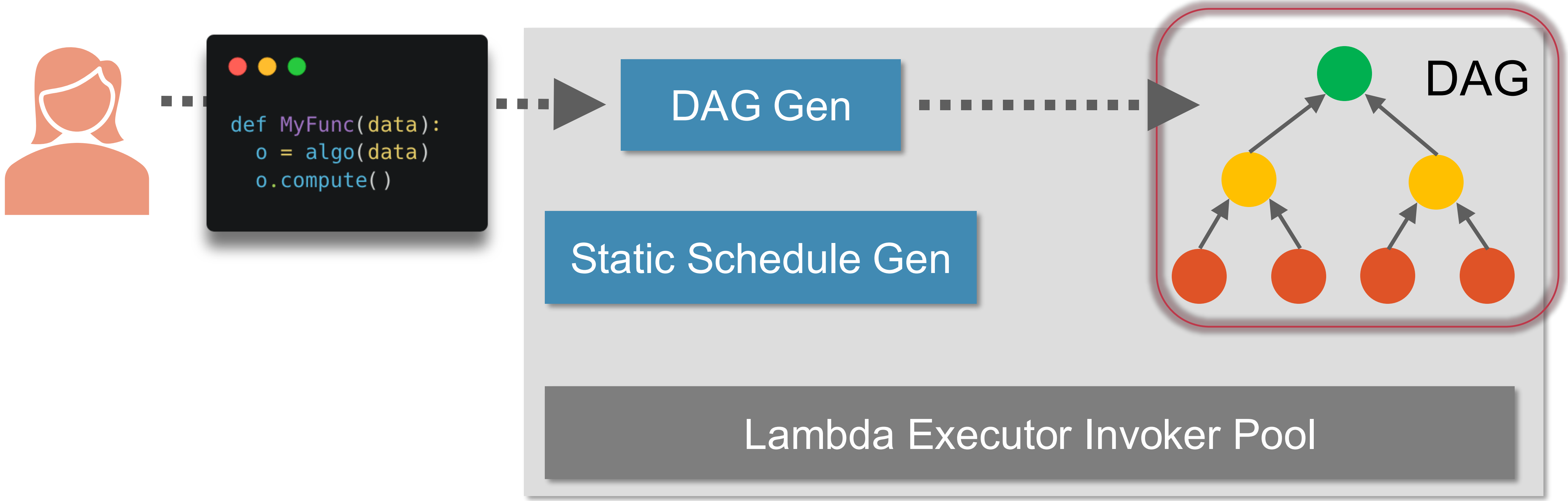
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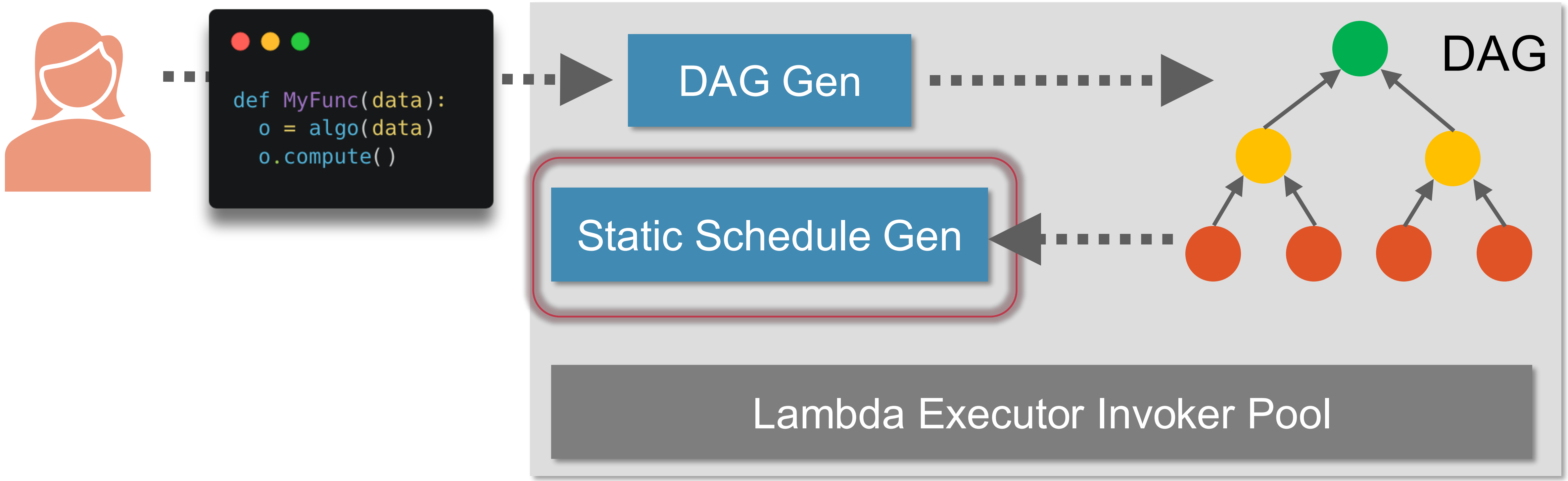
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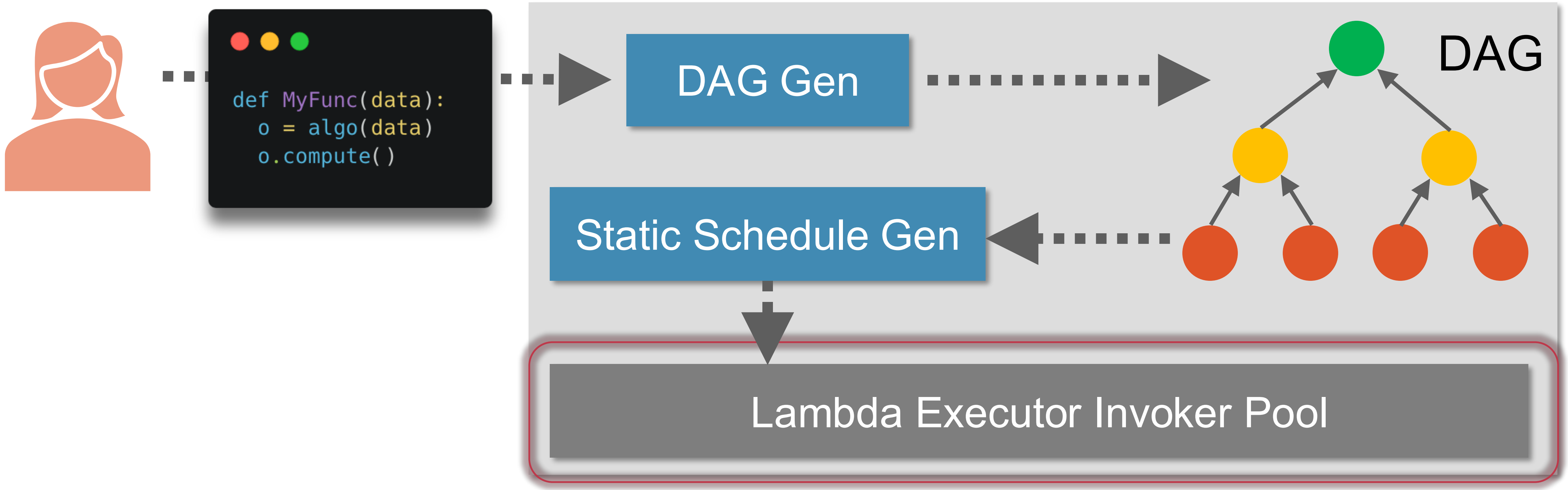
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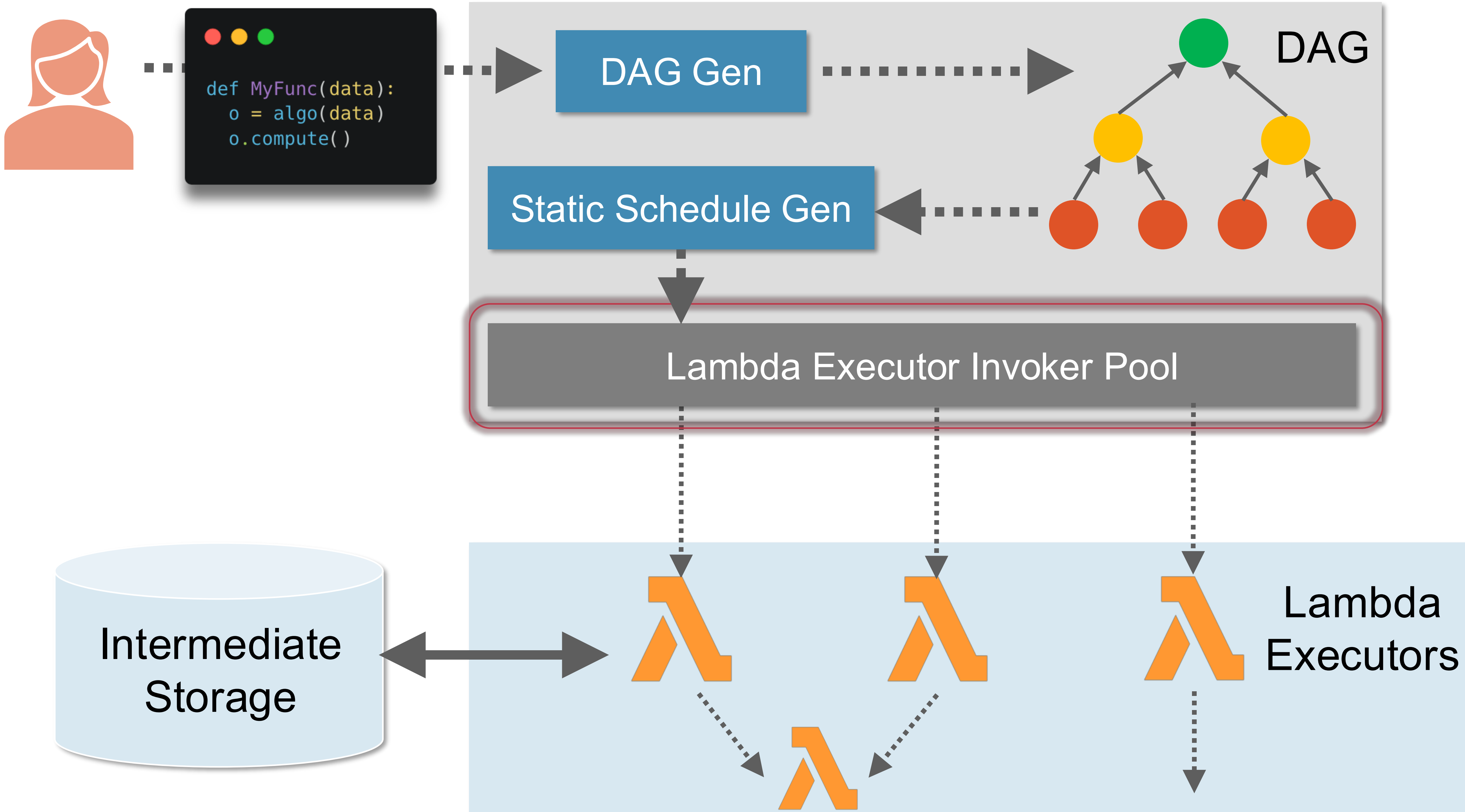

