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, matplotlib

Frameworks for O(100s GB)

Apache Spark, DASK, hadoop, MPI

Today's data analytics landscape

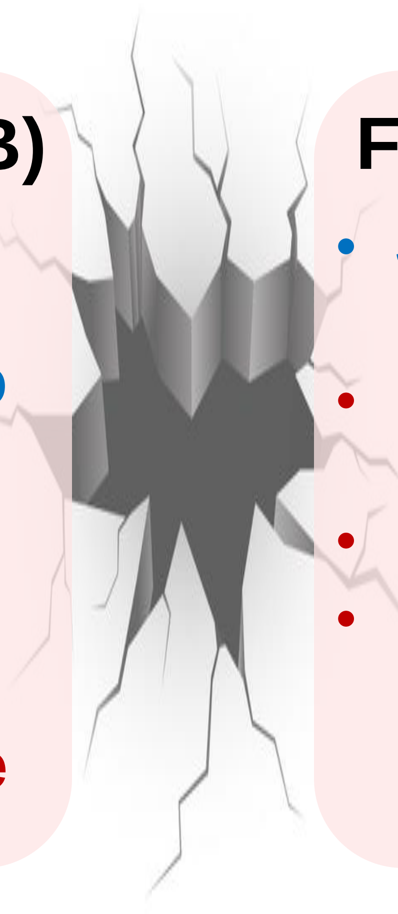
Libraries efficient for O(1MB)

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**

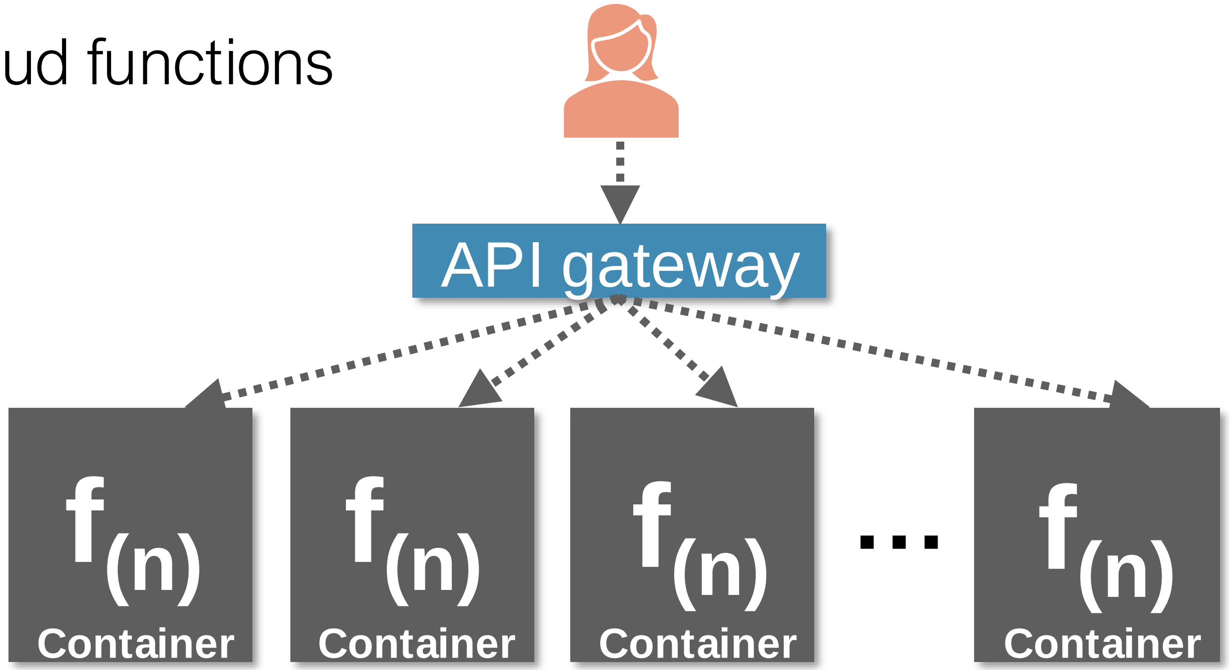
- **Function-as-a-Service (FaaS):** Cloud functions as a basic deployment unit

AWS Lambda

Azure Functions

Google Cloud Functions

Alibaba Function Compute

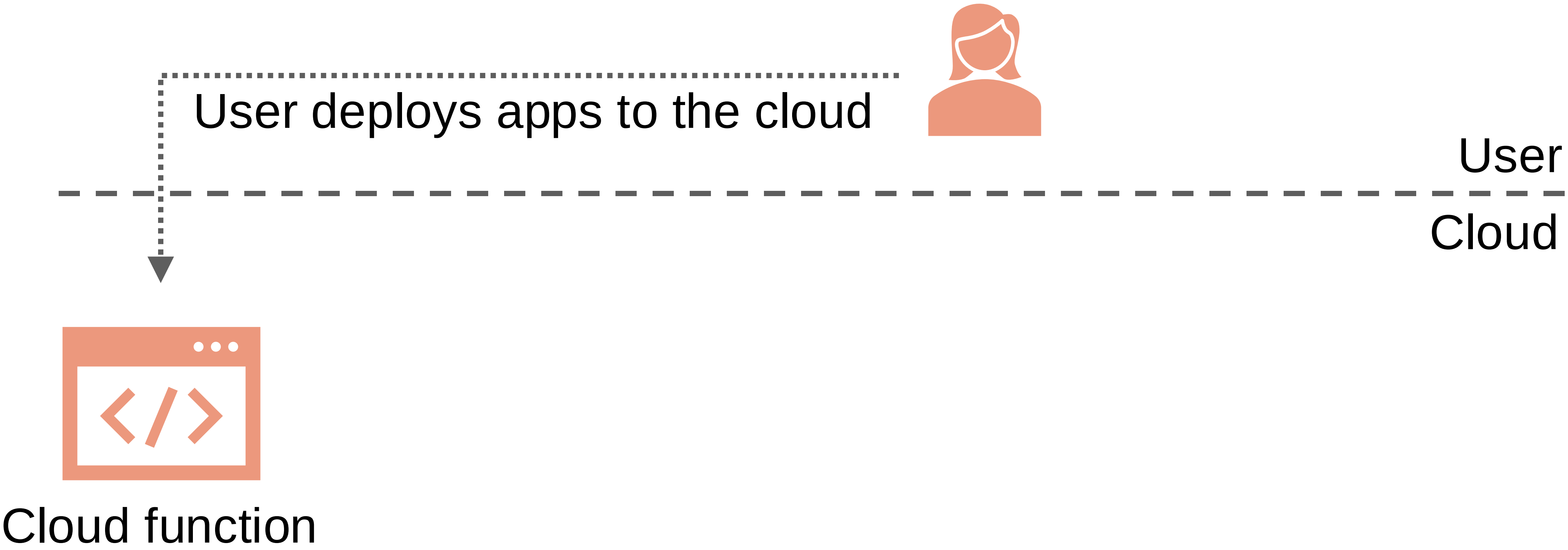


Function-as-a-Service (FaaS)

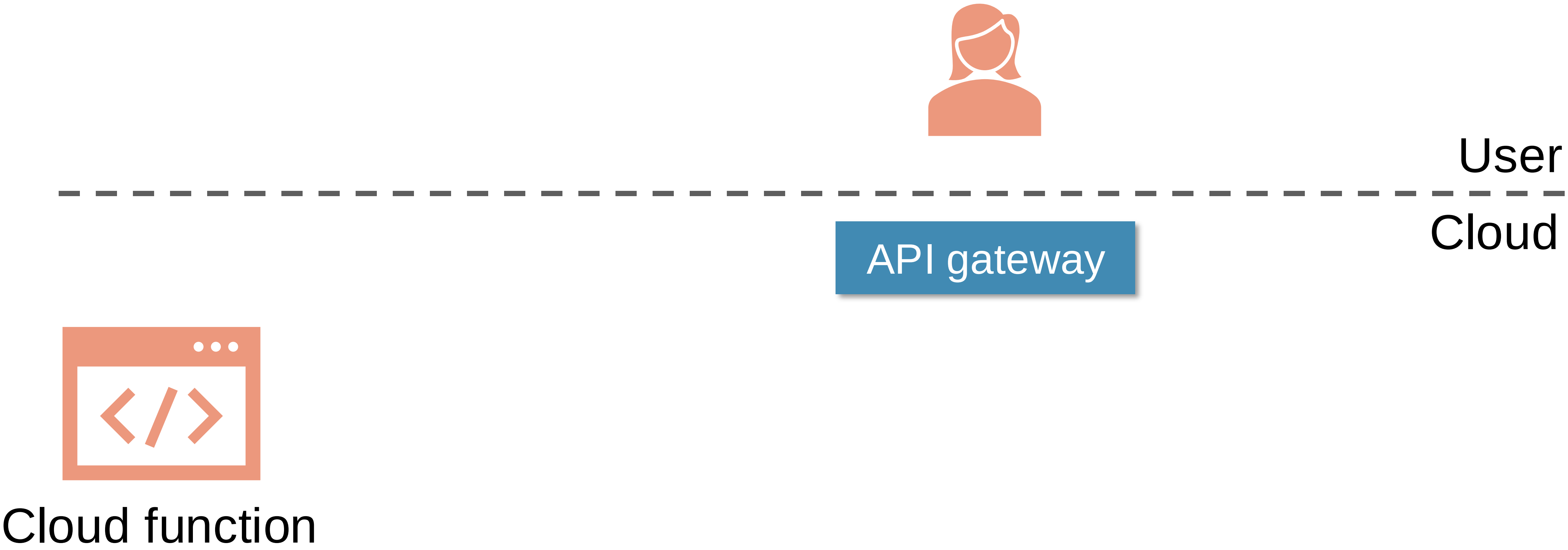
User

Cloud

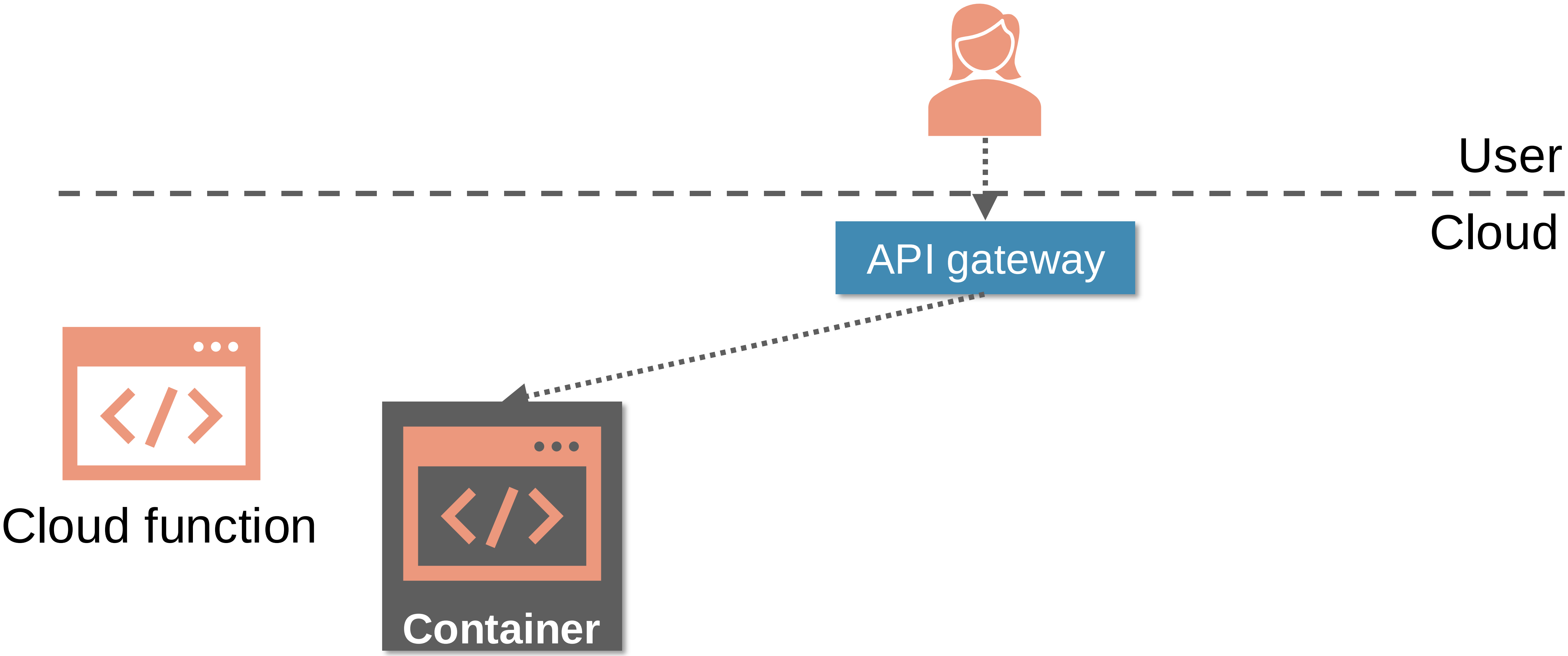
Function-as-a-Service (FaaS)



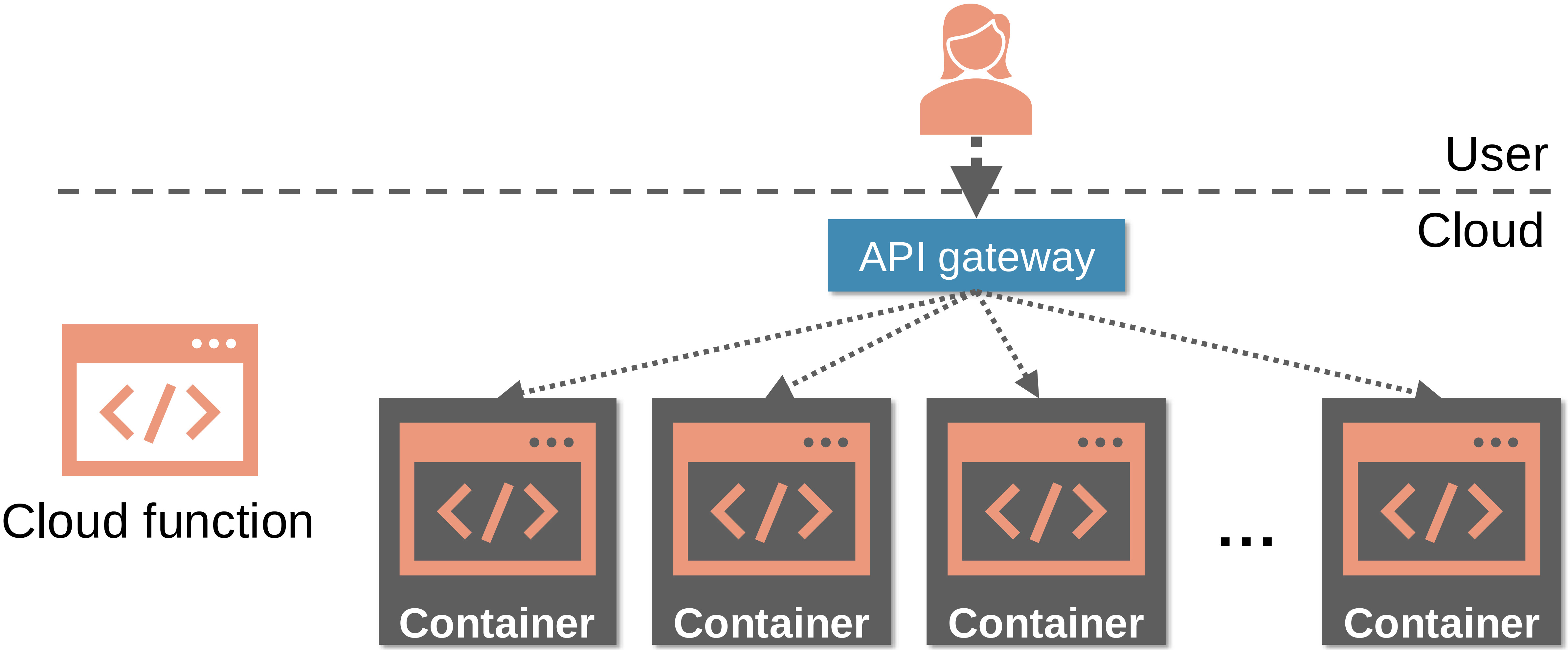
Function-as-a-Service (FaaS)



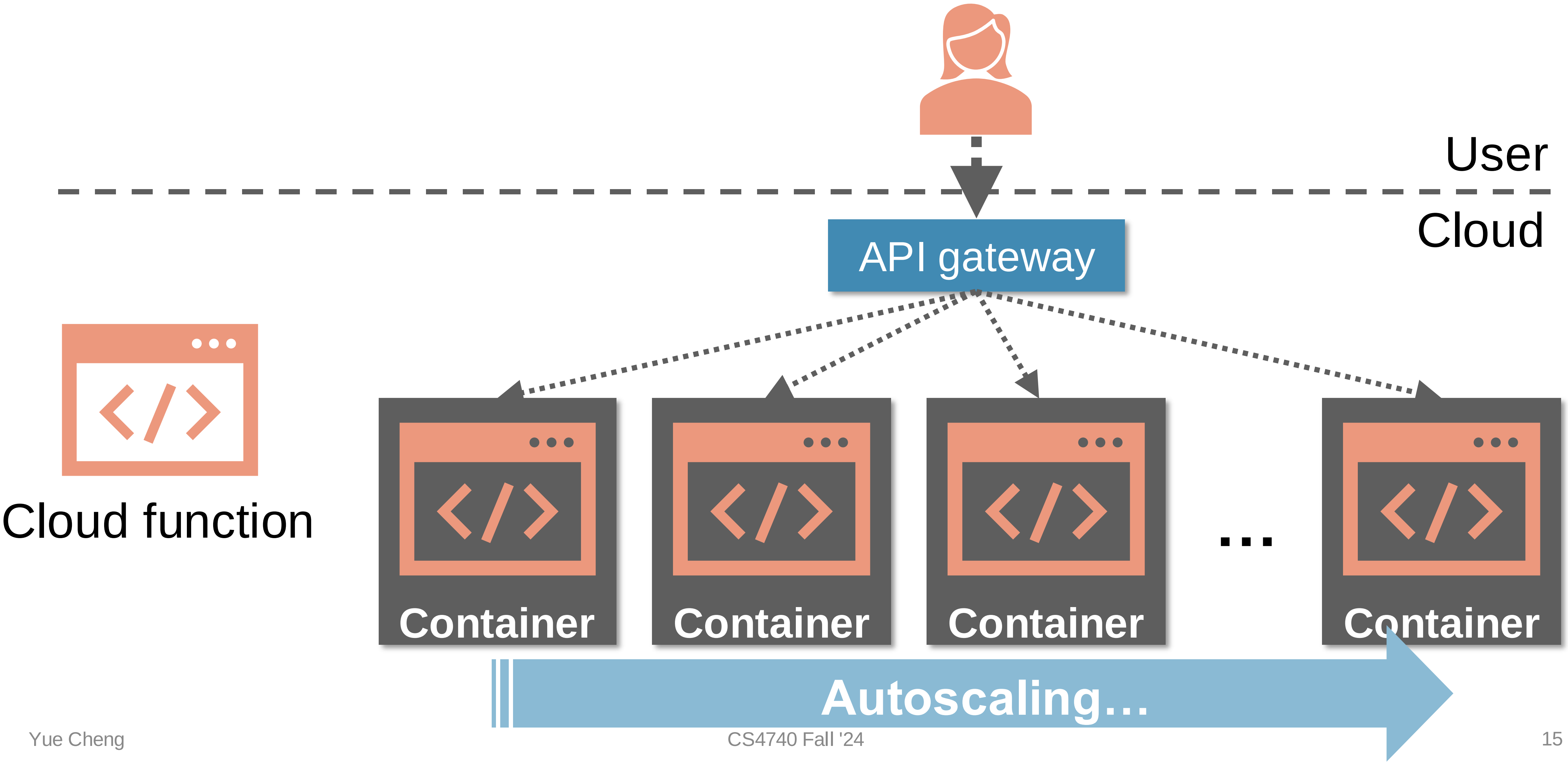
Function-as-a-Service (FaaS)