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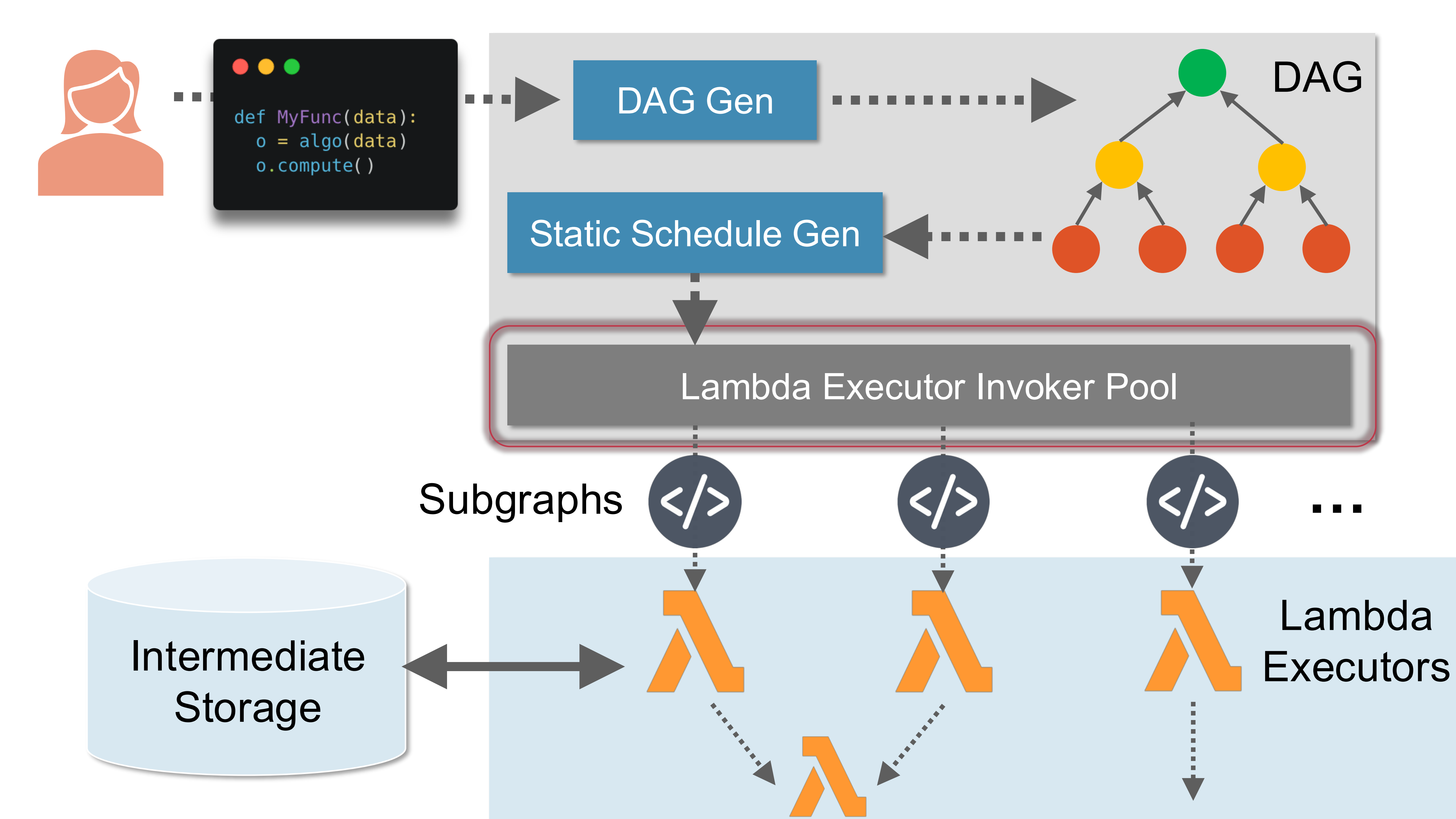

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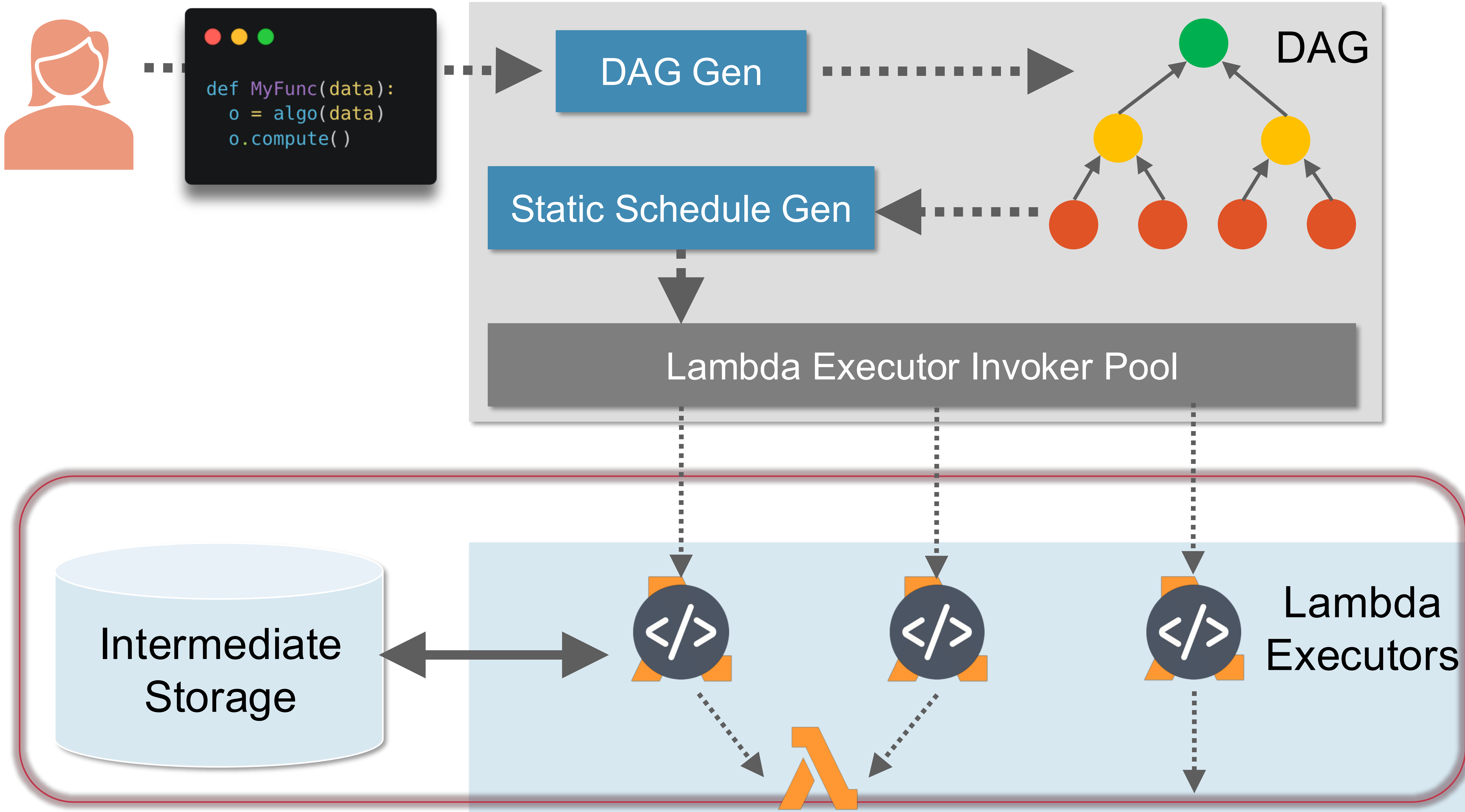

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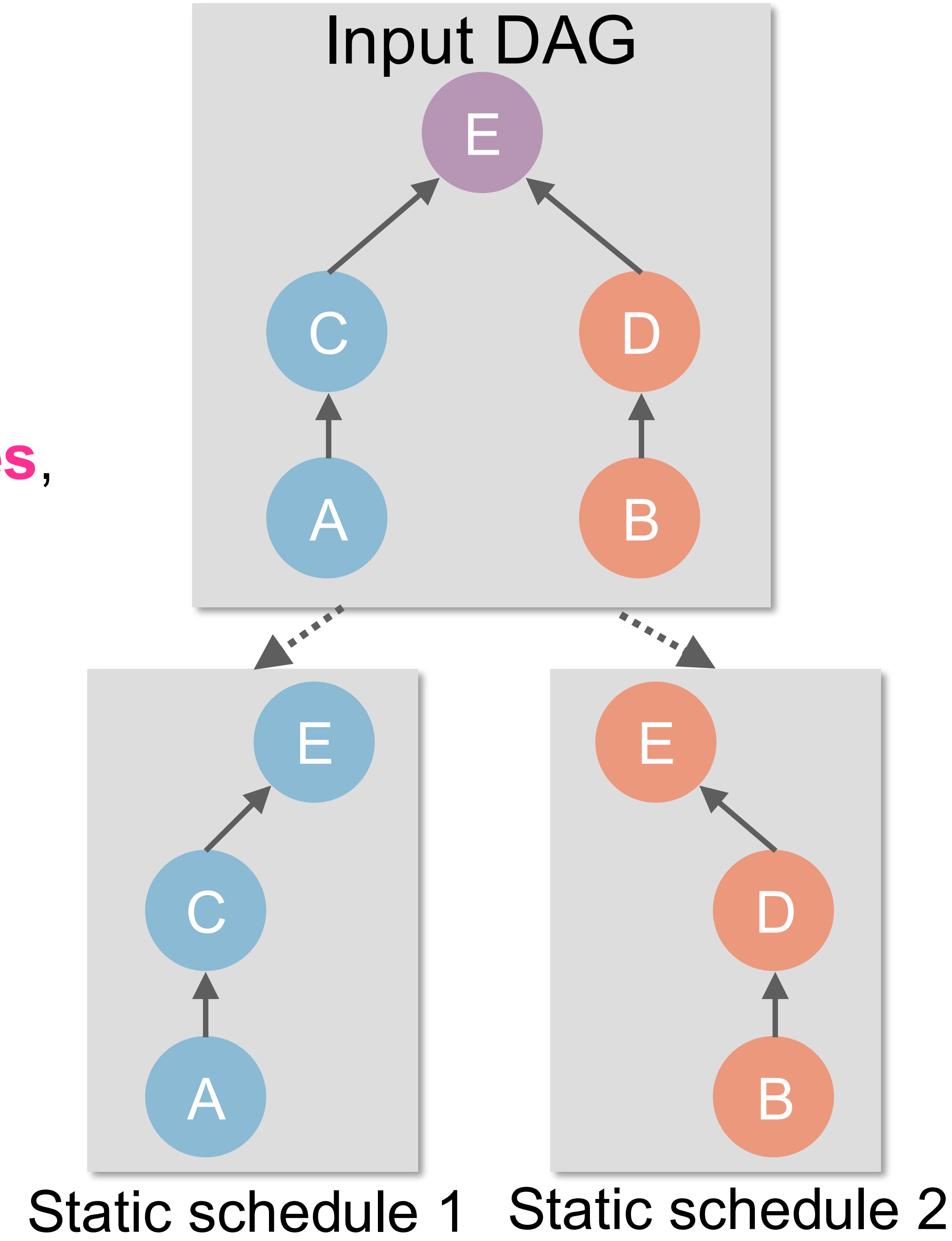
# Scheduling in Wukong

- Combination of **static** and **dynamic** scheduling
- Input DAG partitioned into **static schedules**, or subgraphs of the original DAG
- Serverless executors are assigned a **static schedule**
- Executors use **dynamic scheduling** to enforce data dependencies and **cooperatively** schedule tasks found in multiple static schedules



```
func MyFunc(data):
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```

# Static scheduling

```
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# Static scheduling

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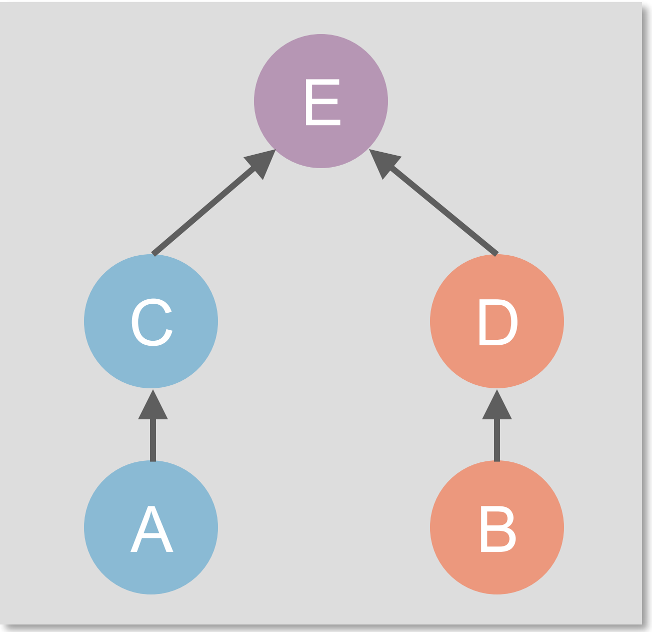
Input DAG

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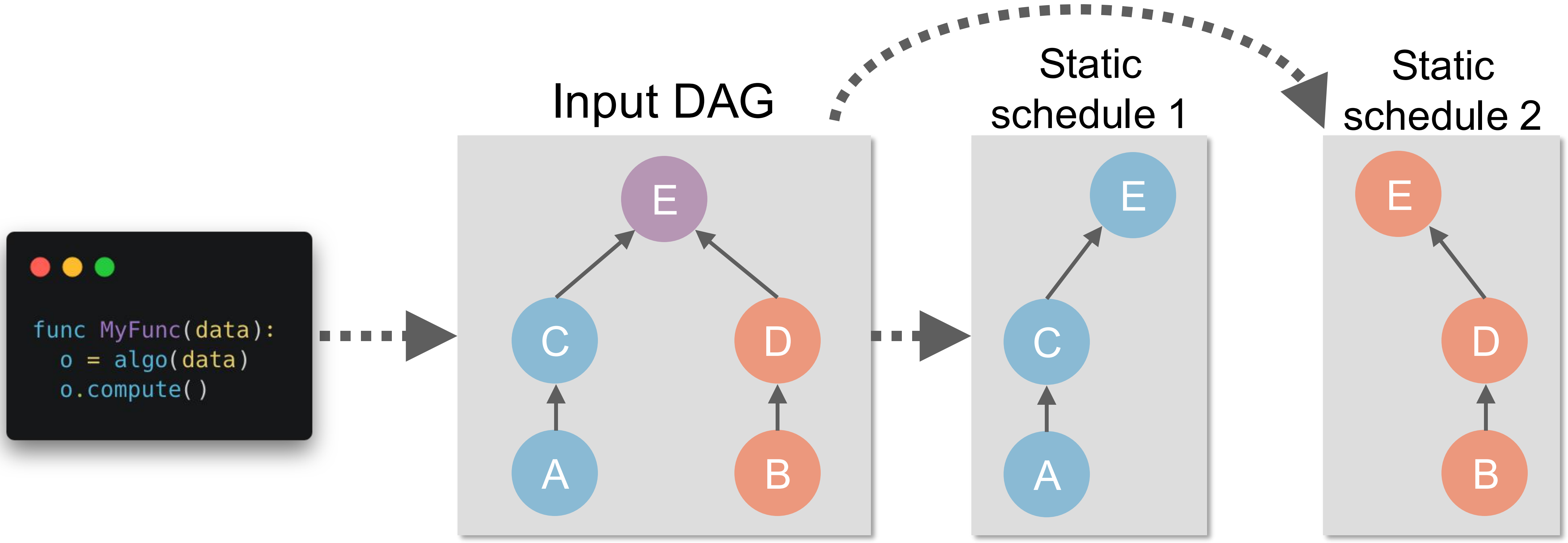