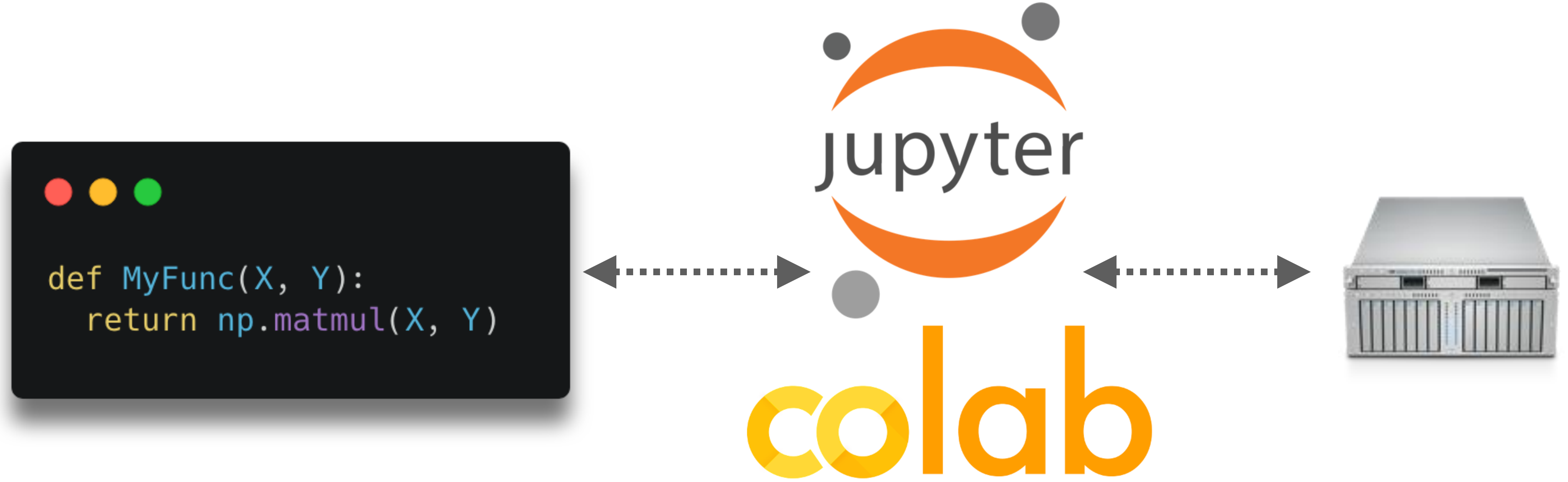
Function-as-a-Service (FaaS)



Function-as-a-Service (FaaS)