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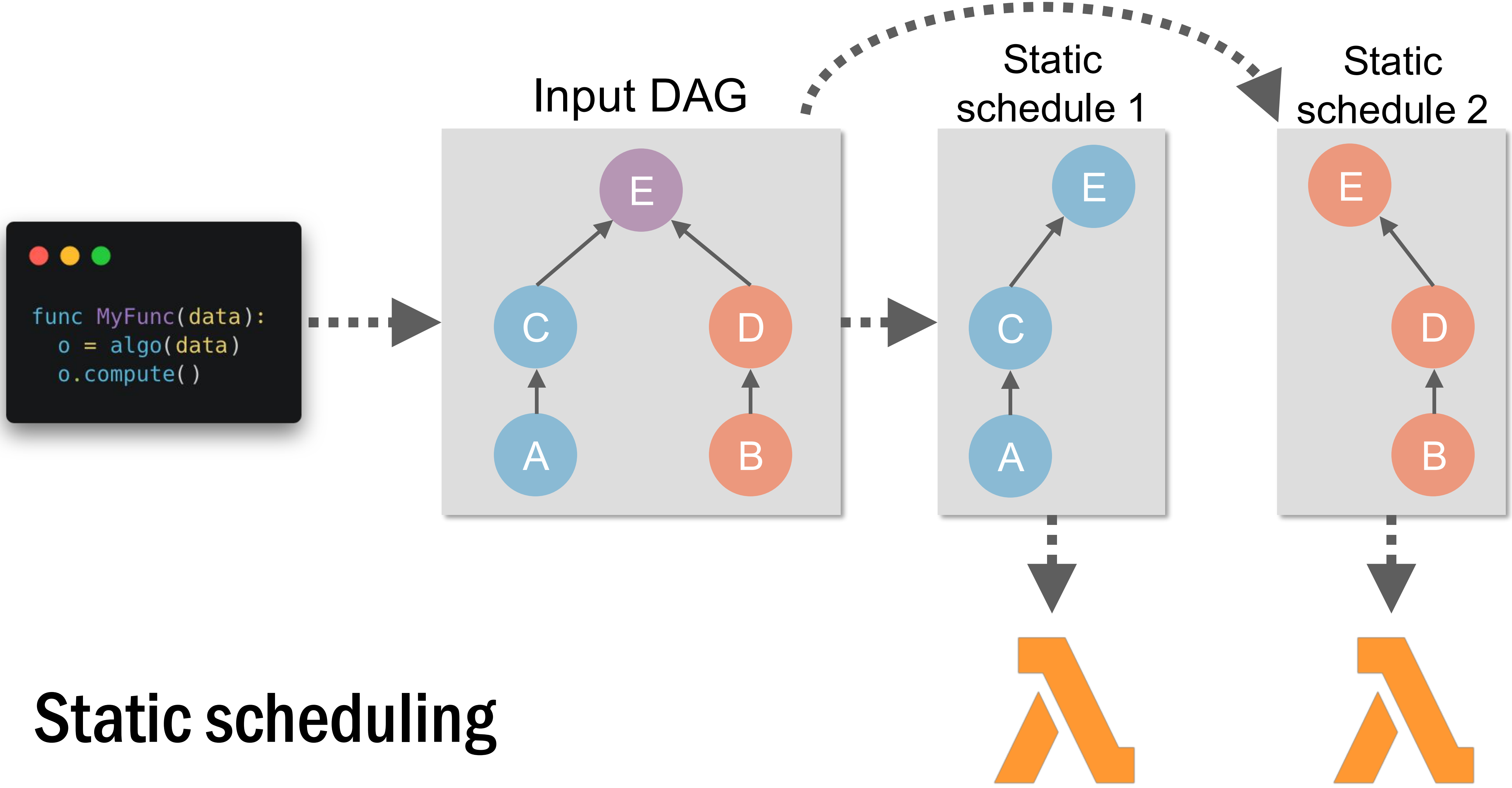


# Static scheduling

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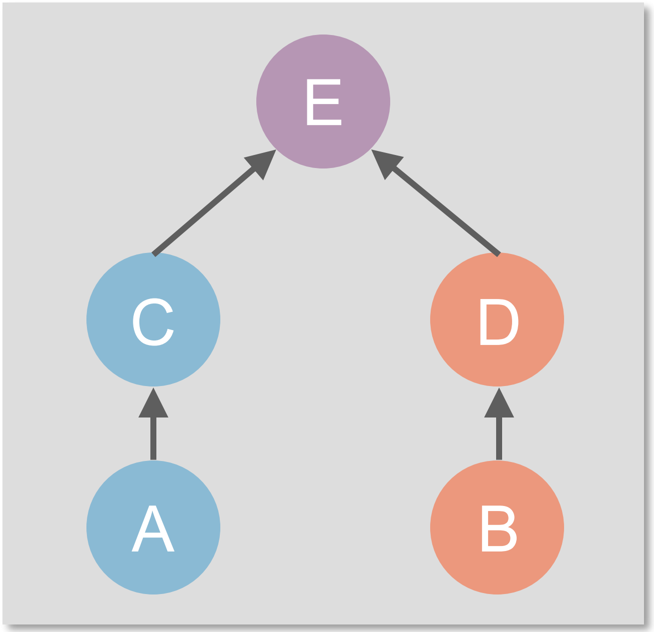


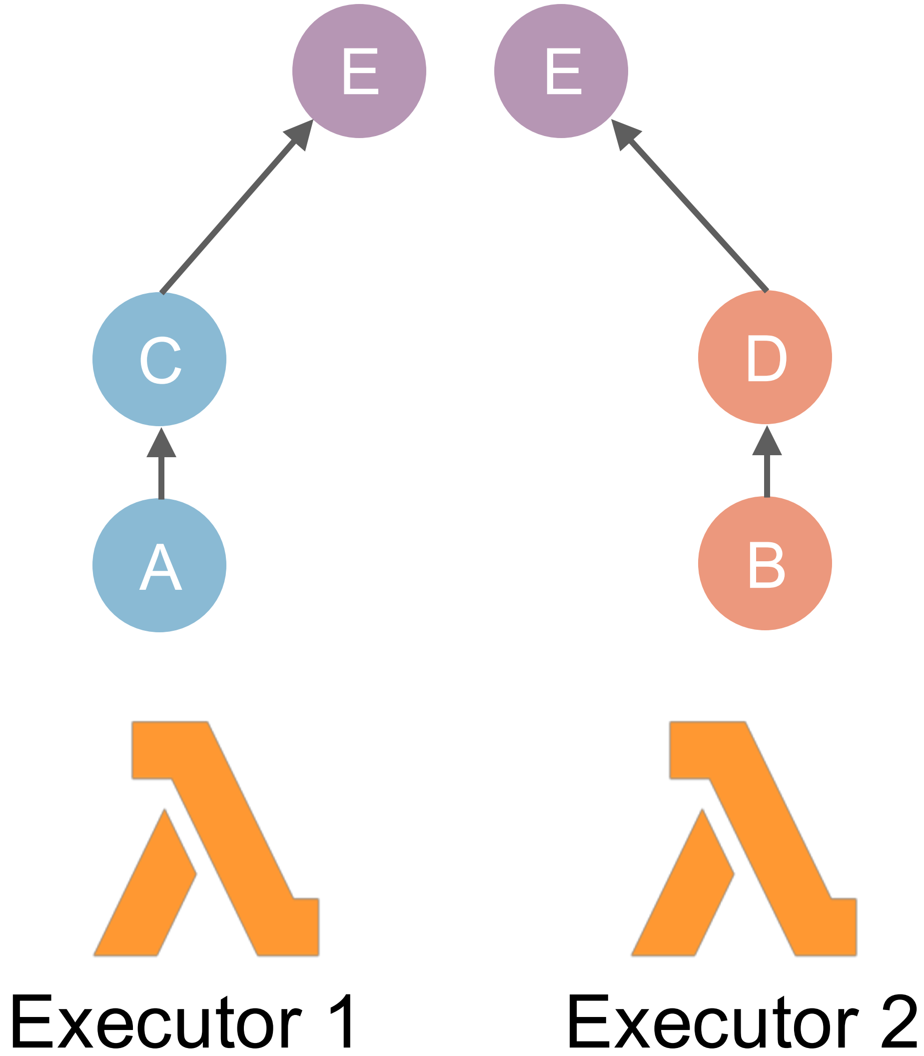


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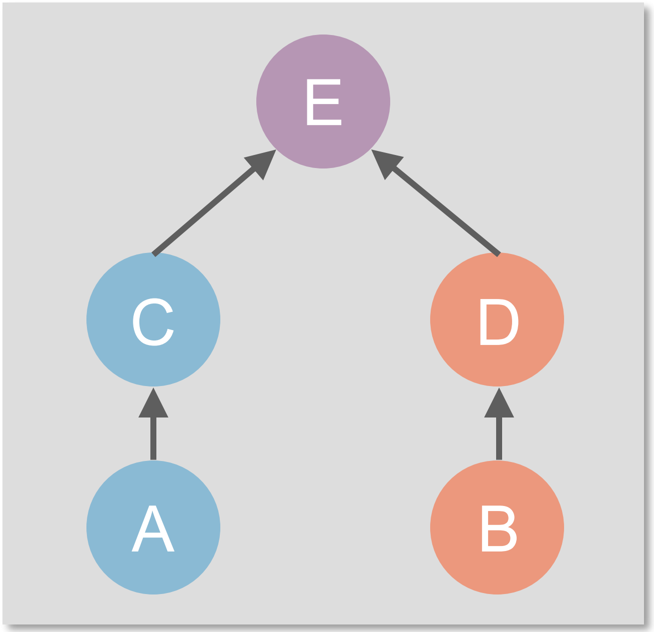