Python analytics: What we have today



Python analytics: What we have today

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)
```

Manually deployed distributed computing cluster

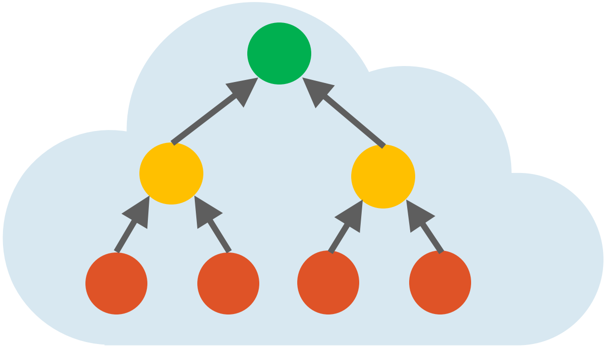
User writes interactive analytics and runs it on a notebook server

- 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

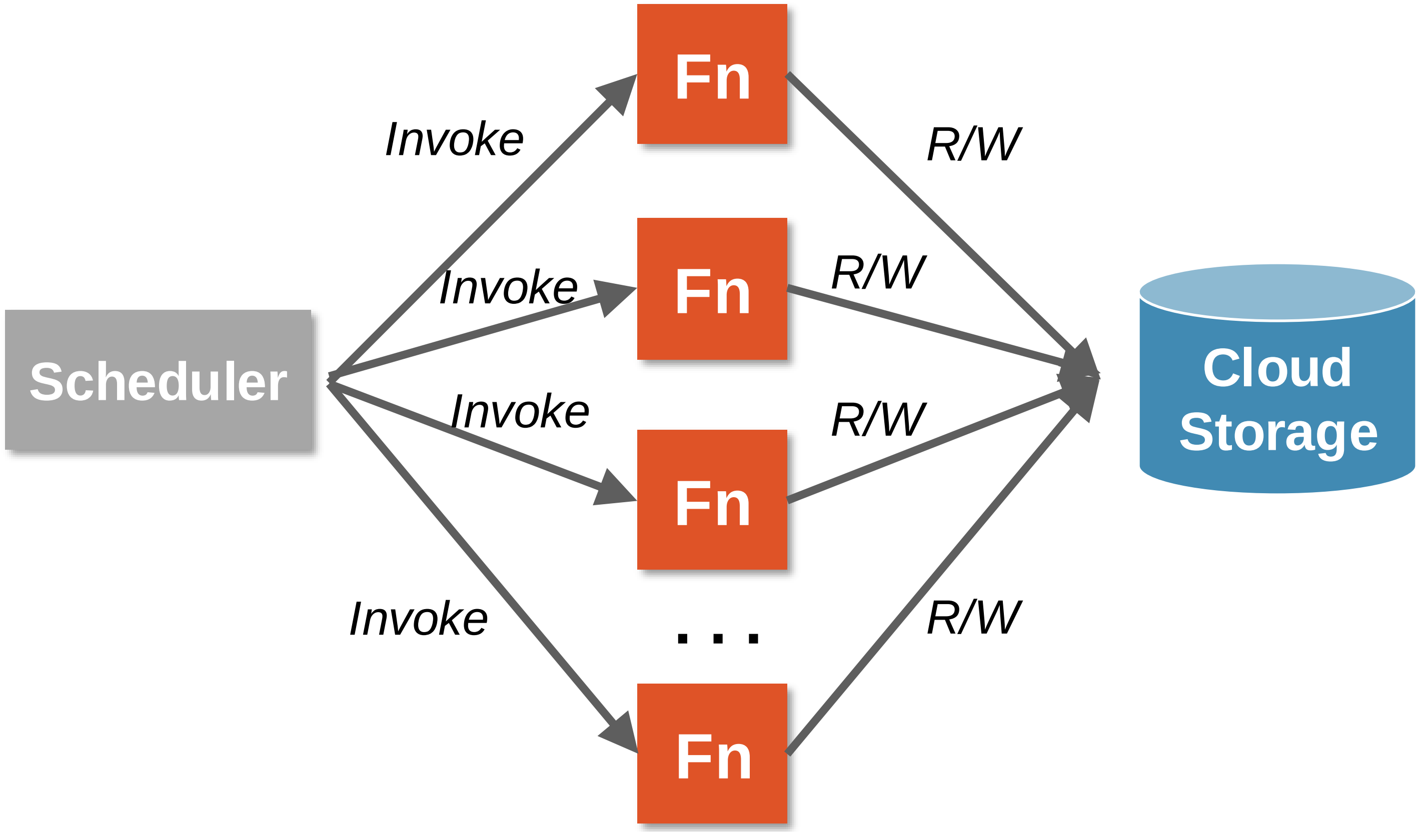
```python
def MyFunc(X, Y):
  return np.matmul(X, Y)
```



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

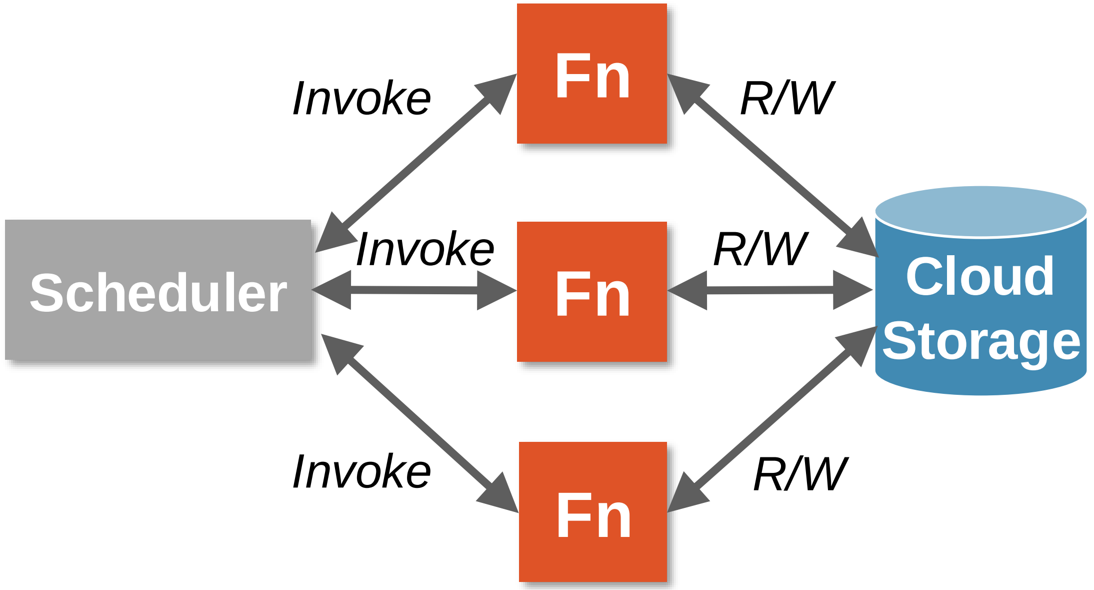
condor

* [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**

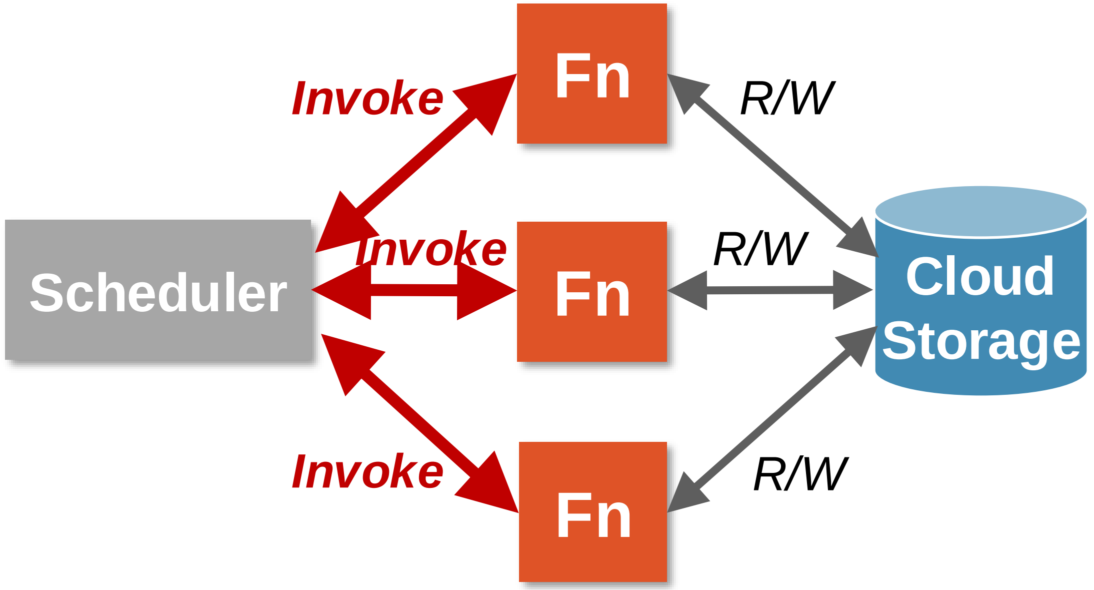
Python analytics on FaaS is slow!

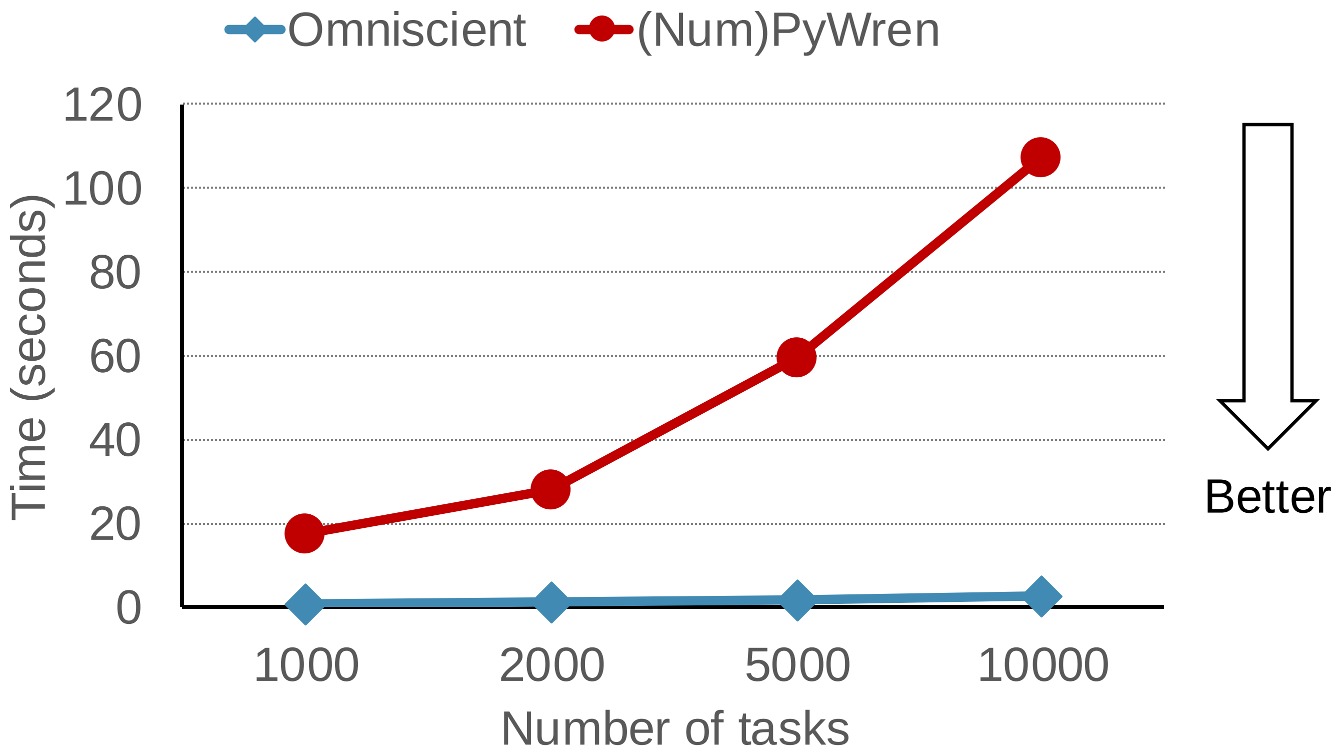


PyWren and numpywren

* [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!



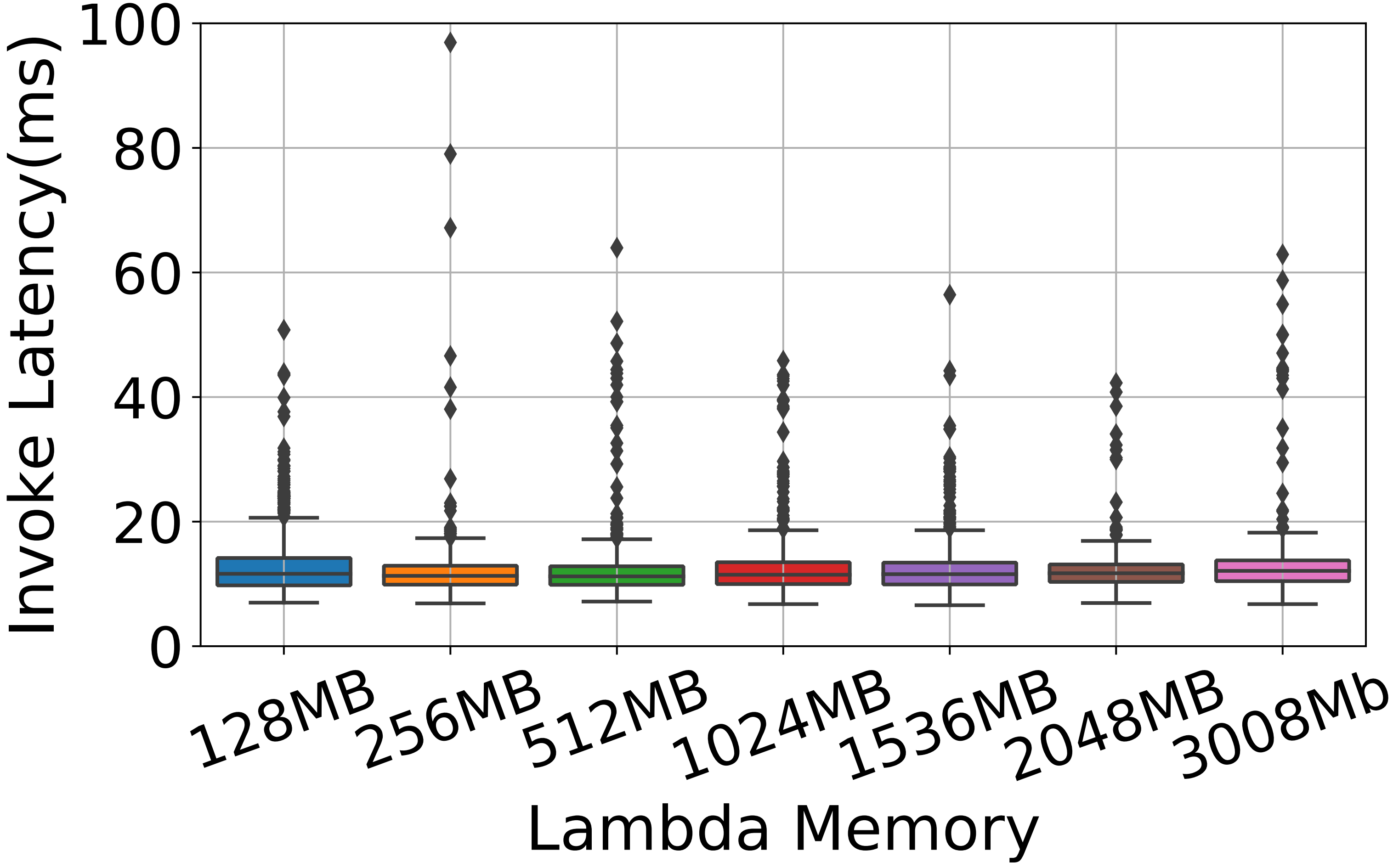


State-of-the-art FaaS frameworks pay huge amounts of FaaS taxes

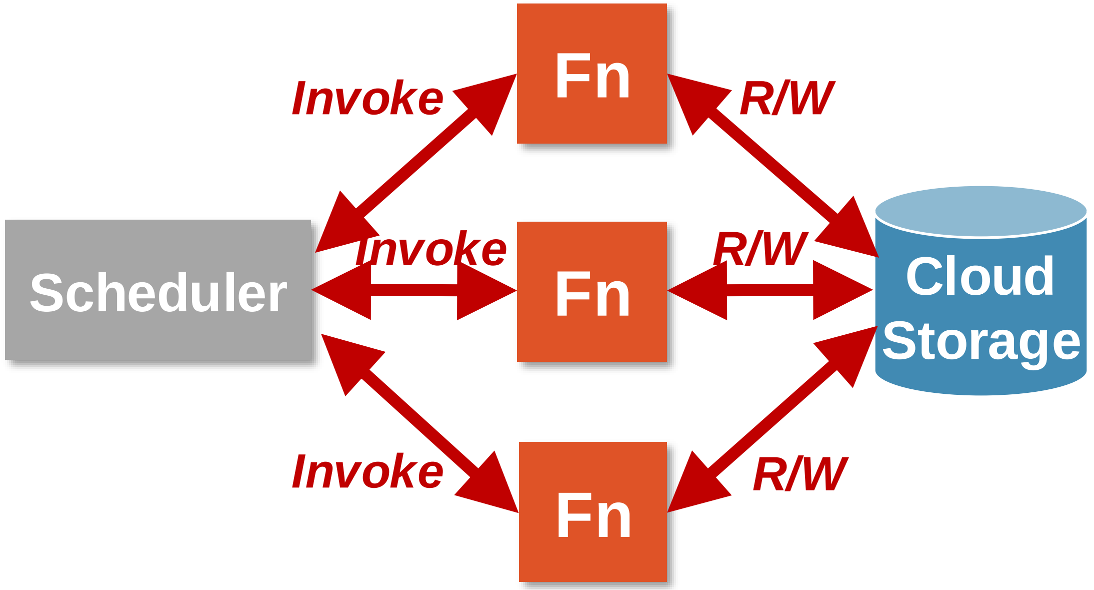
- **Task scheduling bottleneck:** Too slow to scale to thousands of functions

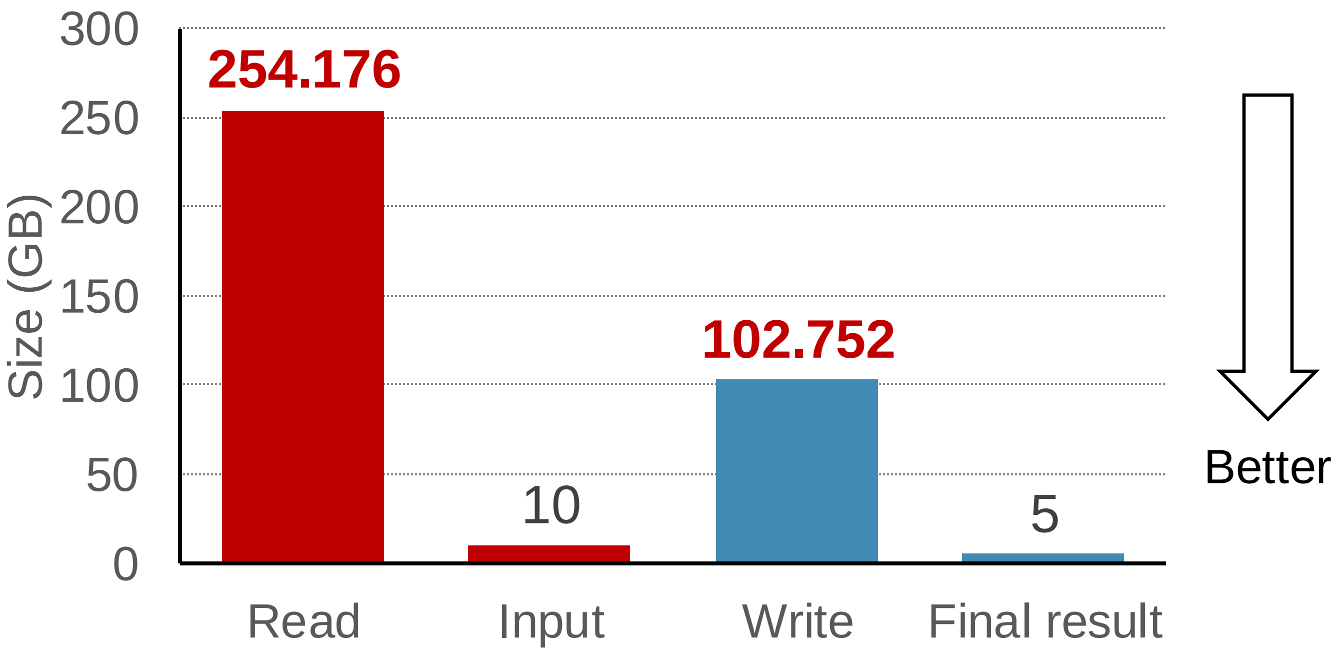
* [PyWren] Occupy the Cloud: Distributed Computing for the 99%. In ACM SoCC'17.
* [numpywren] Serverless linear algebra. In ACM SoCC'20.

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

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

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

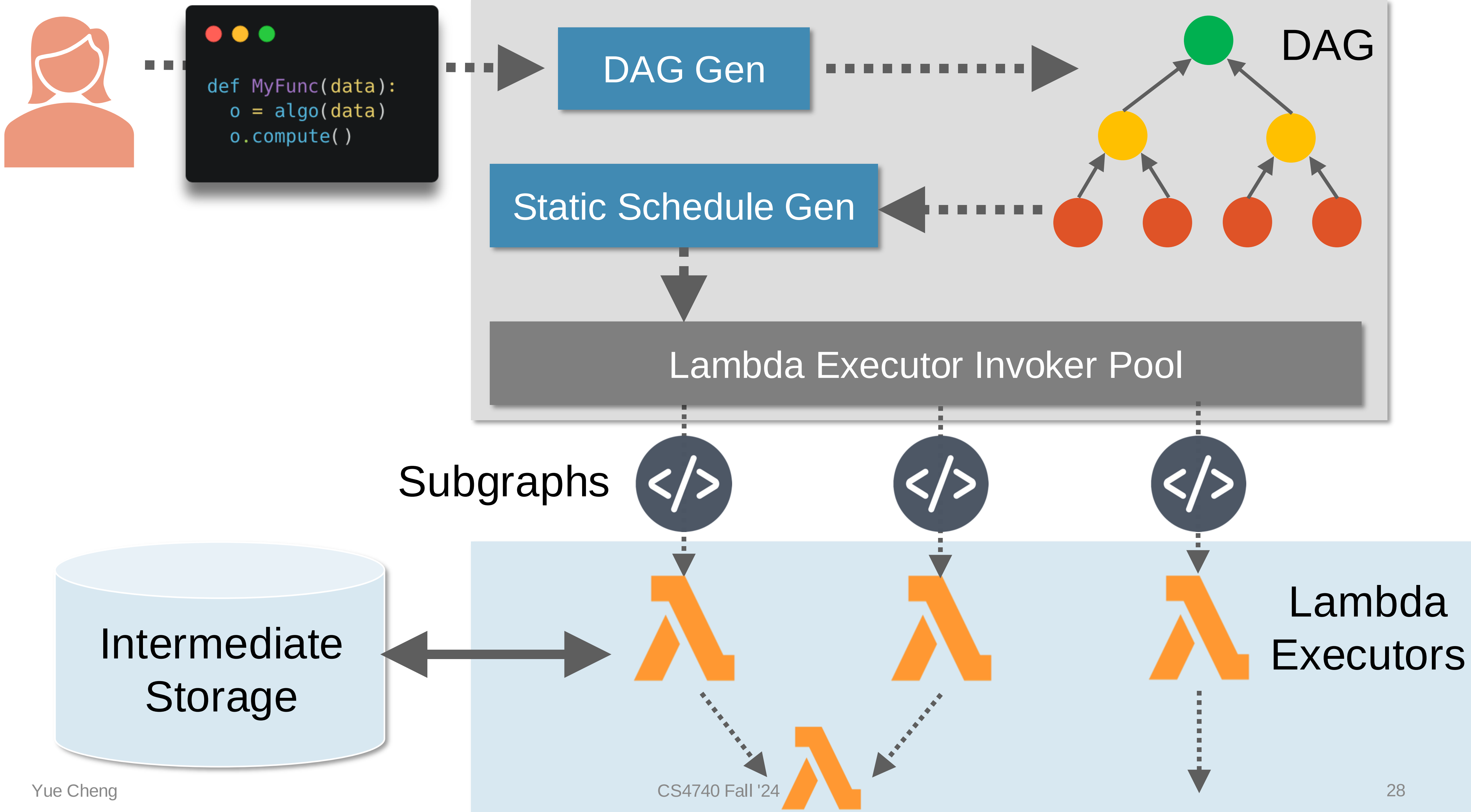
- Functions schedule tasks by invoking functions
- Functions execute multiple tasks to reduce data movement cost
- Functions scale out / in autonomously

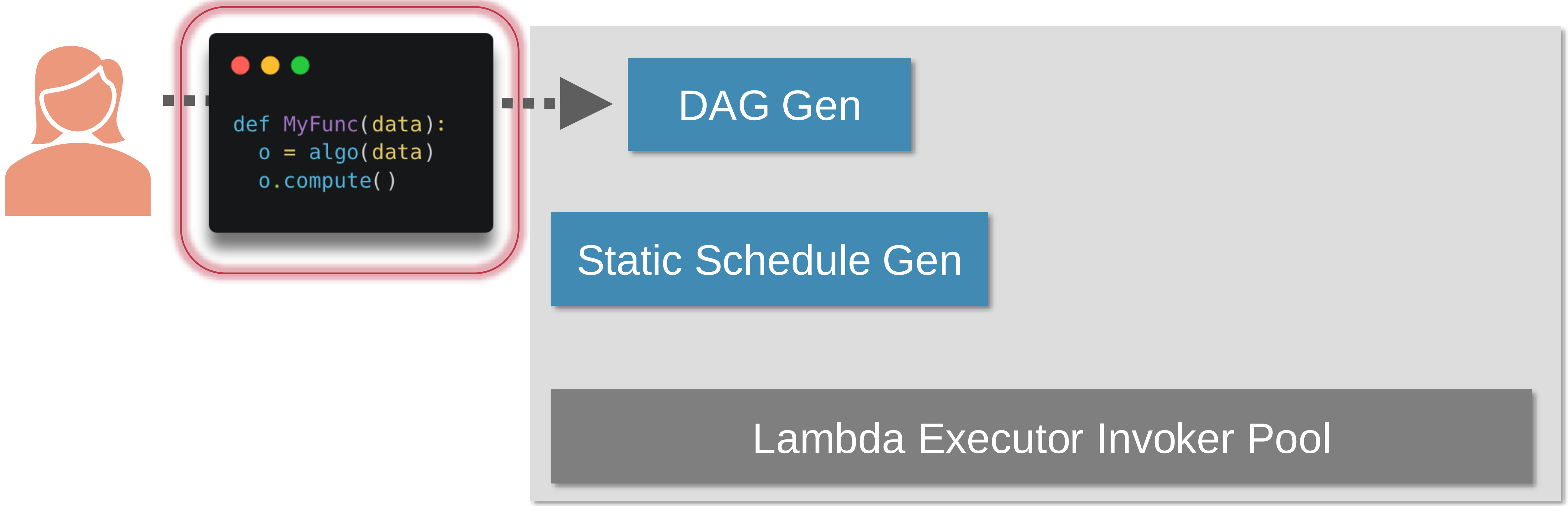
Naturally enables multiple benefits

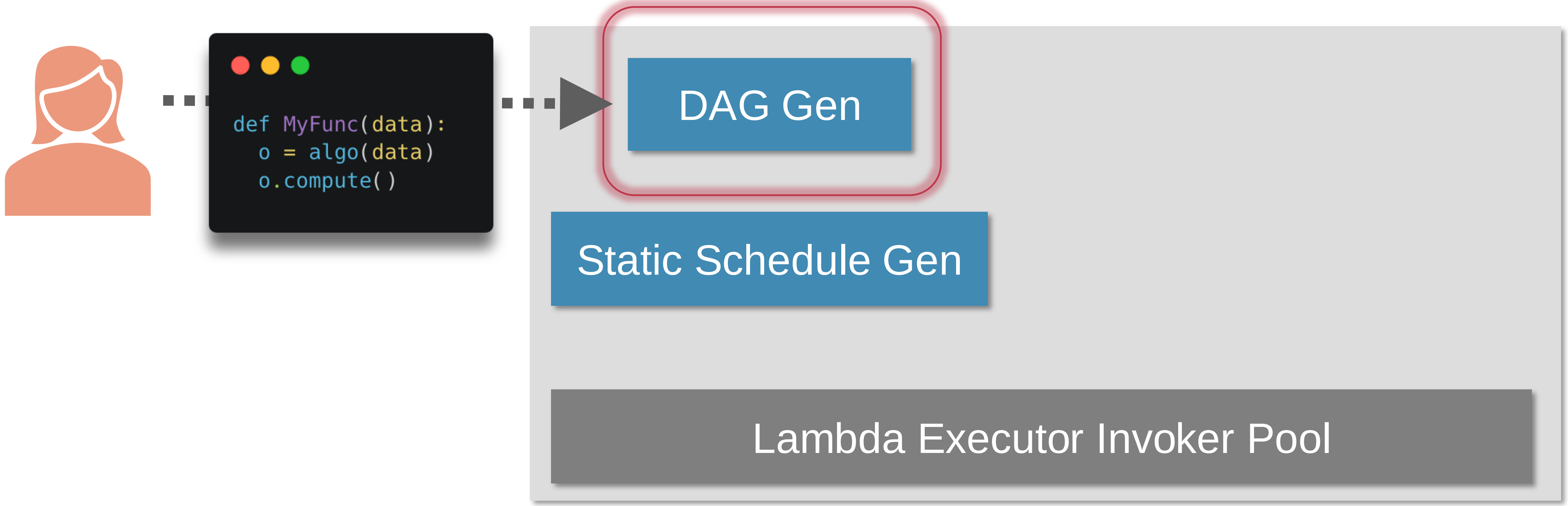
Exploits autoscaling for scalability

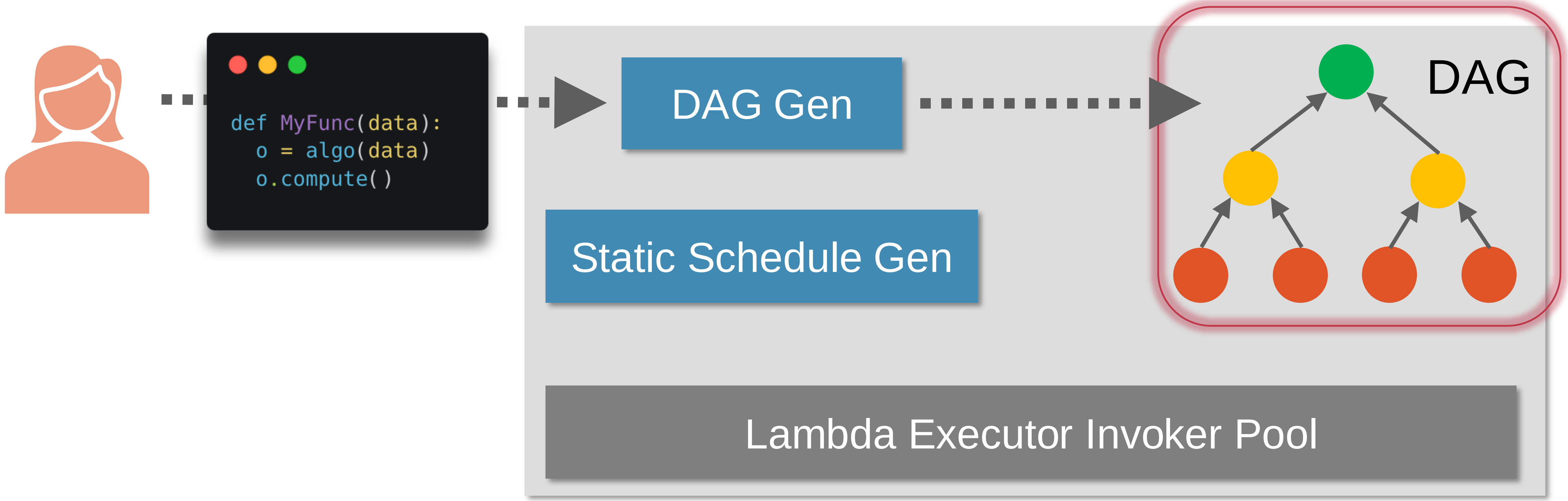
Improved data locality

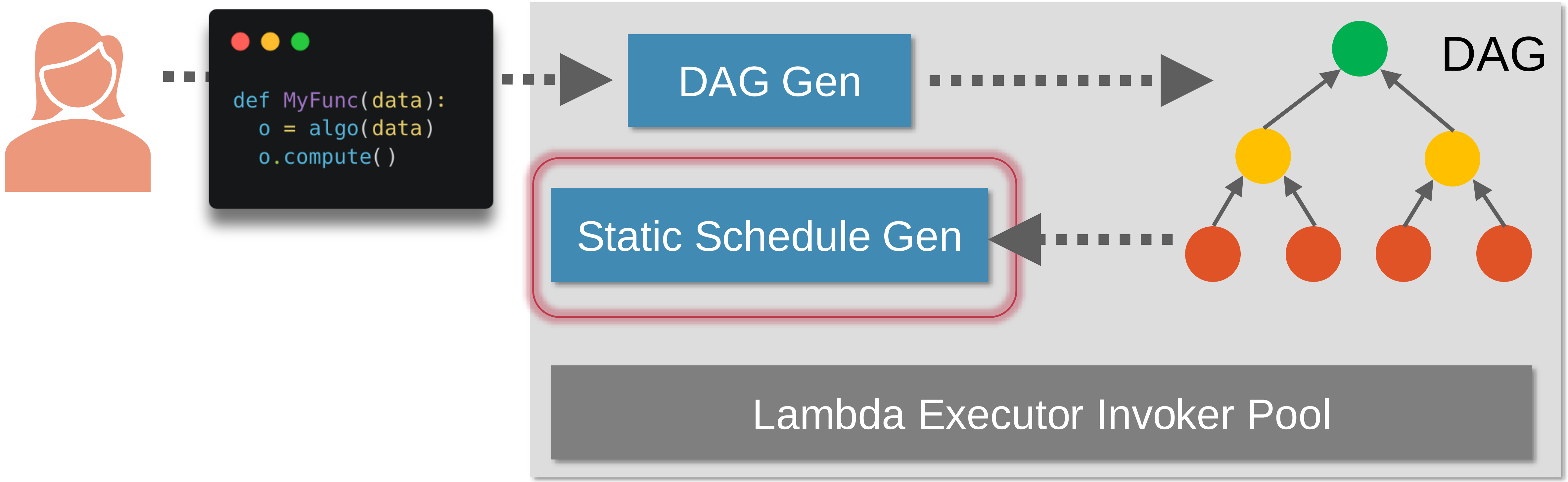
No tedious cluster configuration


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

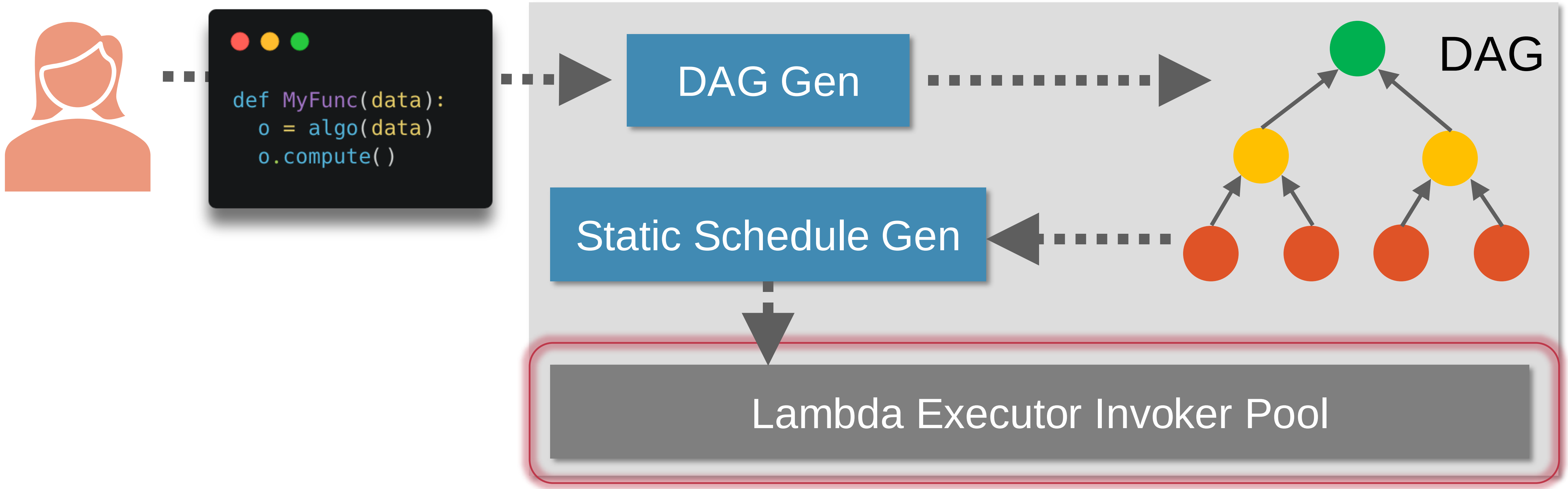

def MyFunc(data):
o = algo(data)
o.compute()
DAG Gen
Static Schedule Gen
Lambda Executor Invoker Pool

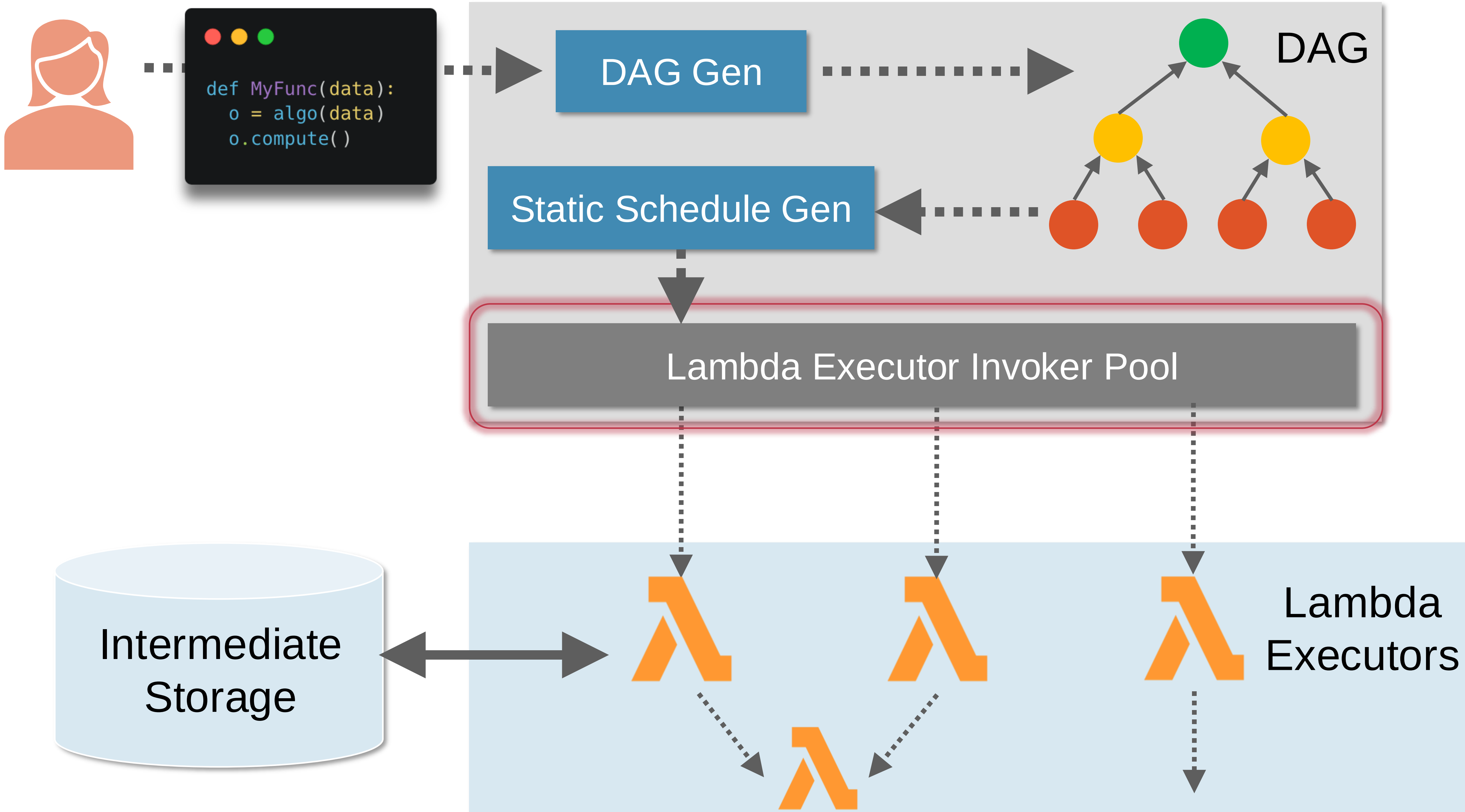

def MyFunc(data):
o = algo(data)
o.compute()
DAG Gen
Static Schedule Gen
Lambda Executor Invoker Pool


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

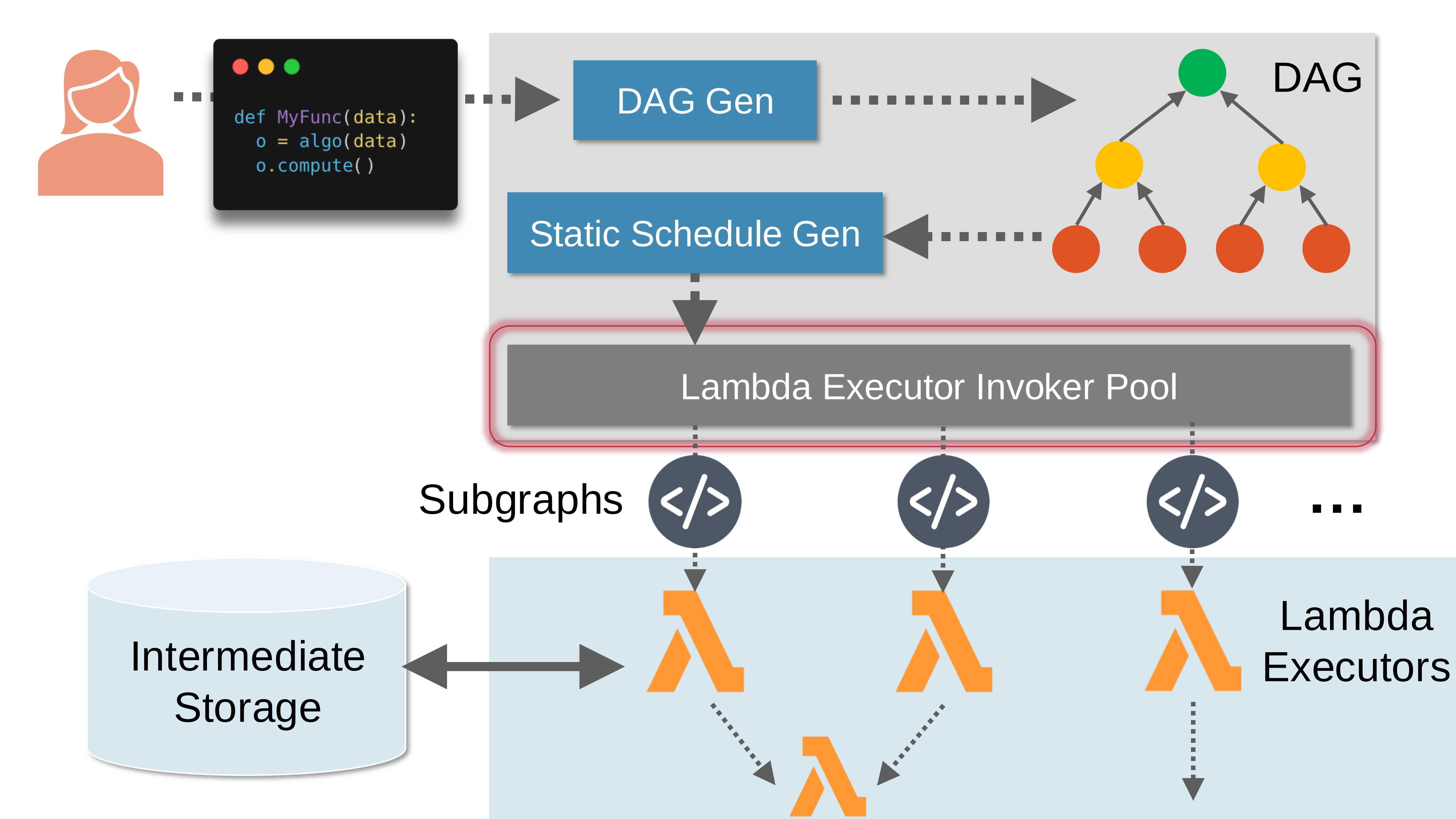


def MyFunc(data):
o = algo(data)
o.compute()
DAG Gen
DAG
Static Schedule Gen
Lambda Executor Invoker Pool

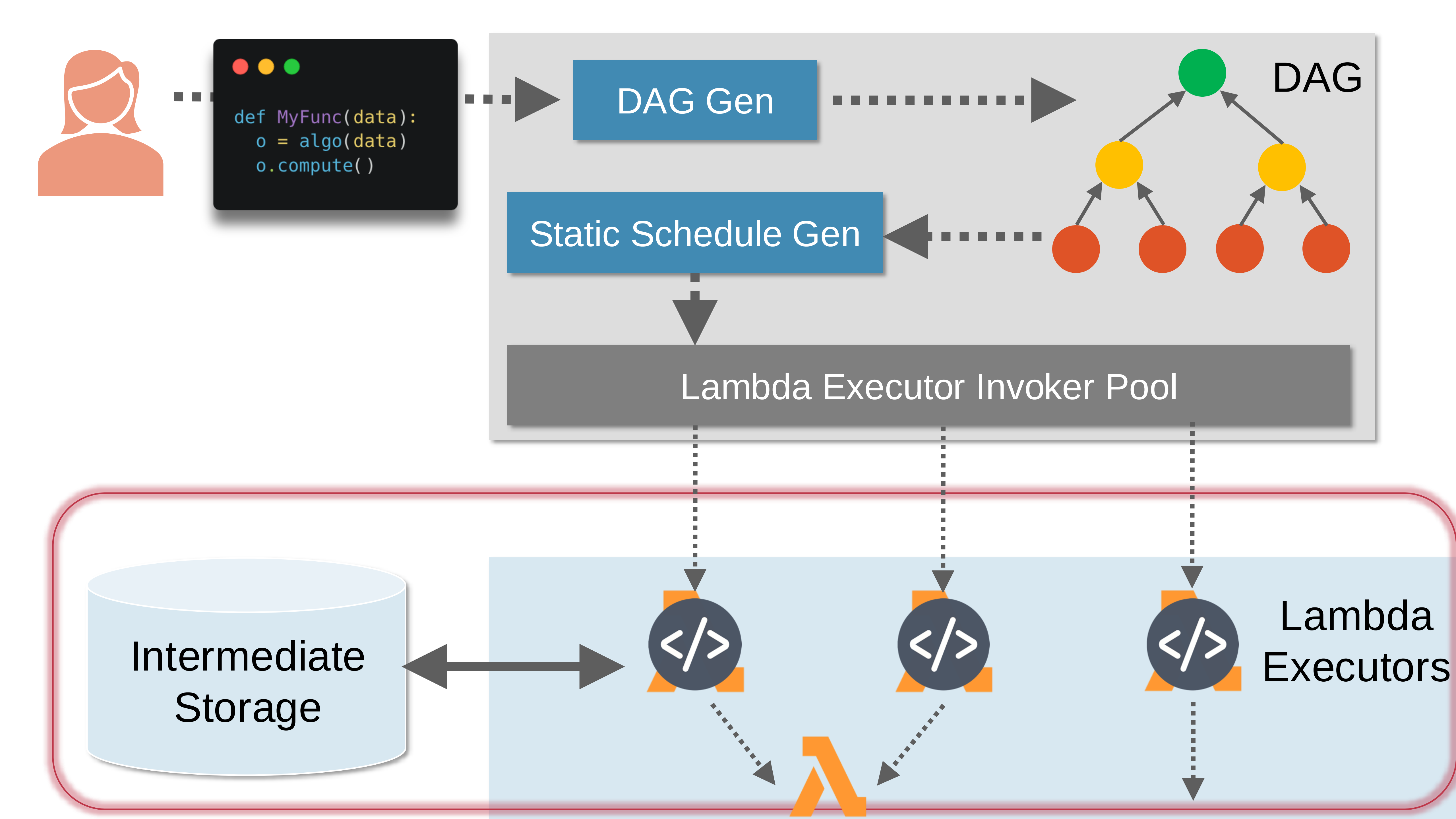

def MyFunc(data):
o = algo(data)
o.compute()
DAG Gen
DAG
Static Schedule Gen
Lambda Executor Invoker Pool



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

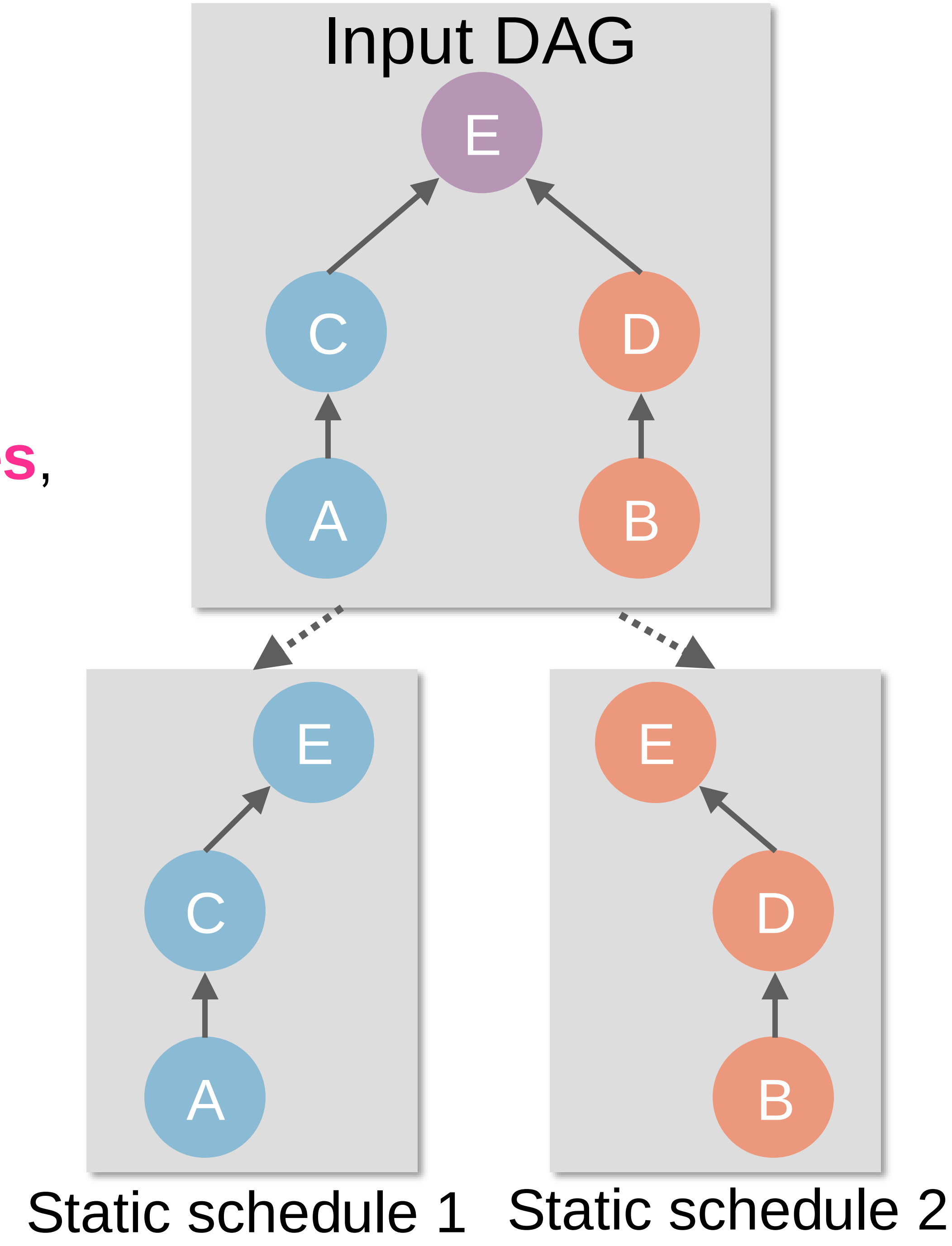


def MyFunc(data):
o = algo(data)
o.compute()
DAG Gen
DAG
Static Schedule Gen
Lambda Executor Invoker Pool
Subgraphs
...
Intermediate Storage
Lambda Executors


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

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):
  o = algo(data)
  o.compute()
```