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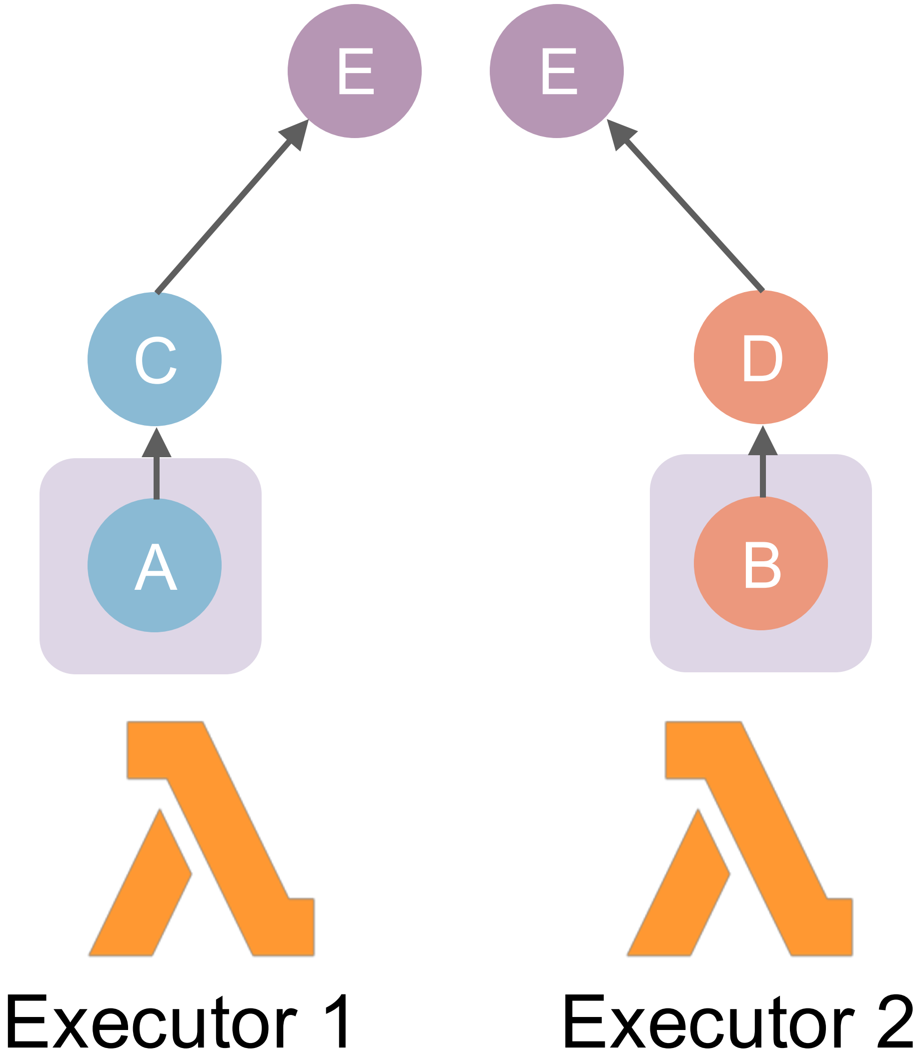

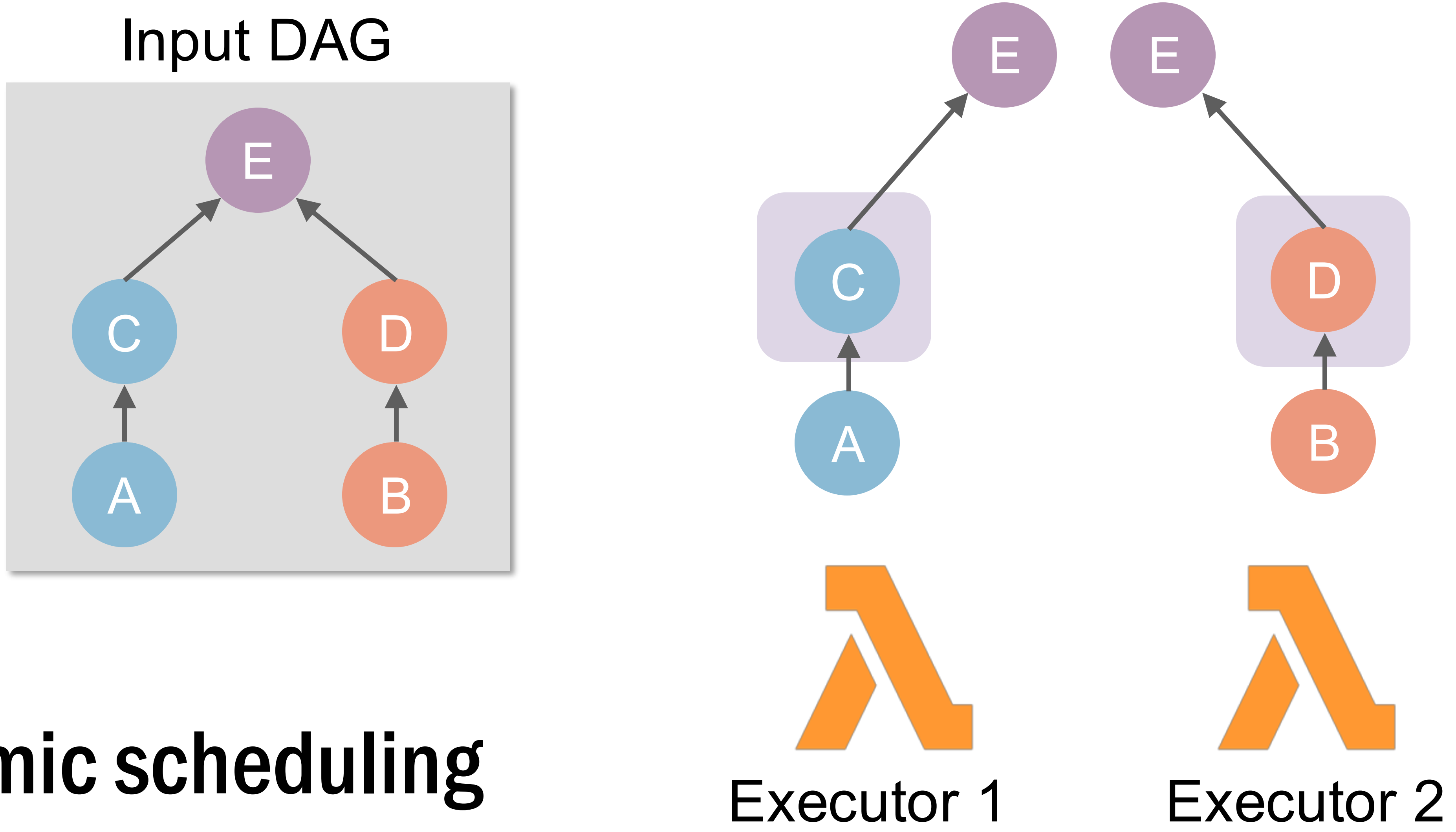


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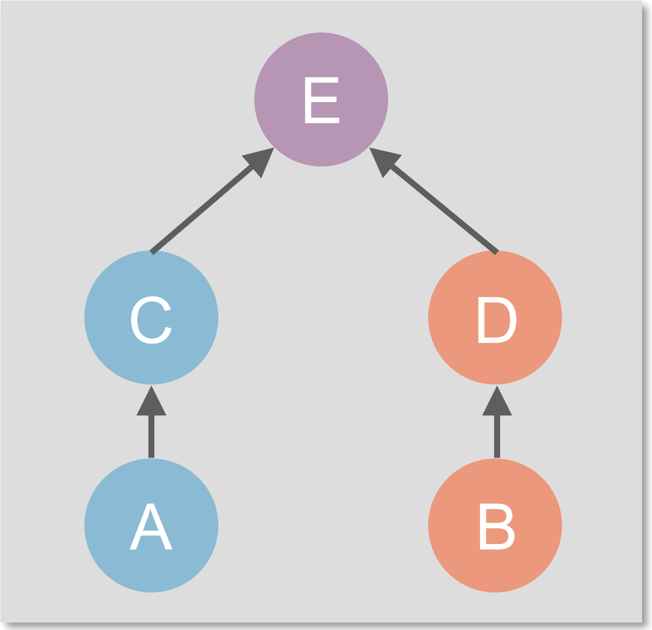