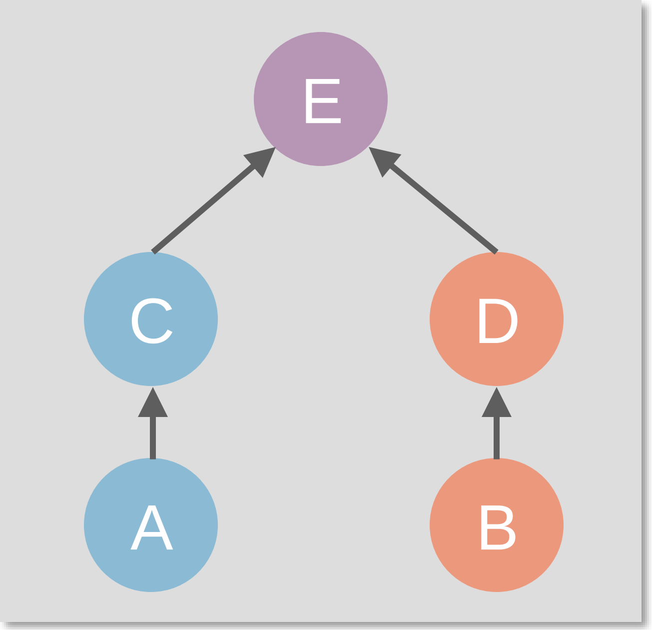
Static scheduling

```
func MyFunc(data):
  o = algo(data)
  o.compute()
```

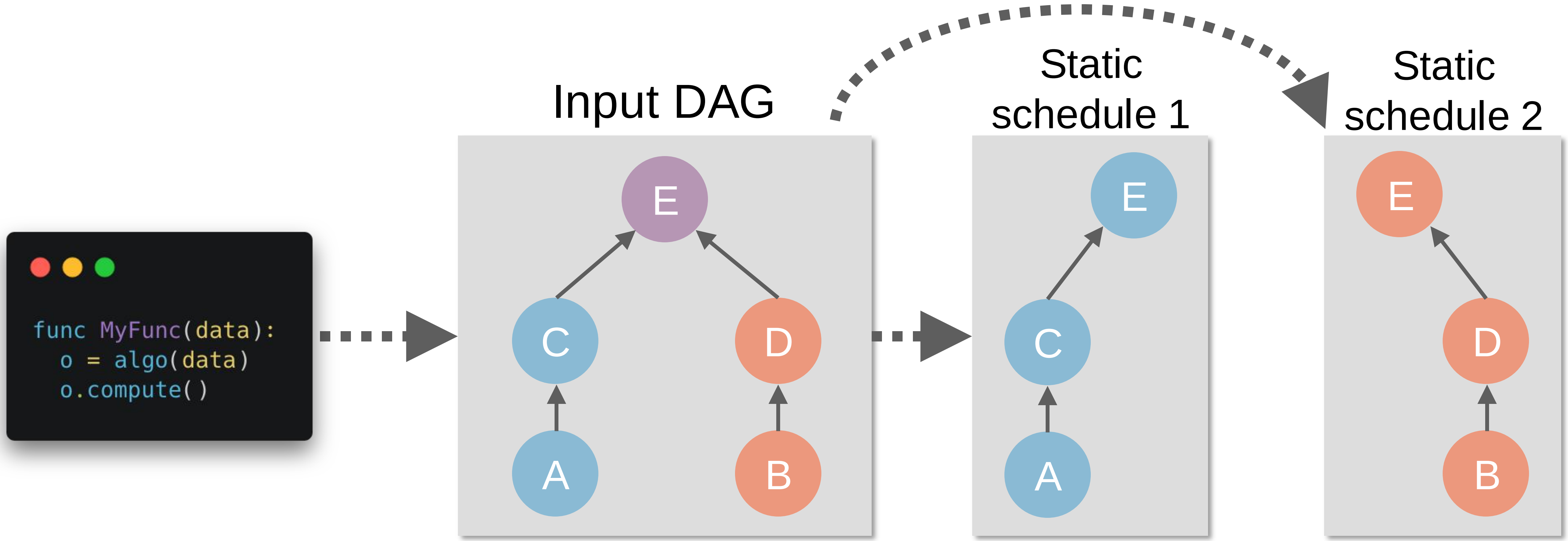
Static scheduling

Input DAG

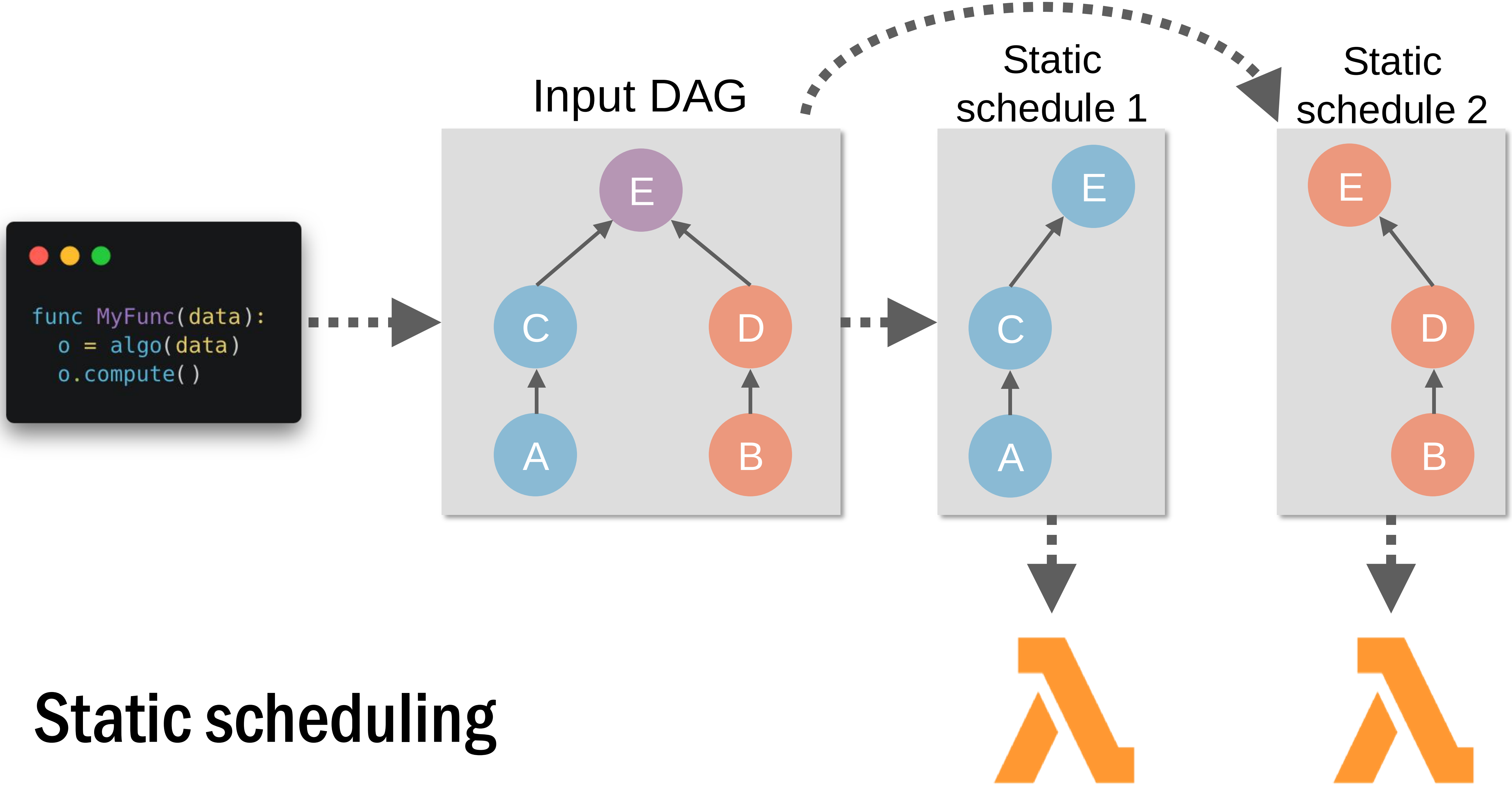
```
func MyFunc(data):
  o = algo(data)
  o.compute()
```



Static scheduling



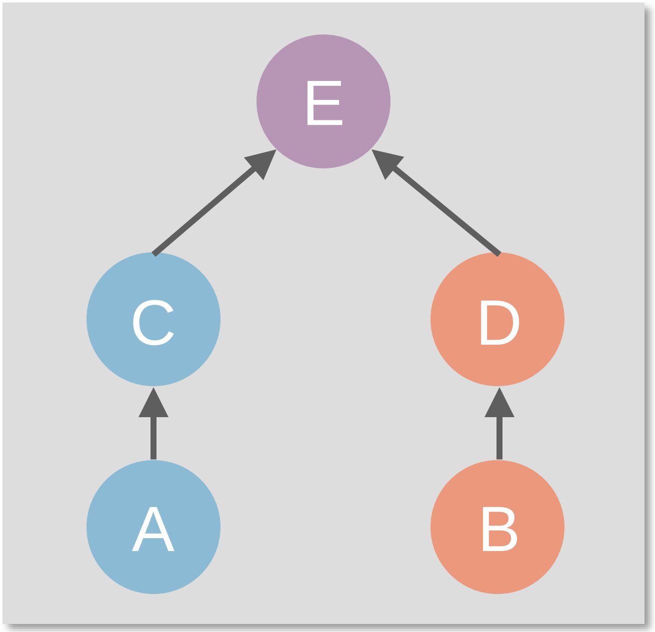
Static scheduling

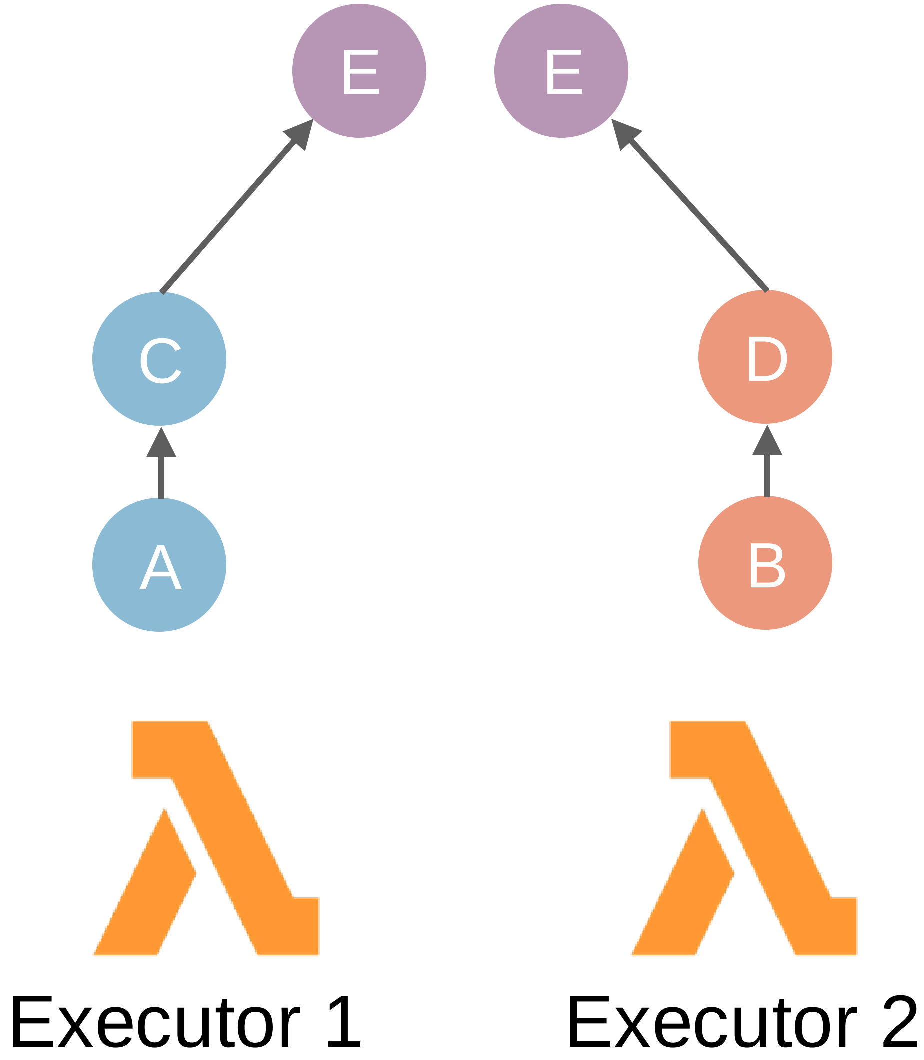


Static scheduling

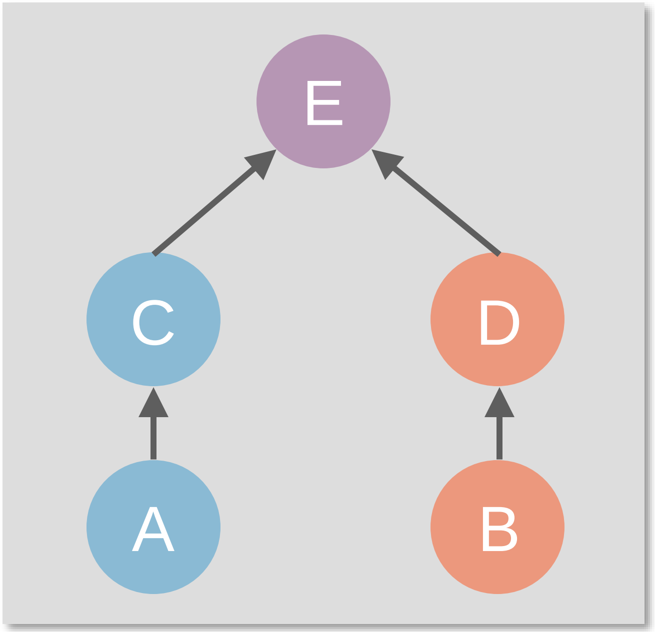
Dynamic scheduling

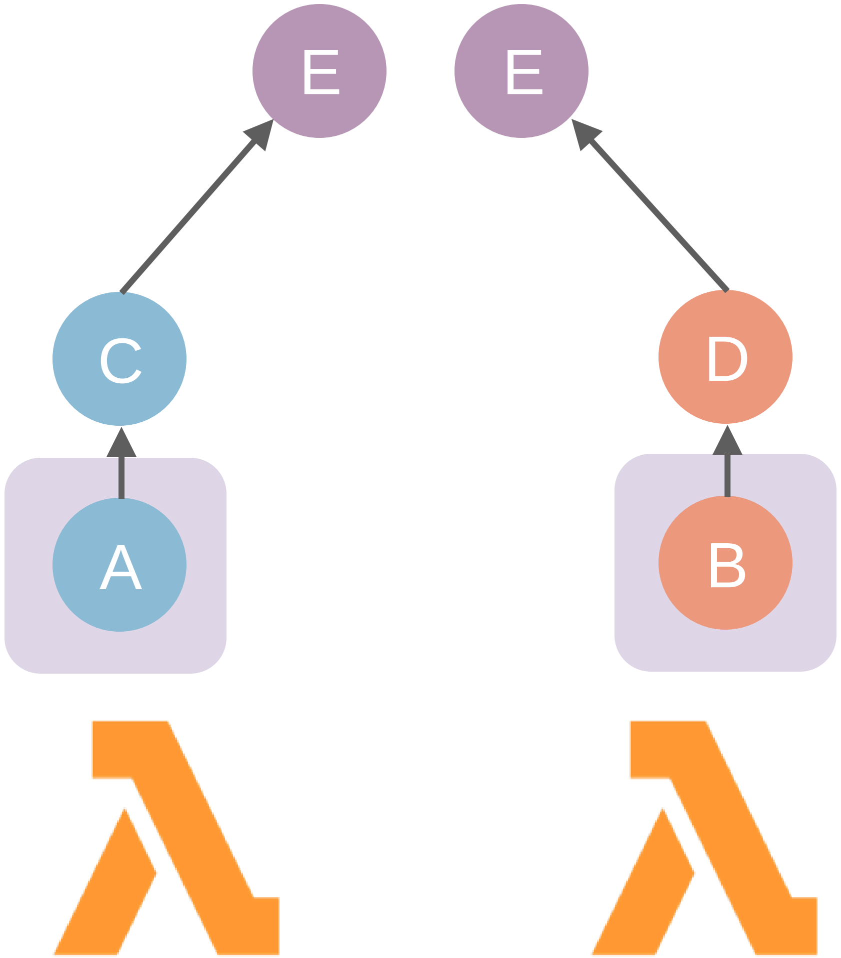
Input DAG





Input DAG



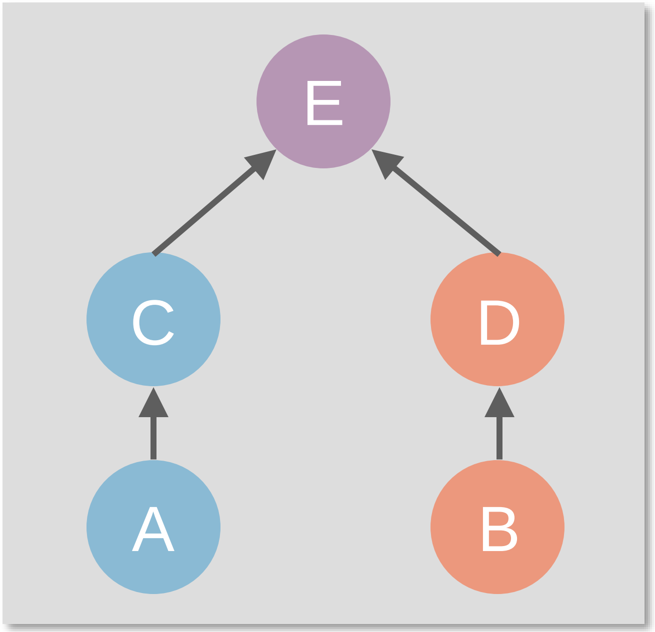


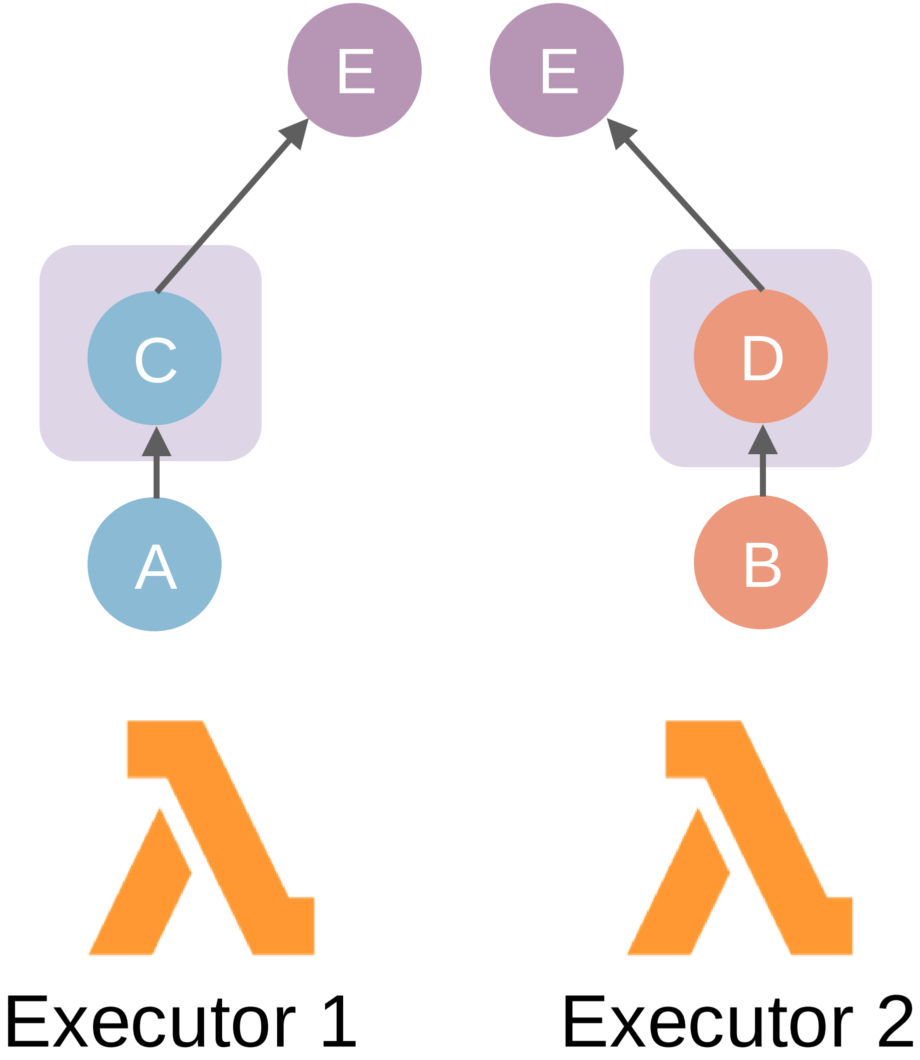
Executor 1

Executor 2

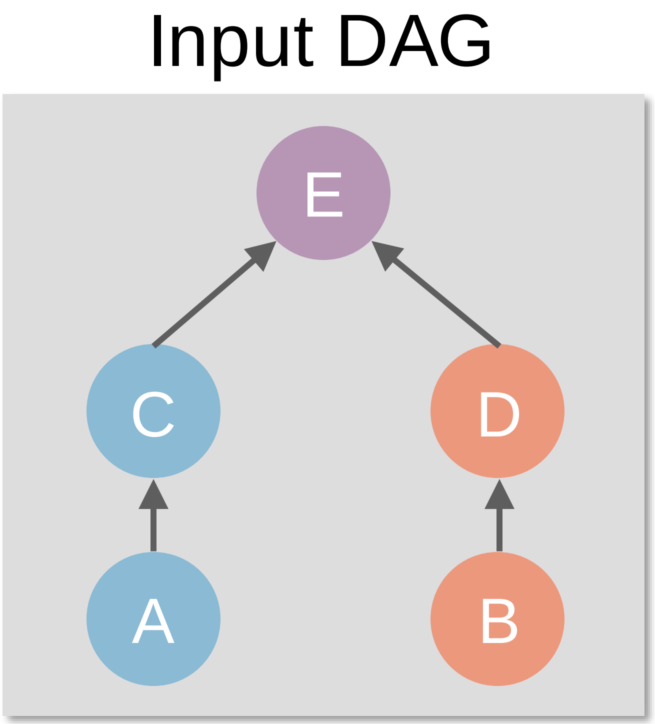
Dynamic scheduling

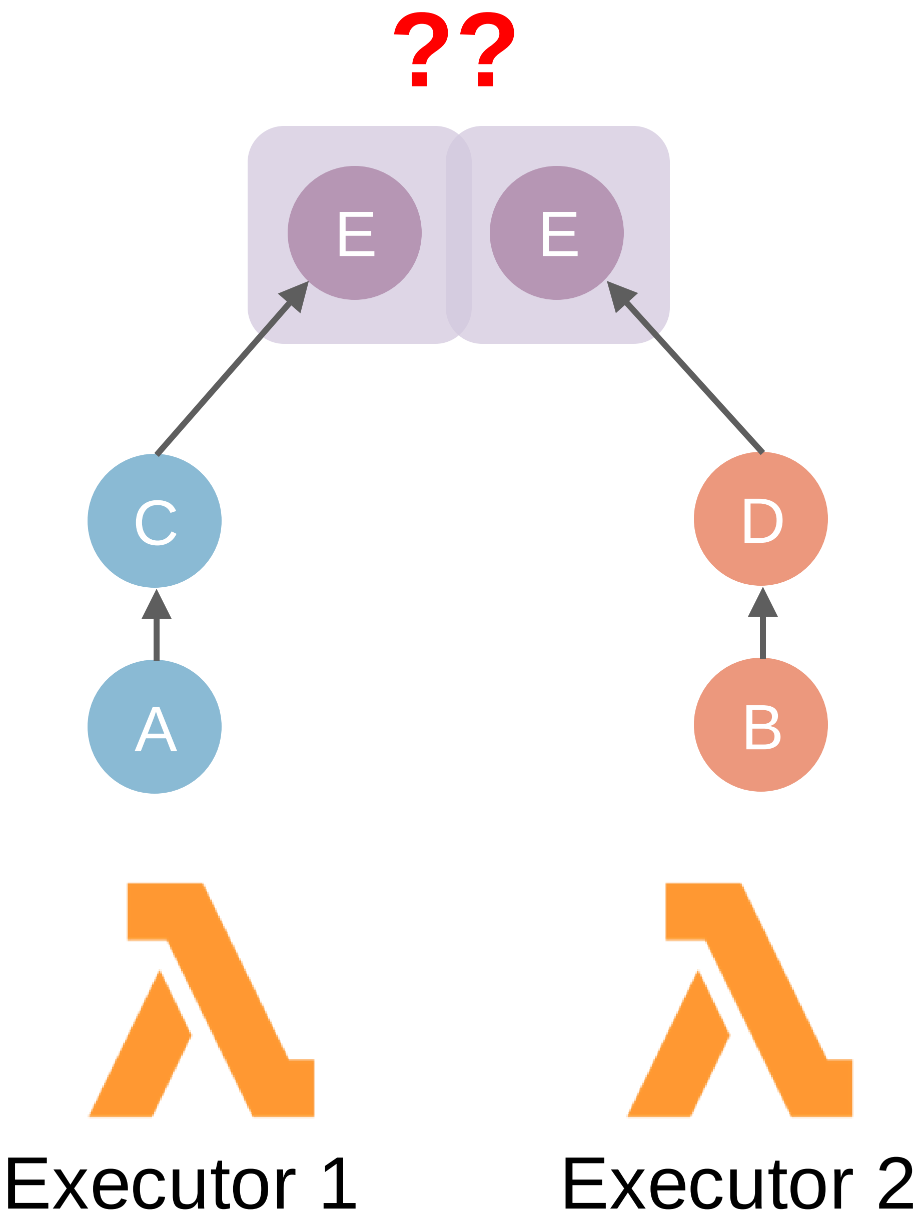
Input DAG





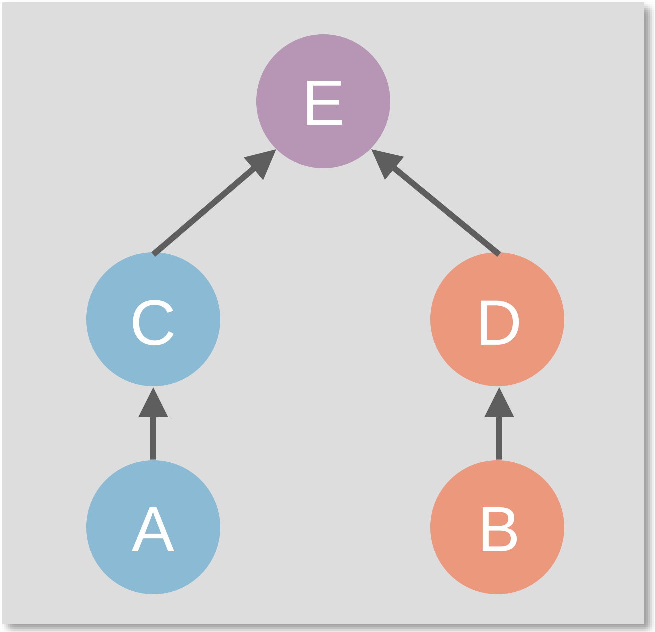
Dynamic scheduling



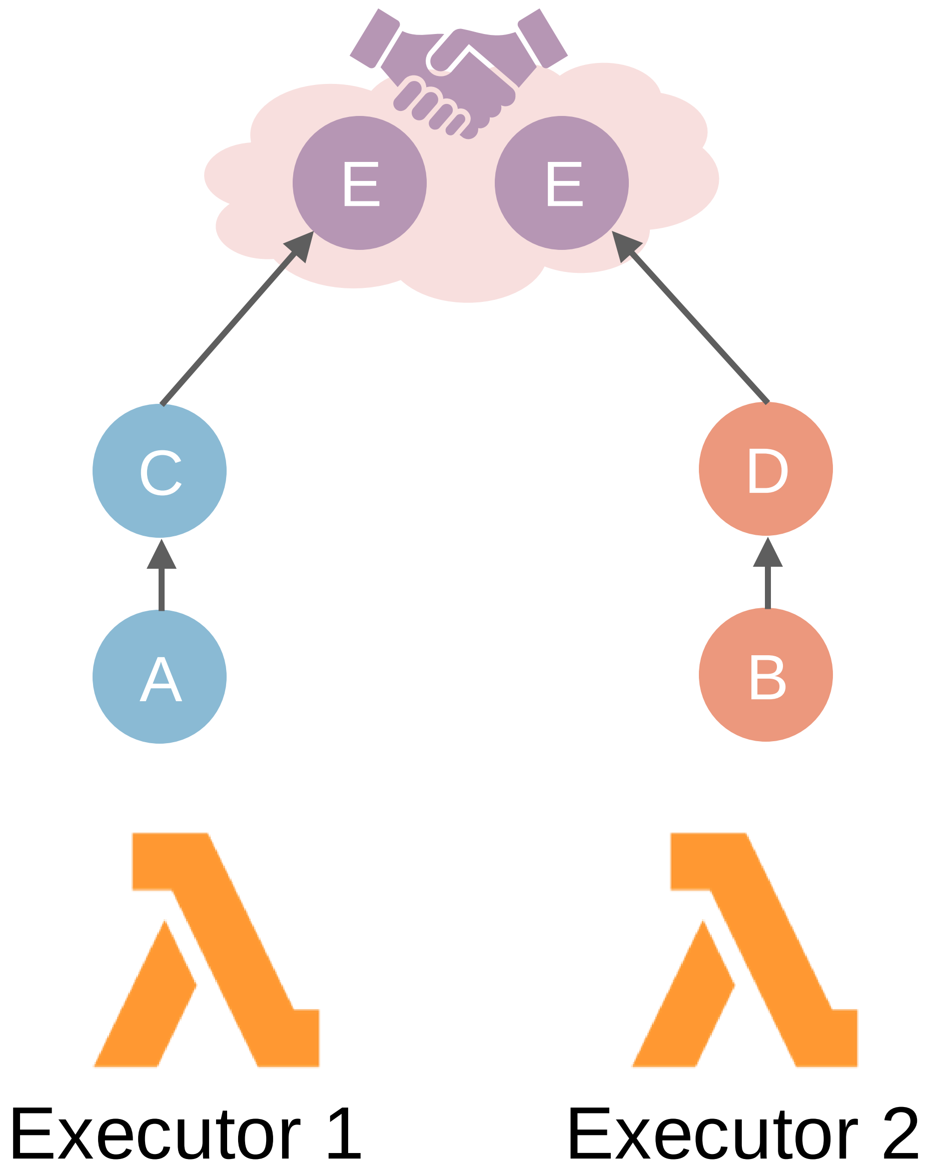


Dynamic scheduling

Input DAG

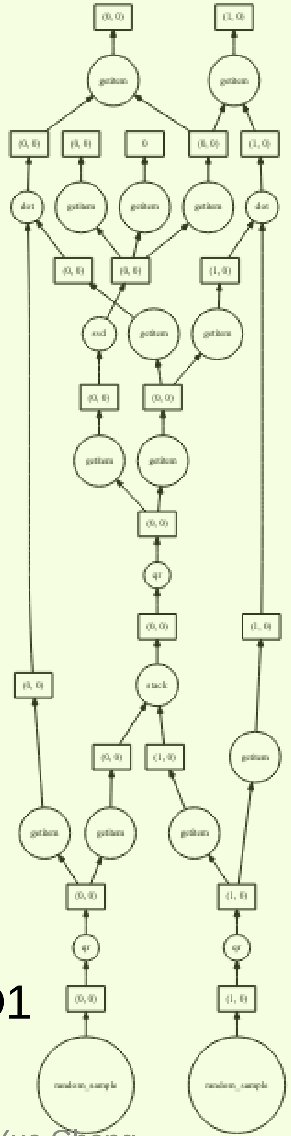


Cooperate

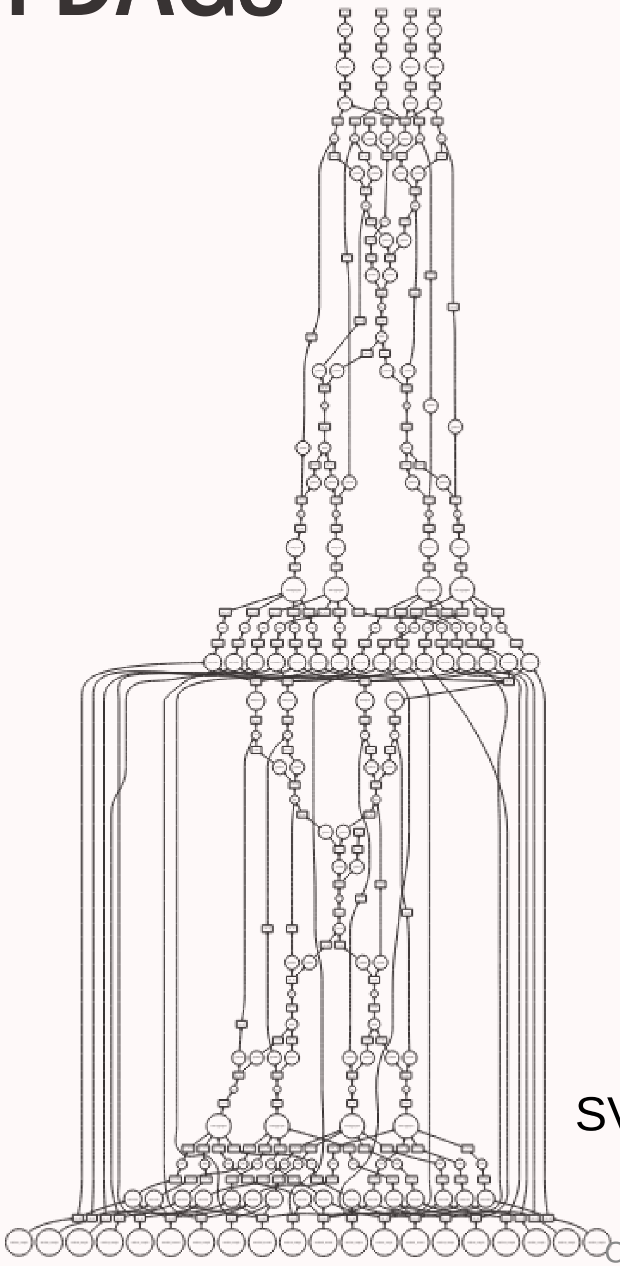


Dynamic scheduling

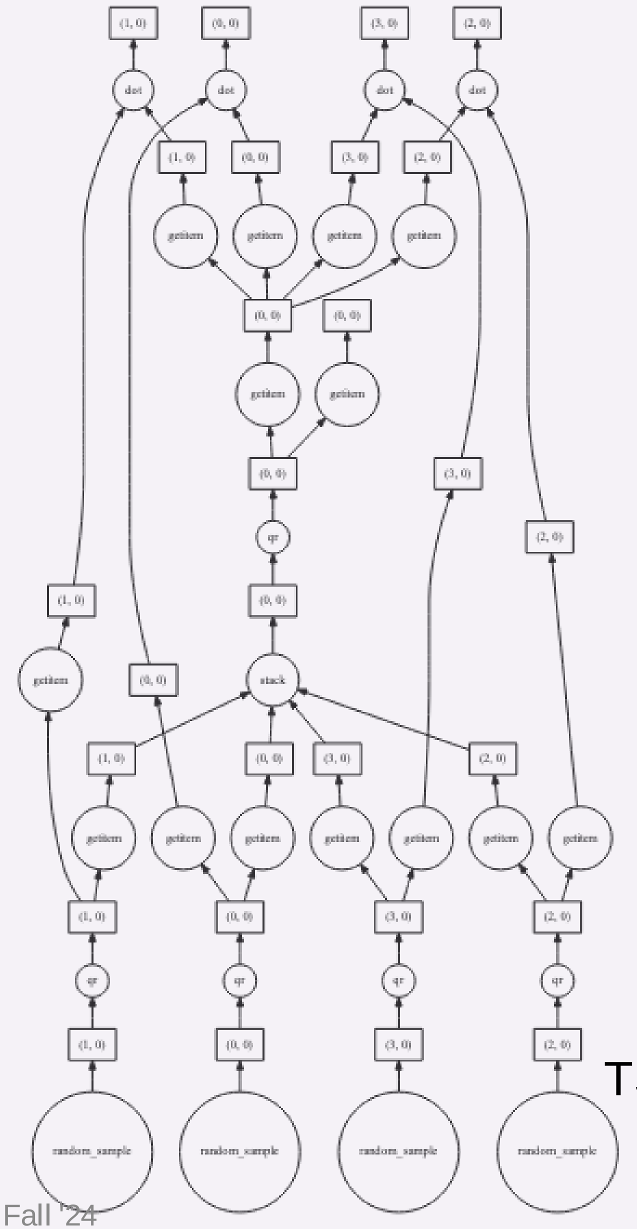
Application DAGs



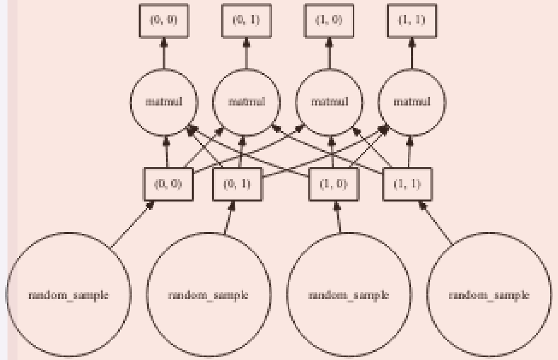
SVD1



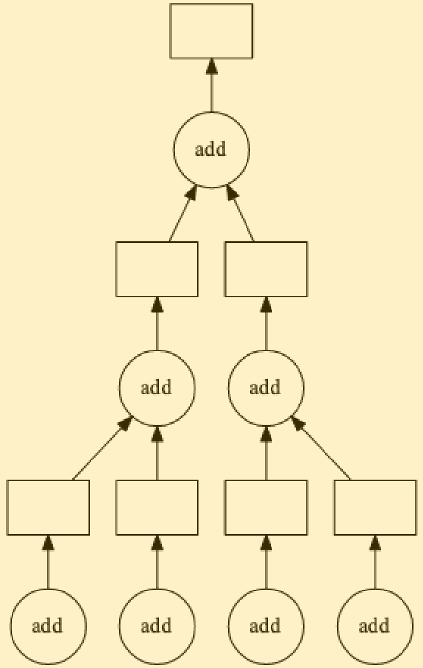
SVD2



TSQR

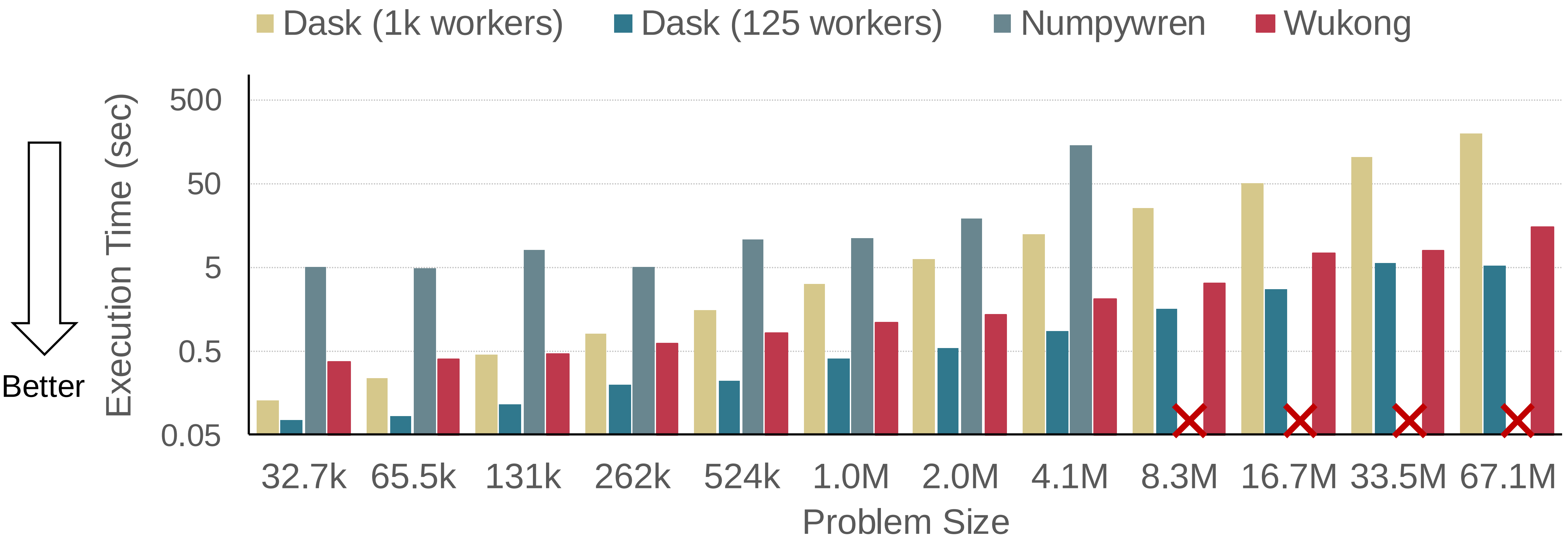


GEMM



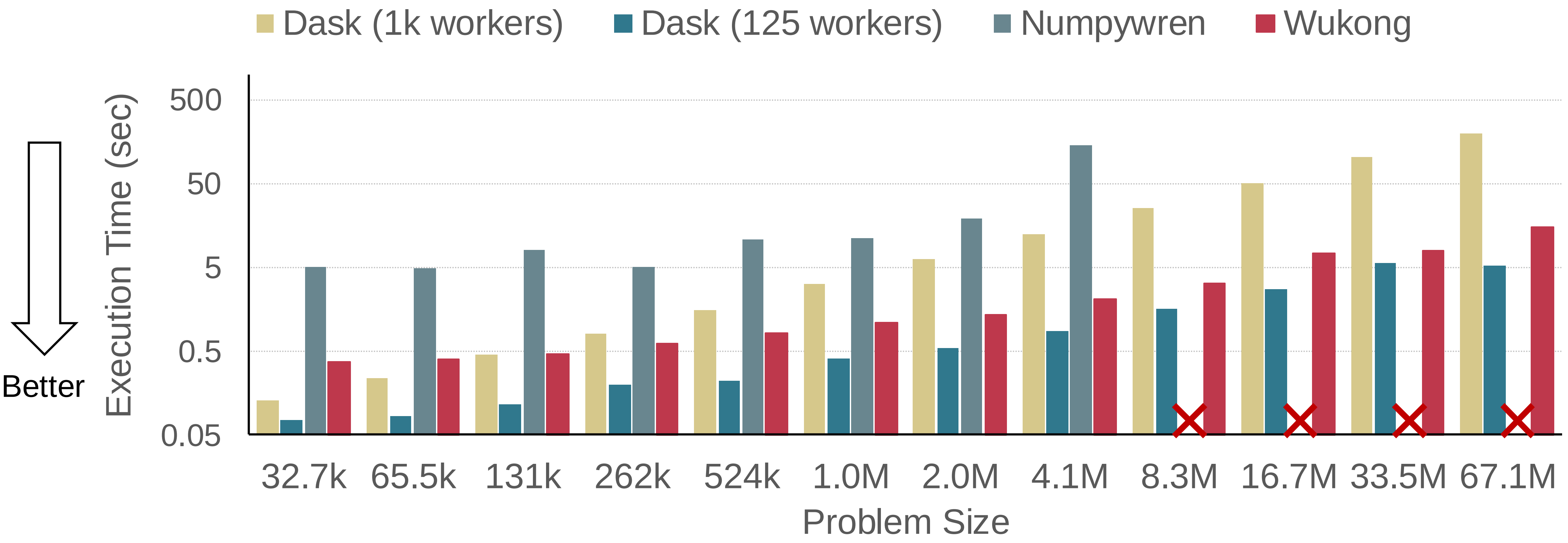
Tree reduction

Application performance: TSQR



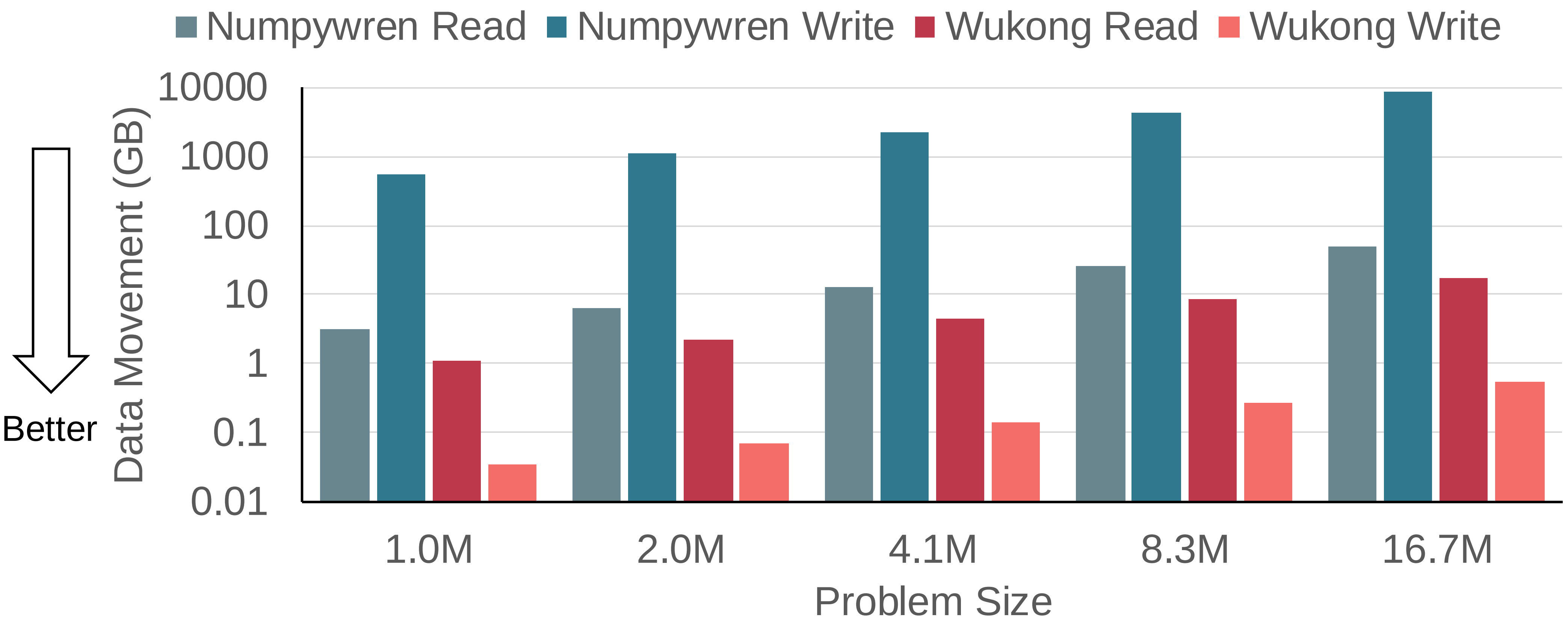
Wukong and numpywren ran on AWS Lambda w/ 3GB memory
Dask distributed ran on 125 c5.4xlarge EC2 VMs w/ 2,000 vCPU cores