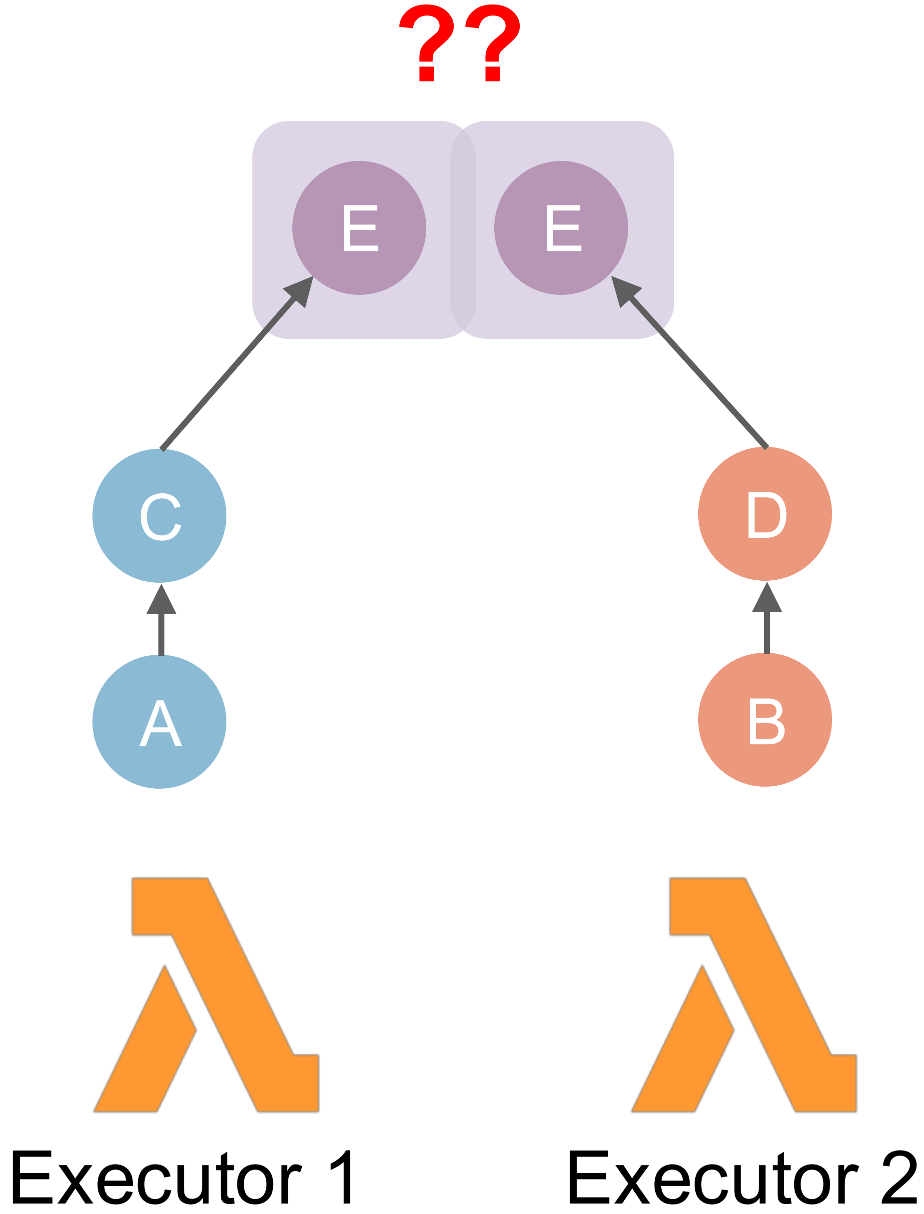


# Dynamic scheduling

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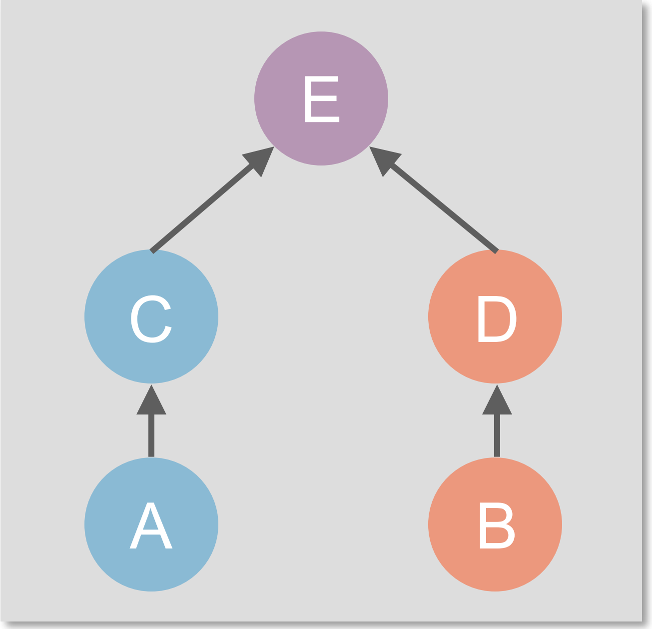
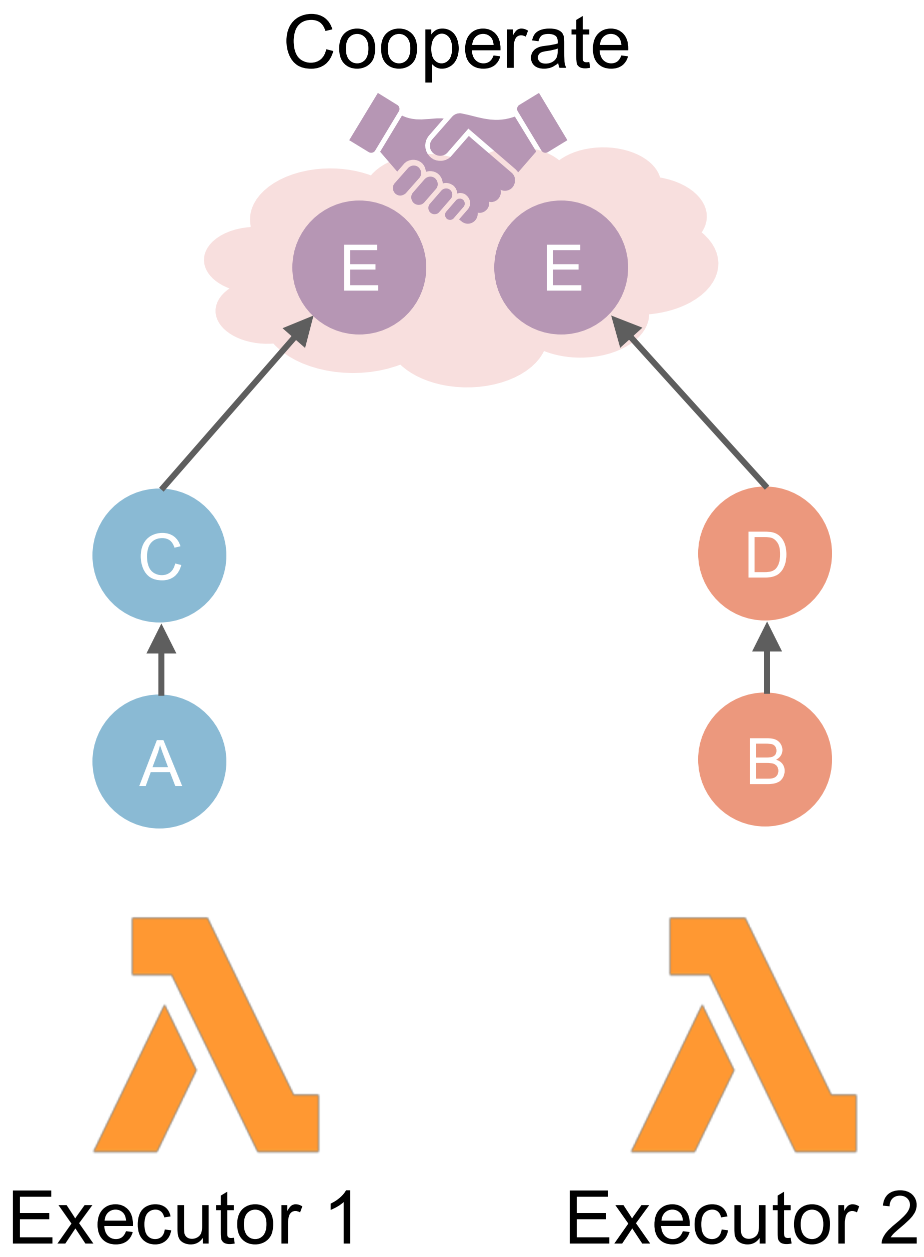
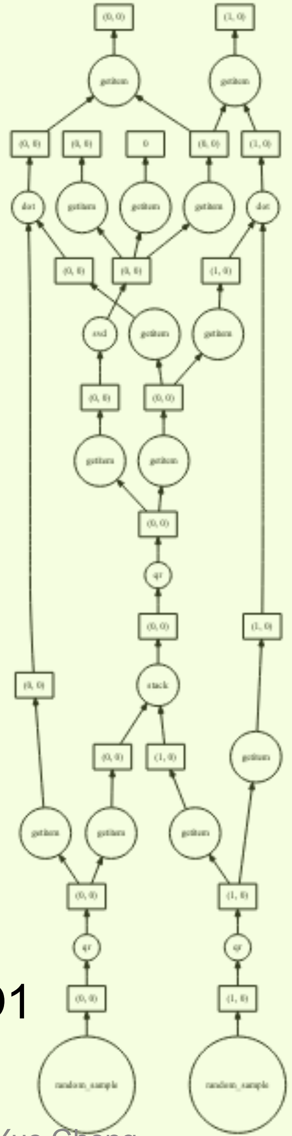