Application performance: TSQR

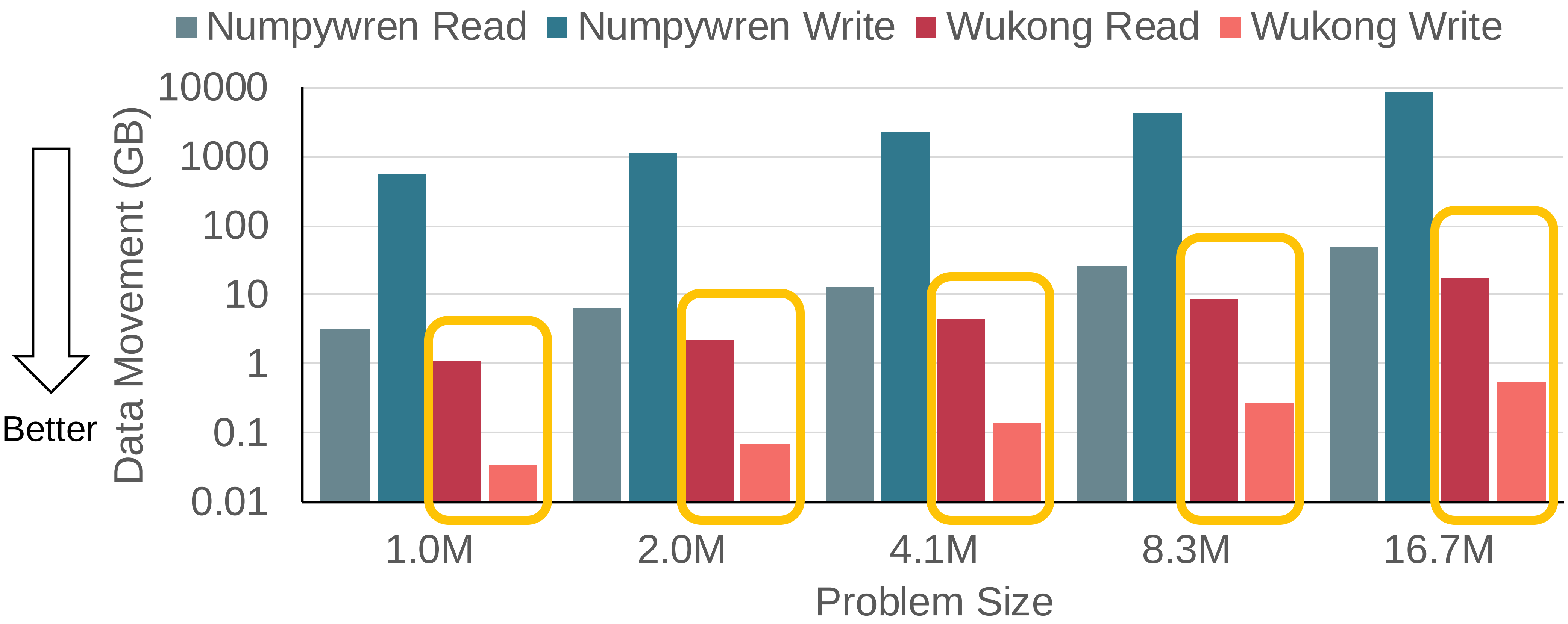


Wukong outperforms numpywren considerably for all problem sizes.

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)

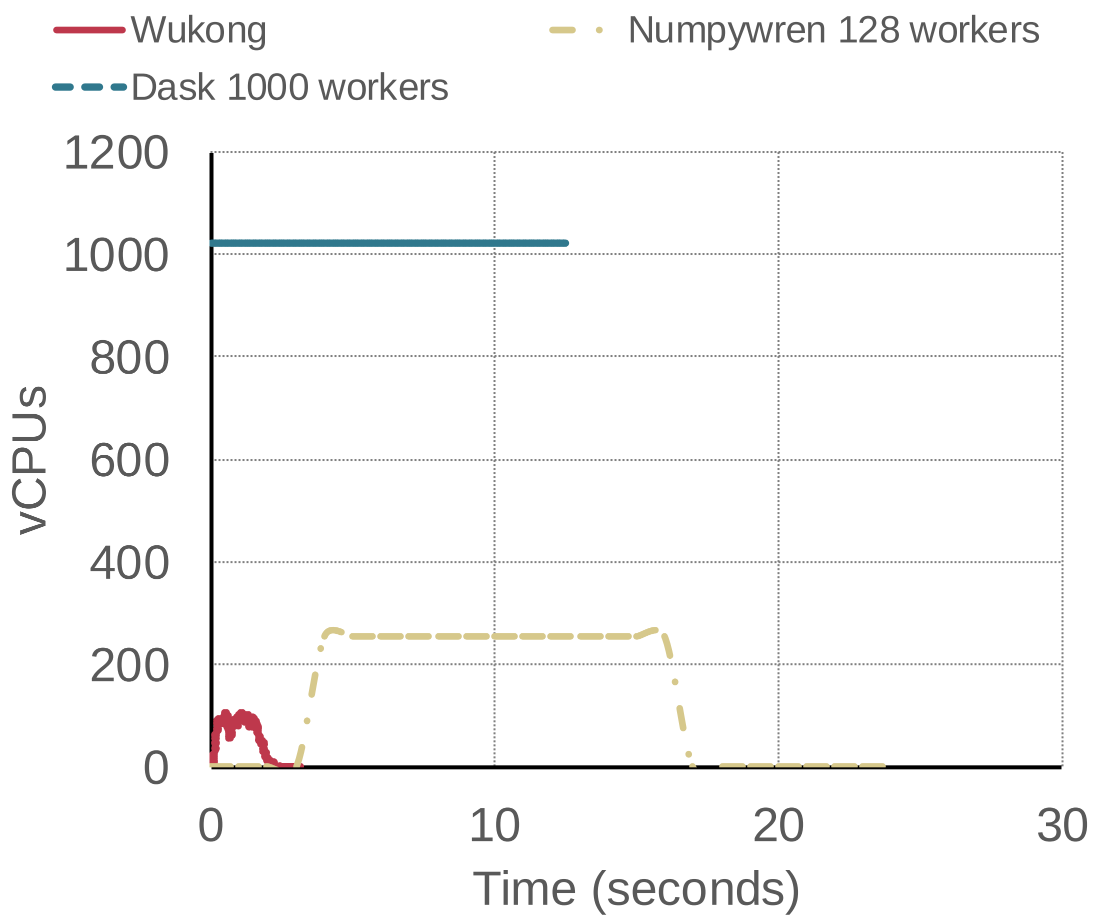
```python
import pandas as pd
import seaborn as sns
import sklearn.datasets
from sklearn.svm import SVC

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()
```