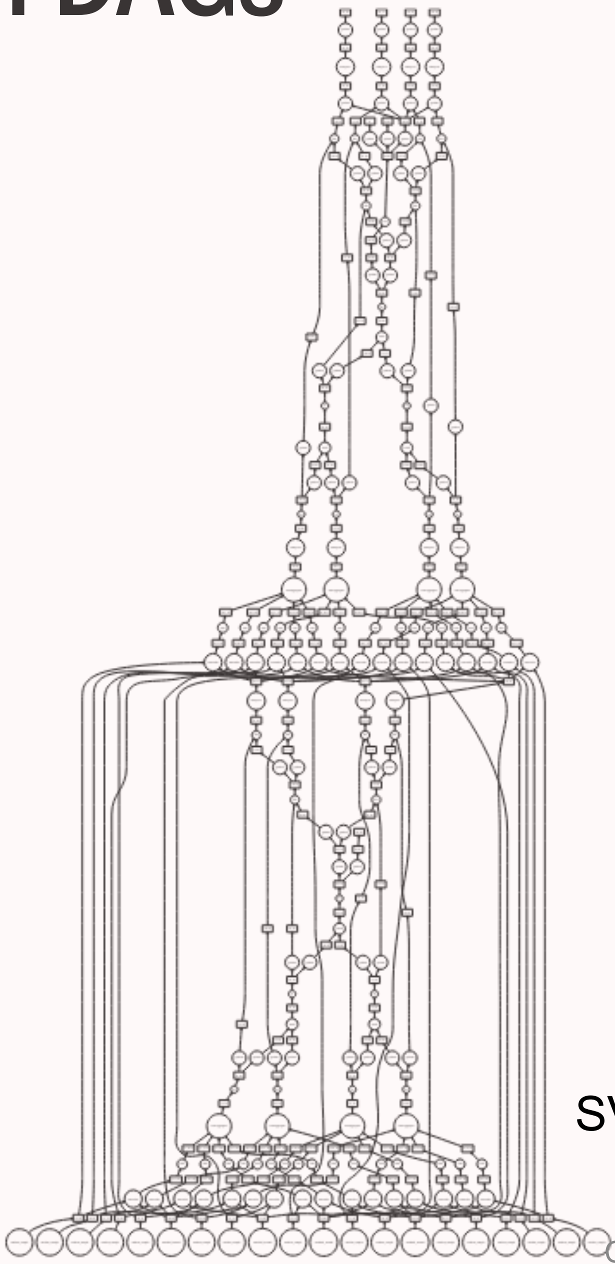




# Dynamic scheduling

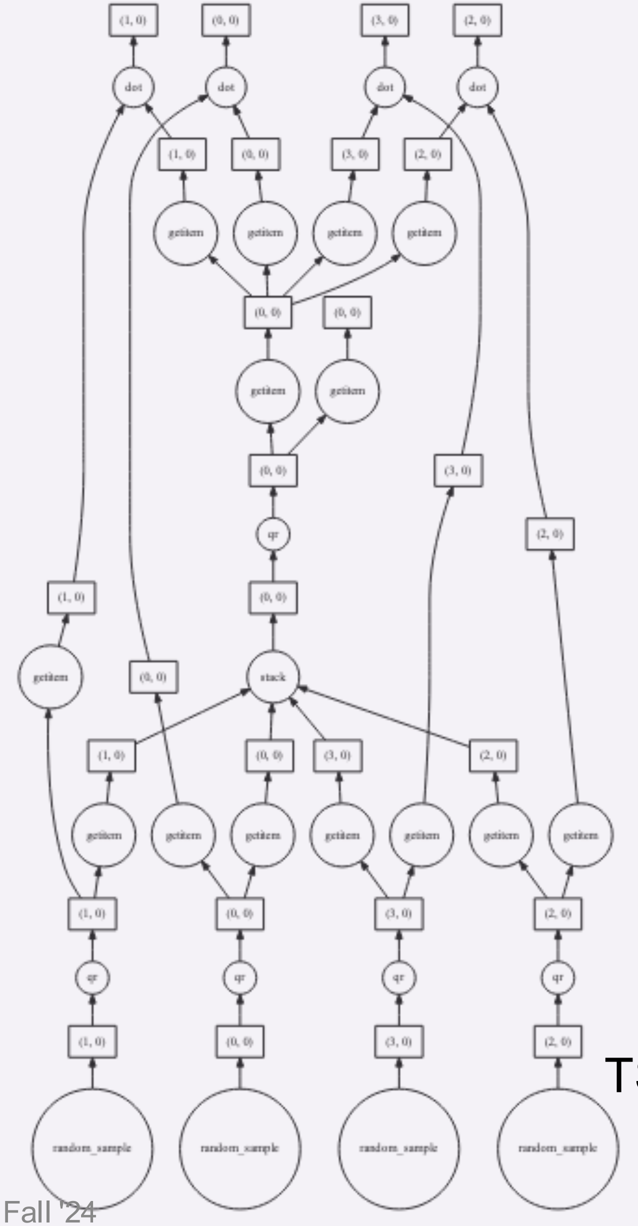
# Application DAGs



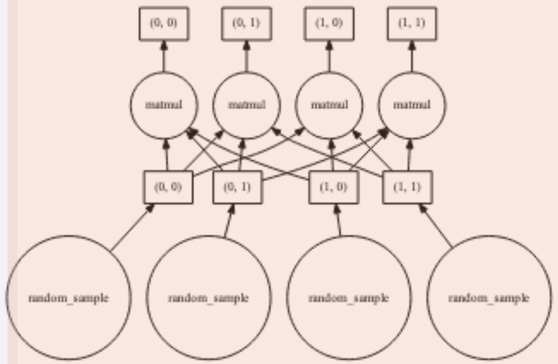
SVD1



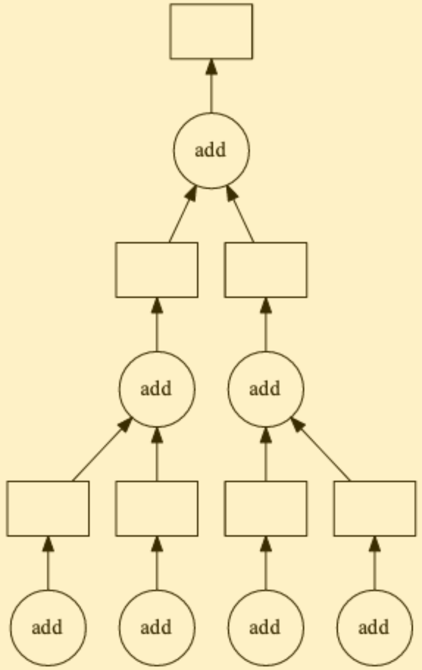
SVD2




TSQR

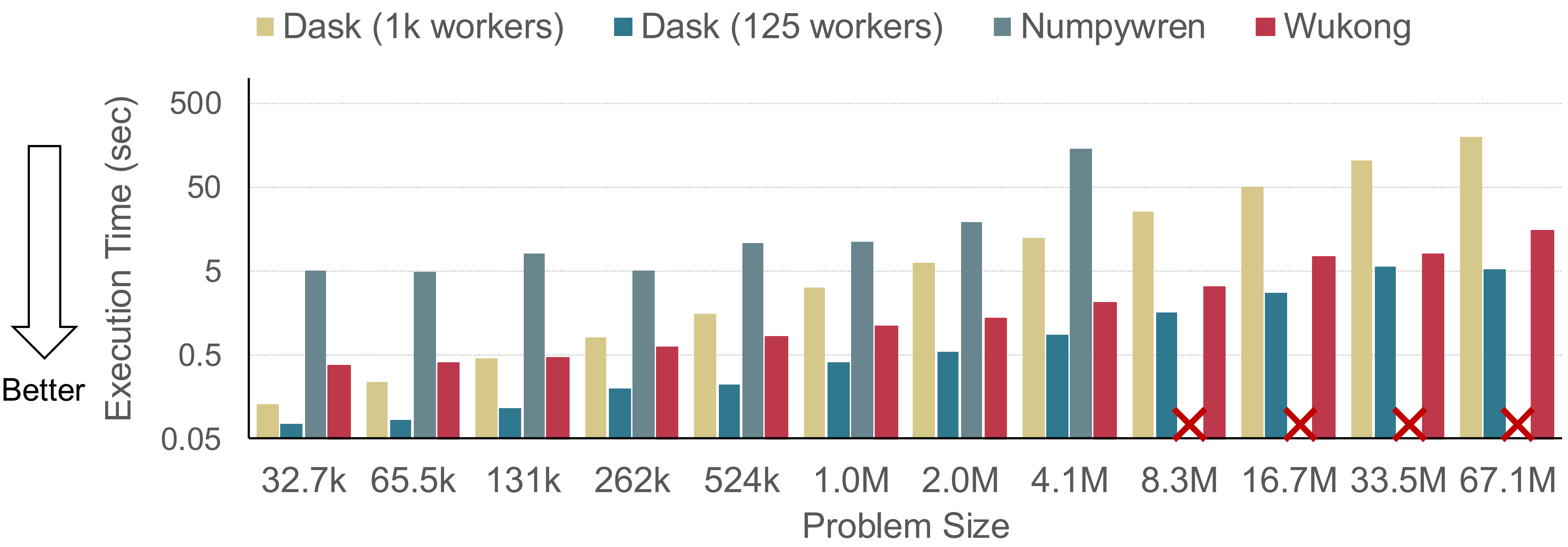



GEMM



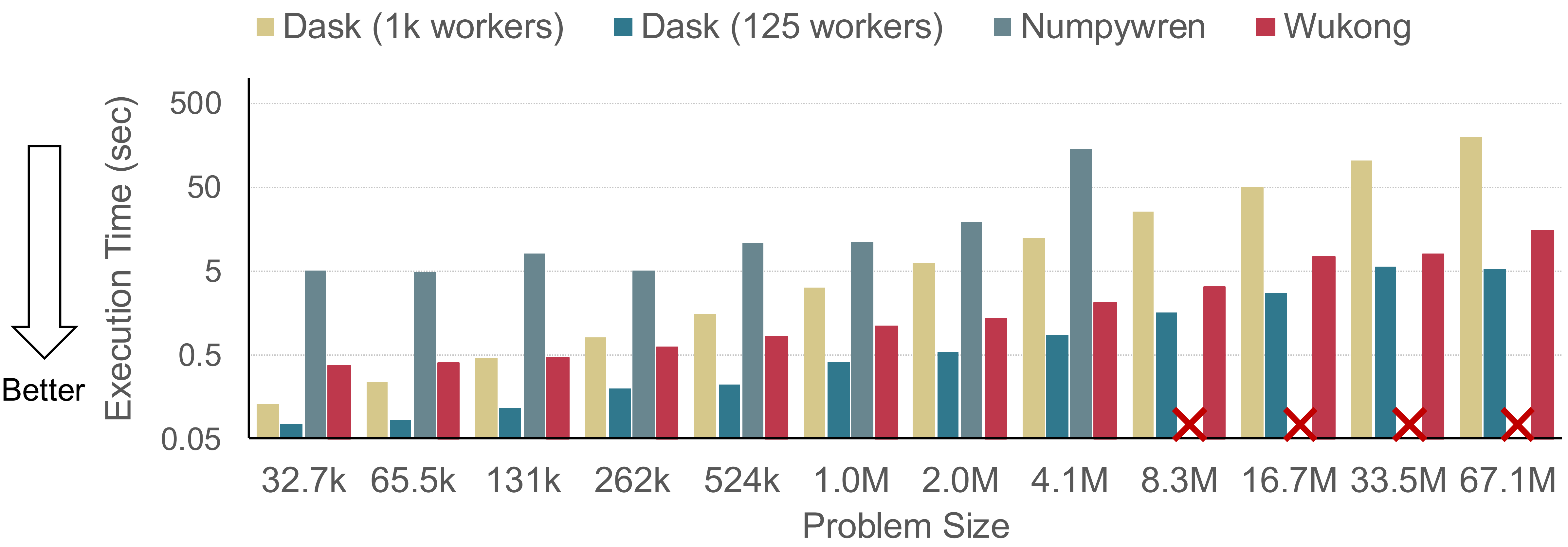

Tree reduction

# Application performance: TSQR



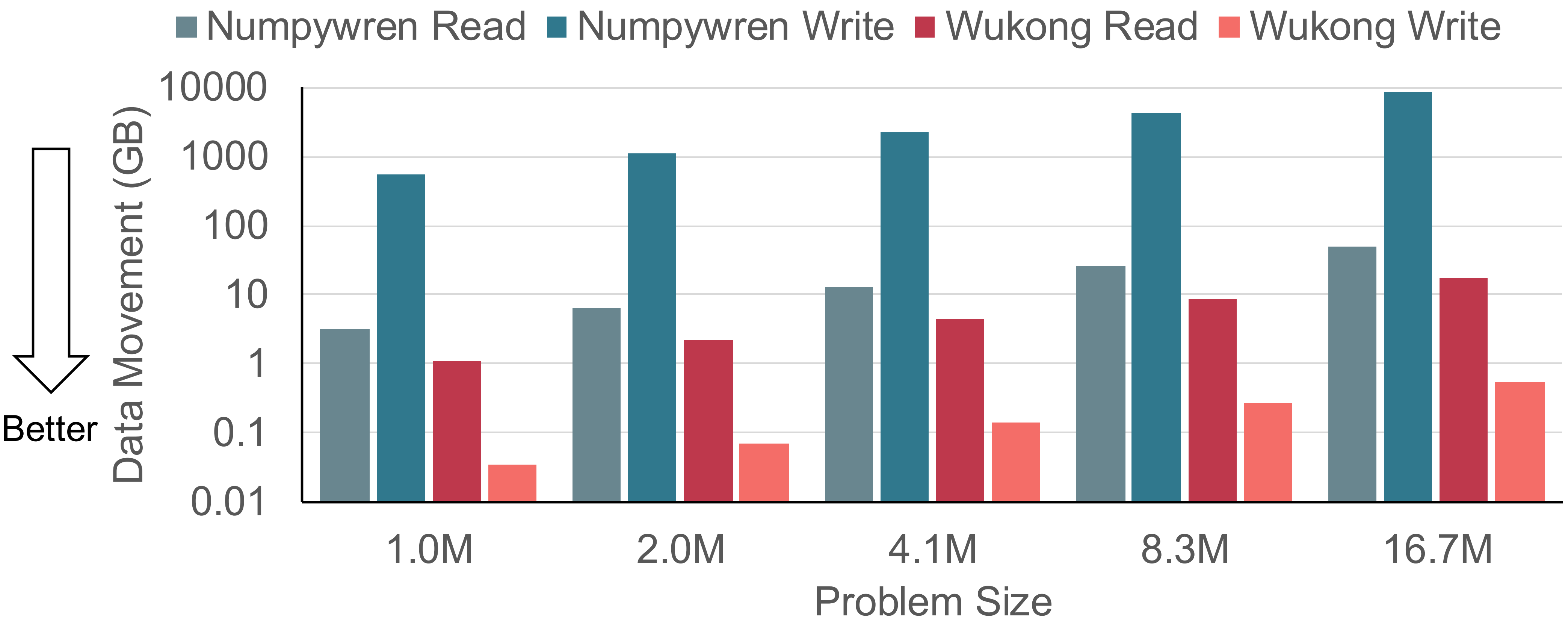

Wukong and numpywren ran on AWS Lambda w/ 3GB memory
Dask distributed ran on 125 c5.4xlarge EC2 VMs w/ 2,000 vCPU cores

# Application performance: TSQR

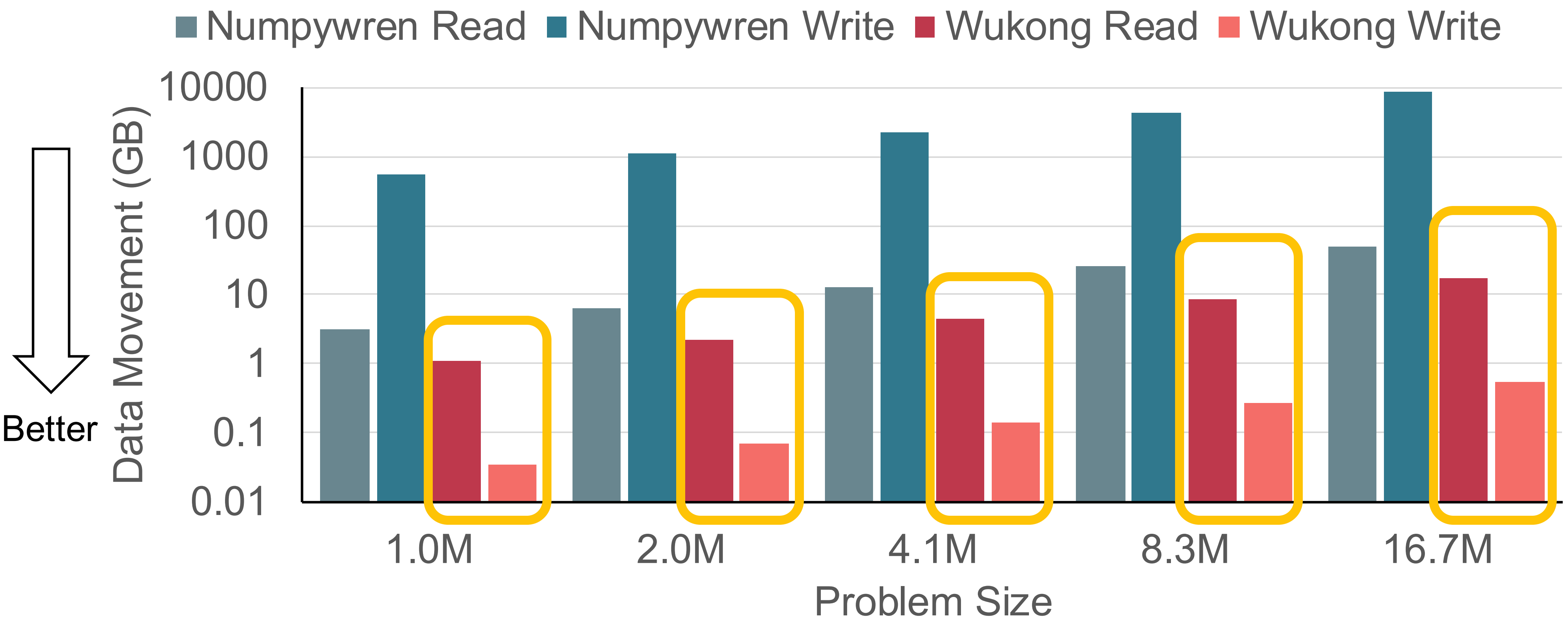



**Wukong outperforms numpywren considerably for all problem sizes.**

# Data movement cost: TSQR



# Data movement cost: TSQR




**Wukong reads and writes considerably less data than numpywren.**

# WUKONG 悟空
## SERVERLESS DAG ENGINE

### Parallelizing Prediction (sklearn.svm.SVC)

```
import pandas as pd
import seaborn as sns
import sklearn.datasets
from sklearn.svm import SVC

import dask_ml.datasets
from dask_ml.wrappers import ParallelPostFit
from distributed import LocalCluster, Client
local_cluster = LocalCluster(host='0.0.0.0:8786',
                   proxy_address = '3.83.198.204',
                   num_fargate_nodes = 10)
client = Client(local_cluster)

X, y = sklearn.datasets.make_classification(n_samples=1000)
clf = ParallelPostFit(SVC(gamma='scale'))
clf.fit(X, y)

X, y = dask_ml.datasets.make_classification(n_samples=800000,
                                            random_state=800000,
                                            chunks=800000 // 20)

# Start the computation.
clf.predict(X).compute()
```

### GEMM (Matrix Multiplication)

```
import dask.array as da
from distributed import LocalCluster, Client
local_cluster = LocalCluster(host='0.0.0.0:8786',
                   proxy_address = '3.83.198.204',
                   num_fargate_nodes = 10)
client = Client(local_cluster)

x = da.random.random((10000, 10000), chunks = (1000, 1000))
y = da.random.random((10000, 10000), chunks = (1000, 1000))
z = da.matmul(x, y)

# Start the computation.
z.compute()
```

[https://github.com/ds2-lab/Wukong](https://github.com/ds2-lab/Wukong)