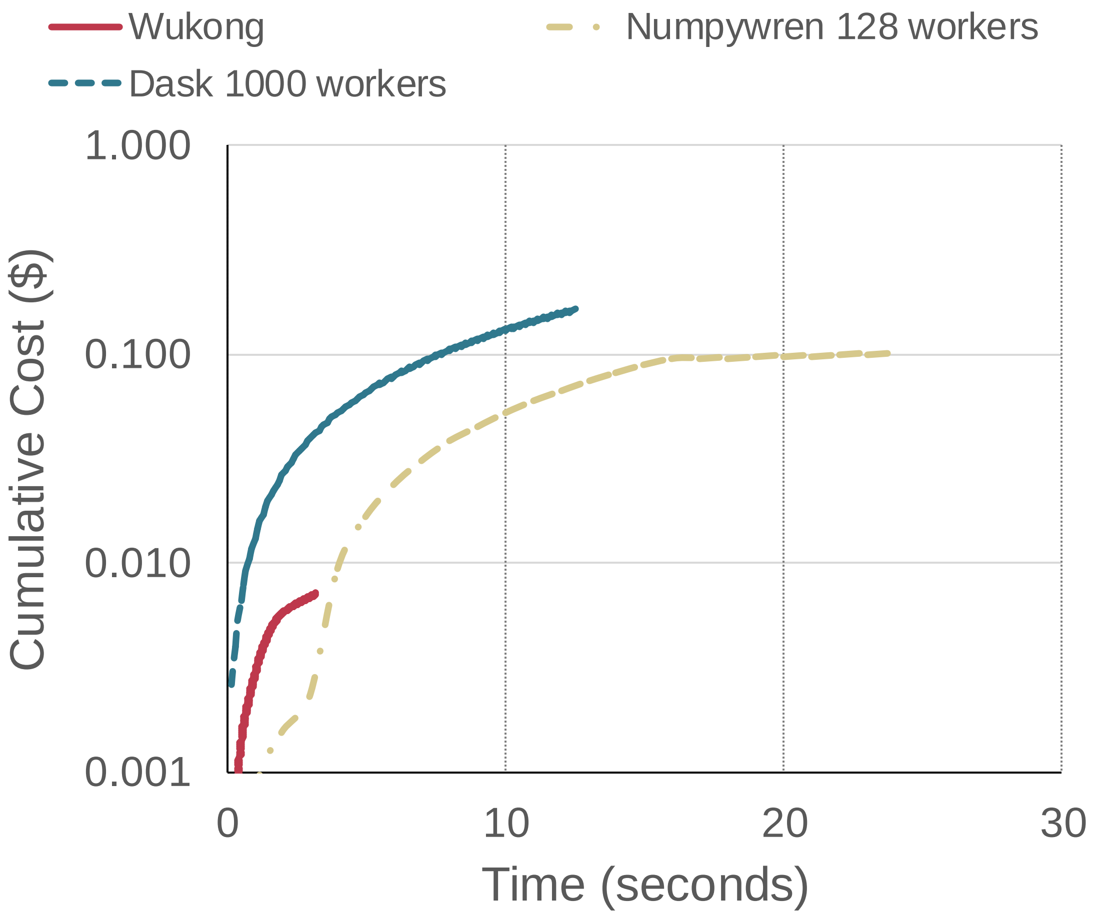
GEMM (Matrix Multiplication)

```python
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

What about elasticity and cost: TSQR





Wukong performance

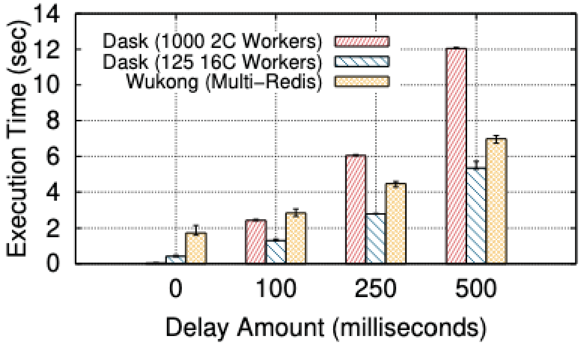


Figure 9: TR.

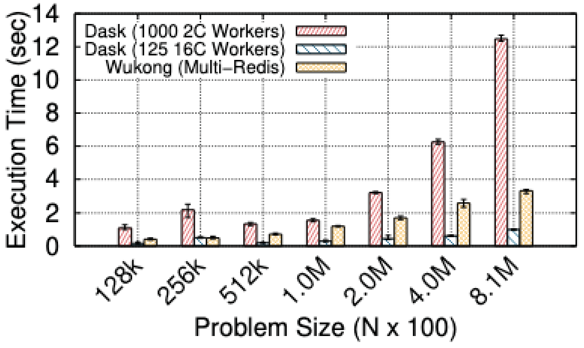


Figure 10: SVD1.

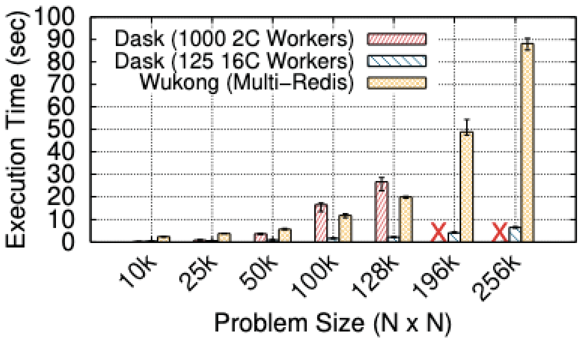


Figure 11: SVD2.

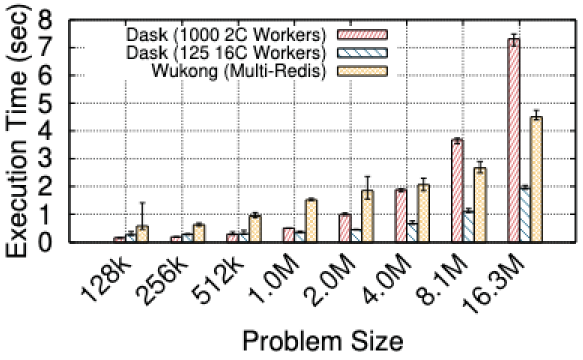


Figure 12: SVC.

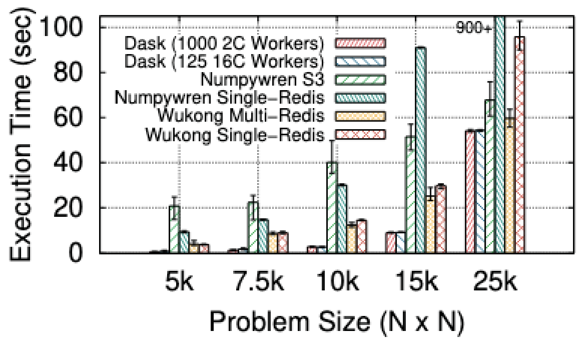


Figure 13: GEMM.

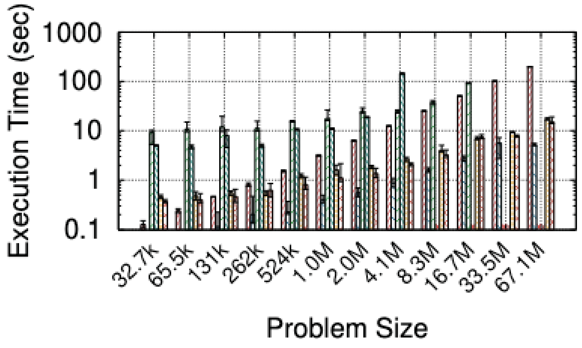


Figure 14: TSQR (log-scale).

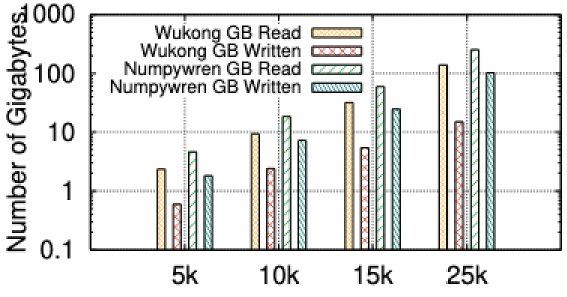


Figure 15: GEMM I/O (log).

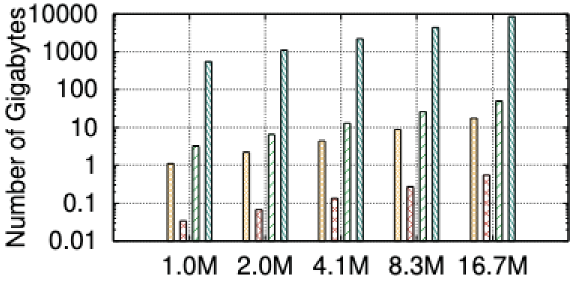
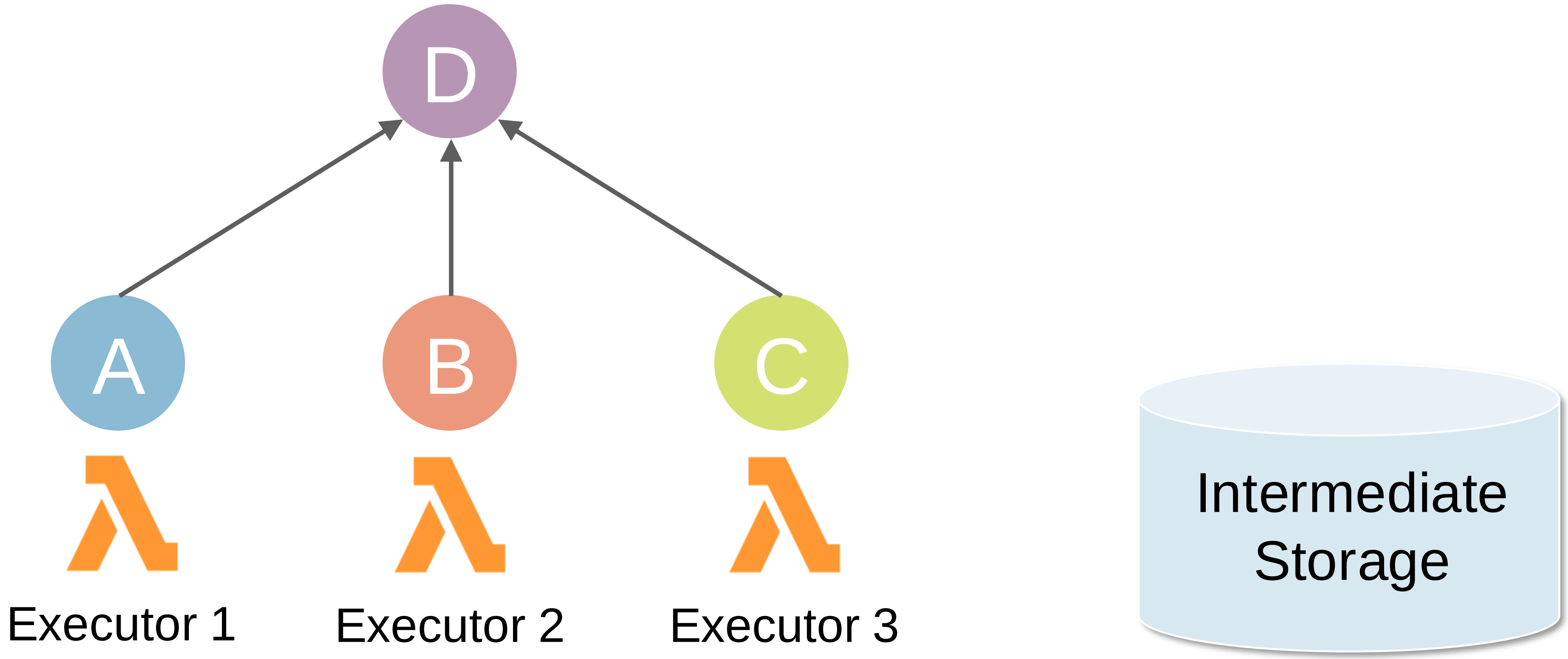


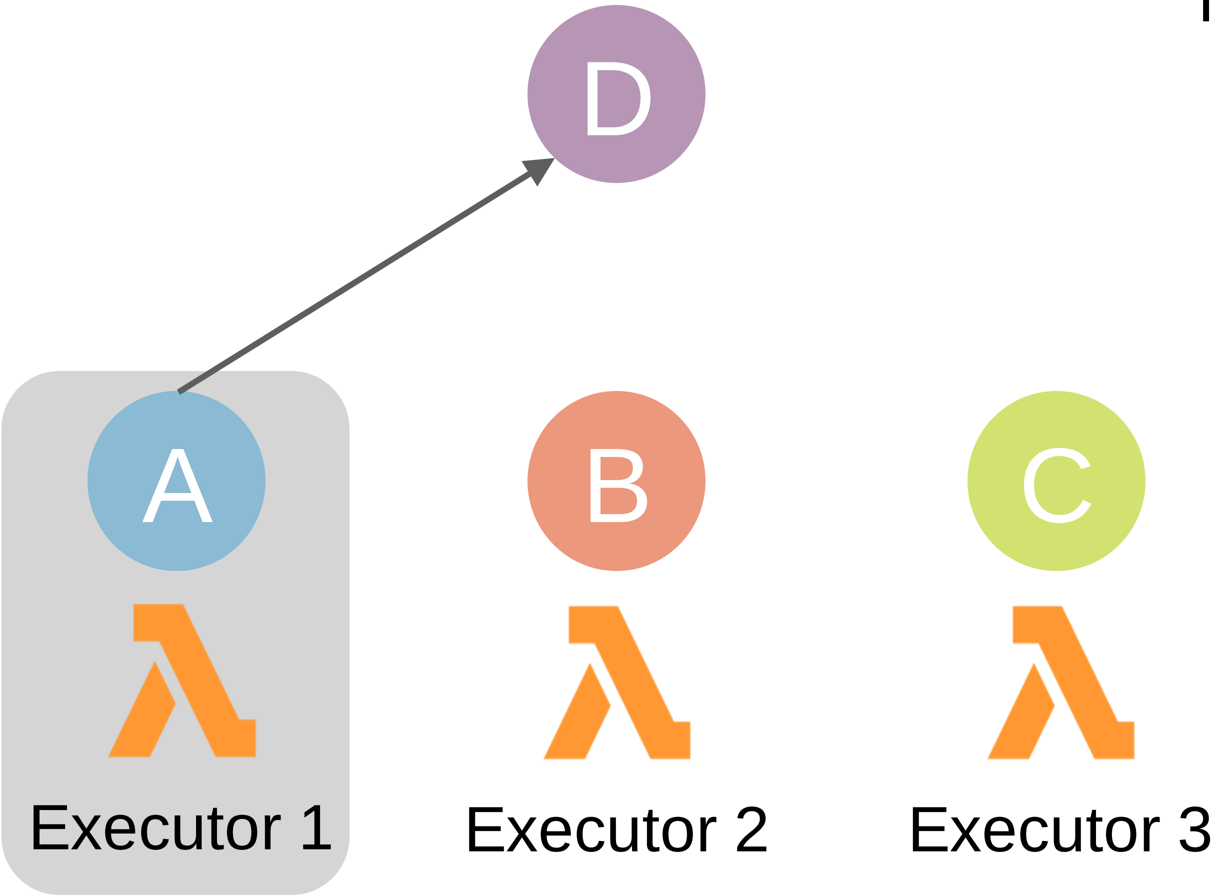
Figure 16: TSQR I/O (log).

Handling fan-in

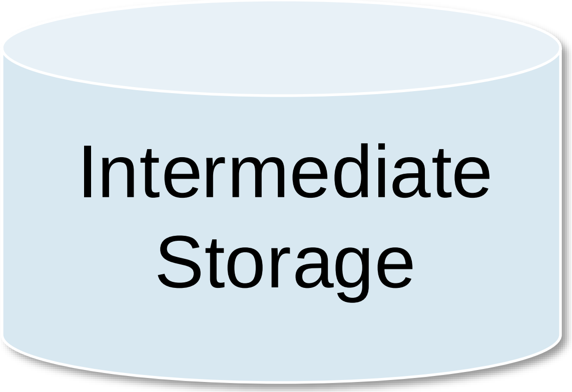


Handling fan-in

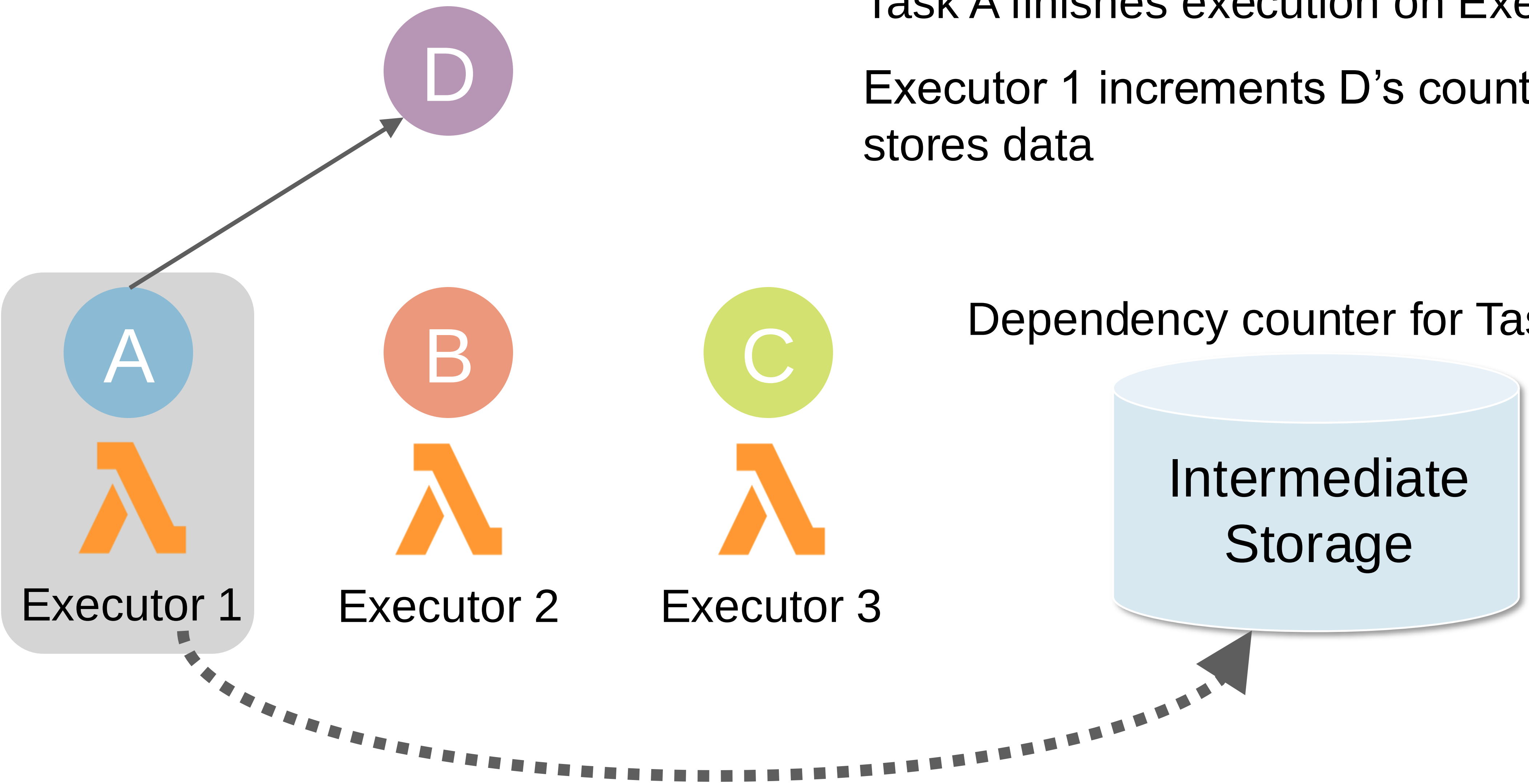
Task A finishes execution on Executor 1



Dependency counter for Task D: 0



Handling fan-in



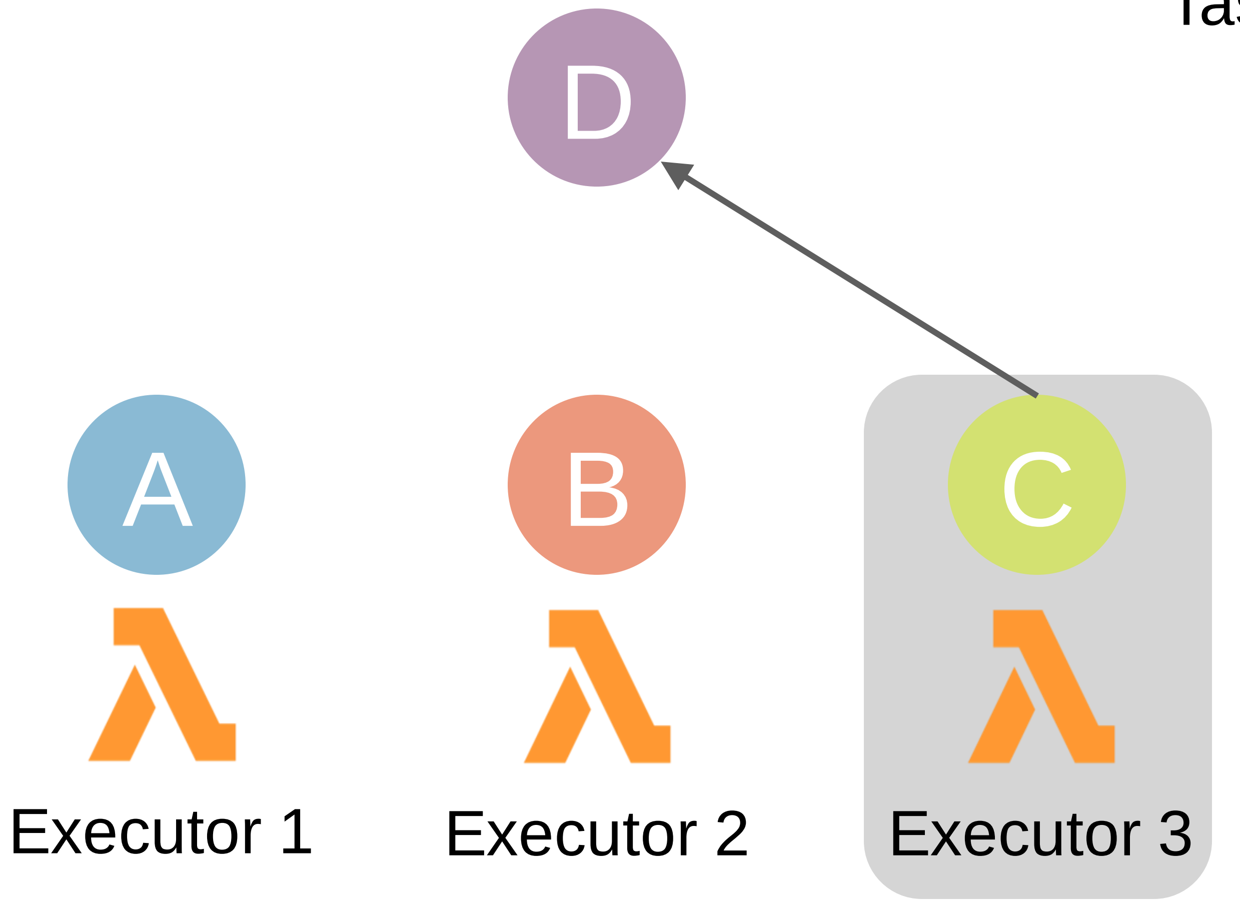
Task A finishes execution on Executor 1

Executor 1 increments D’s counter and stores data

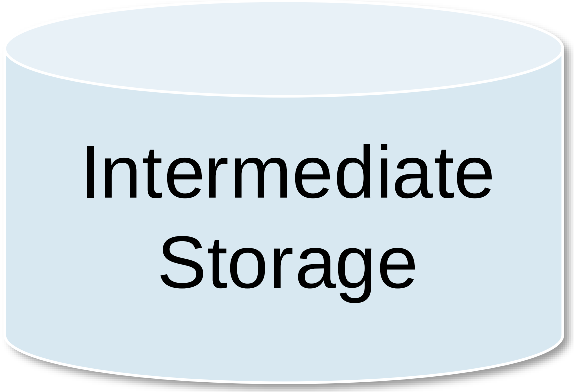
Dependency counter for Task D: **1**

Handling fan-in

Task C finishes execution on Executor 3



Dependency counter for Task D: **1**

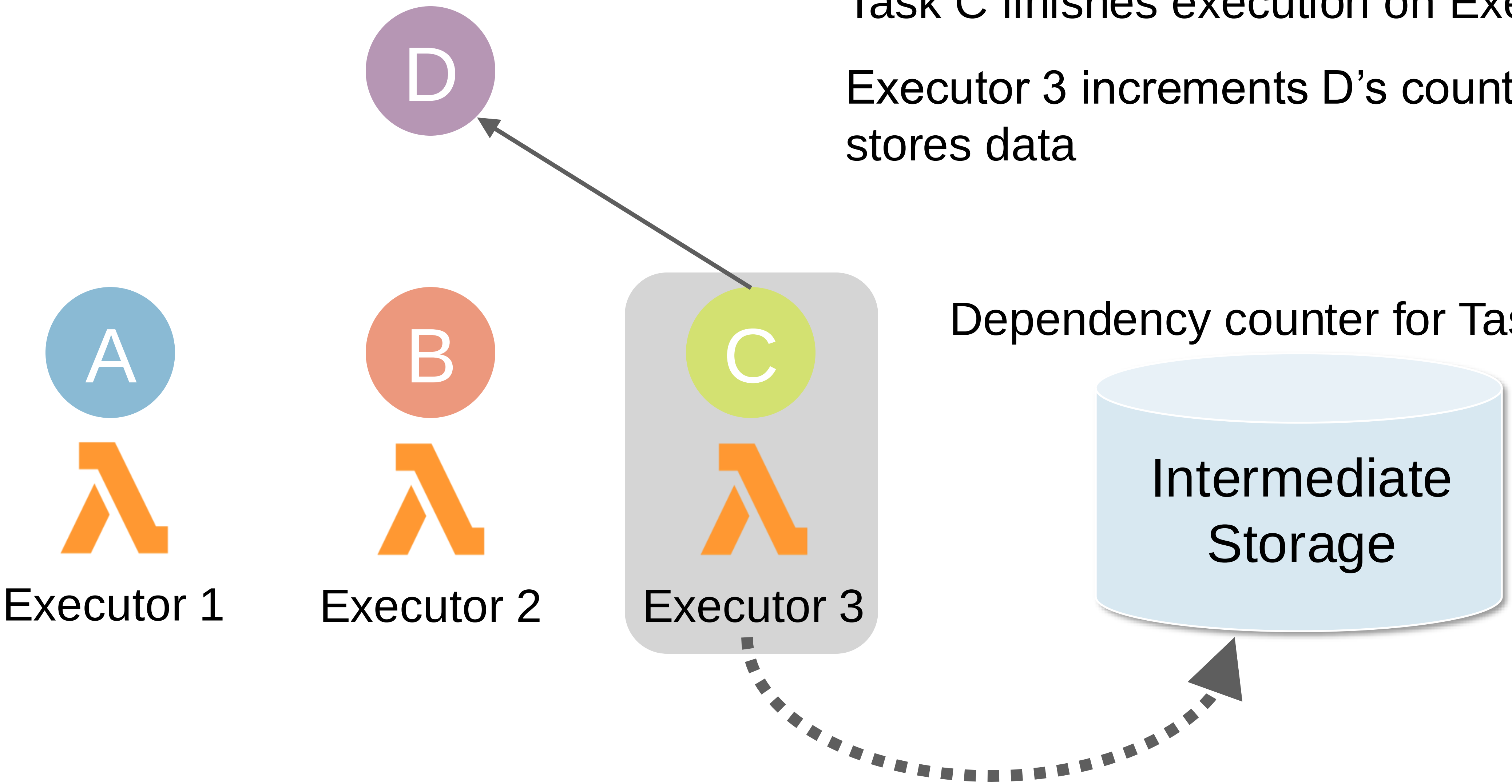


Handling fan-in

Task C finishes execution on Executor 3

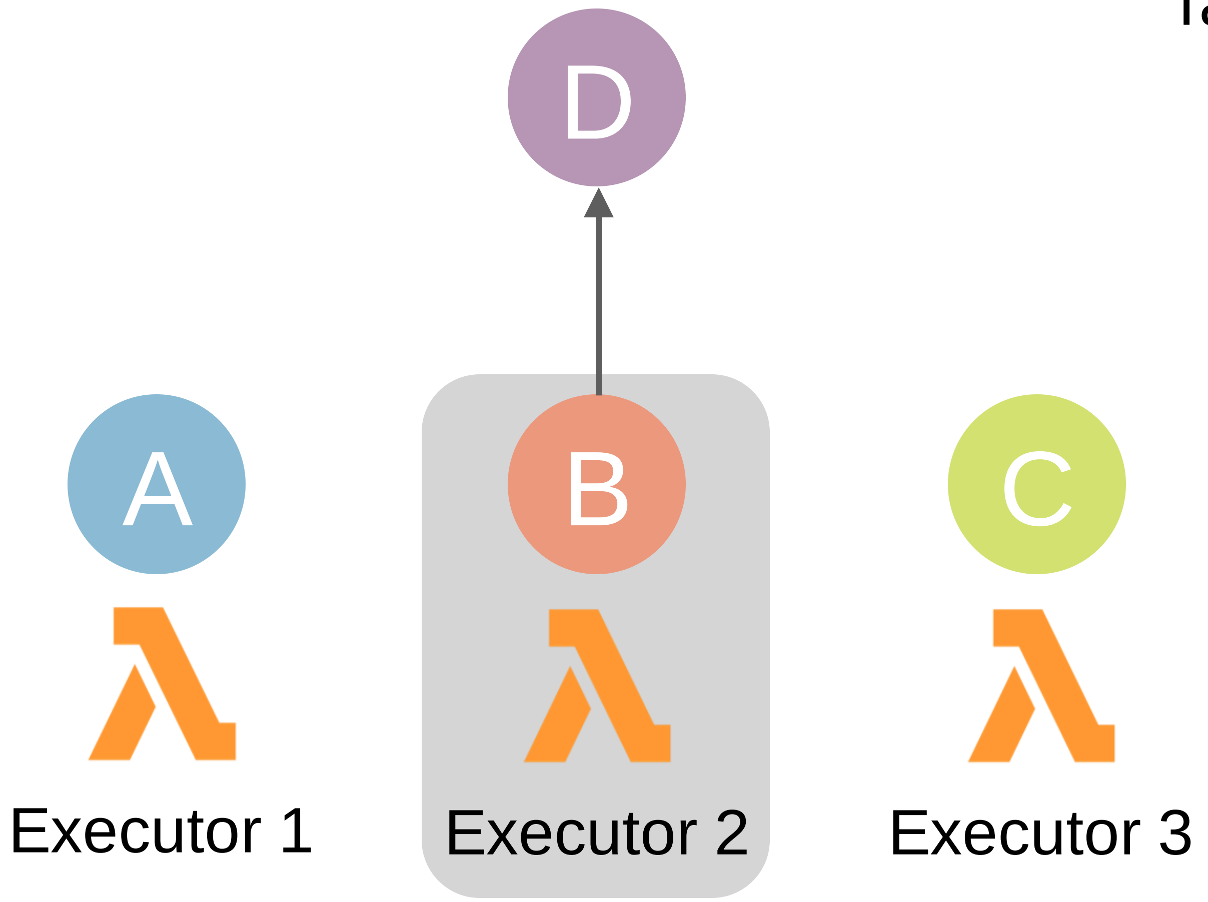
Executor 3 increments D’s counter and stores data

Dependency counter for Task D: **2**

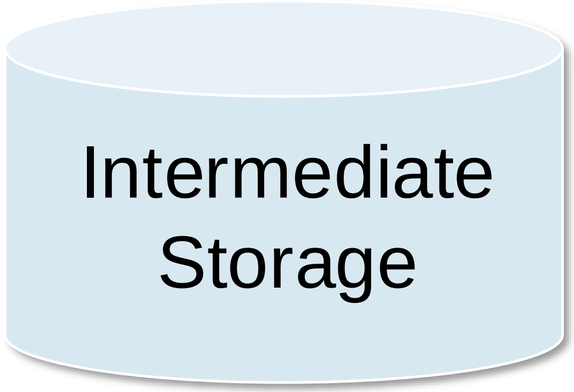


Handling fan-in

Task B finishes execution on Executor 2



Dependency counter for Task D: **2**

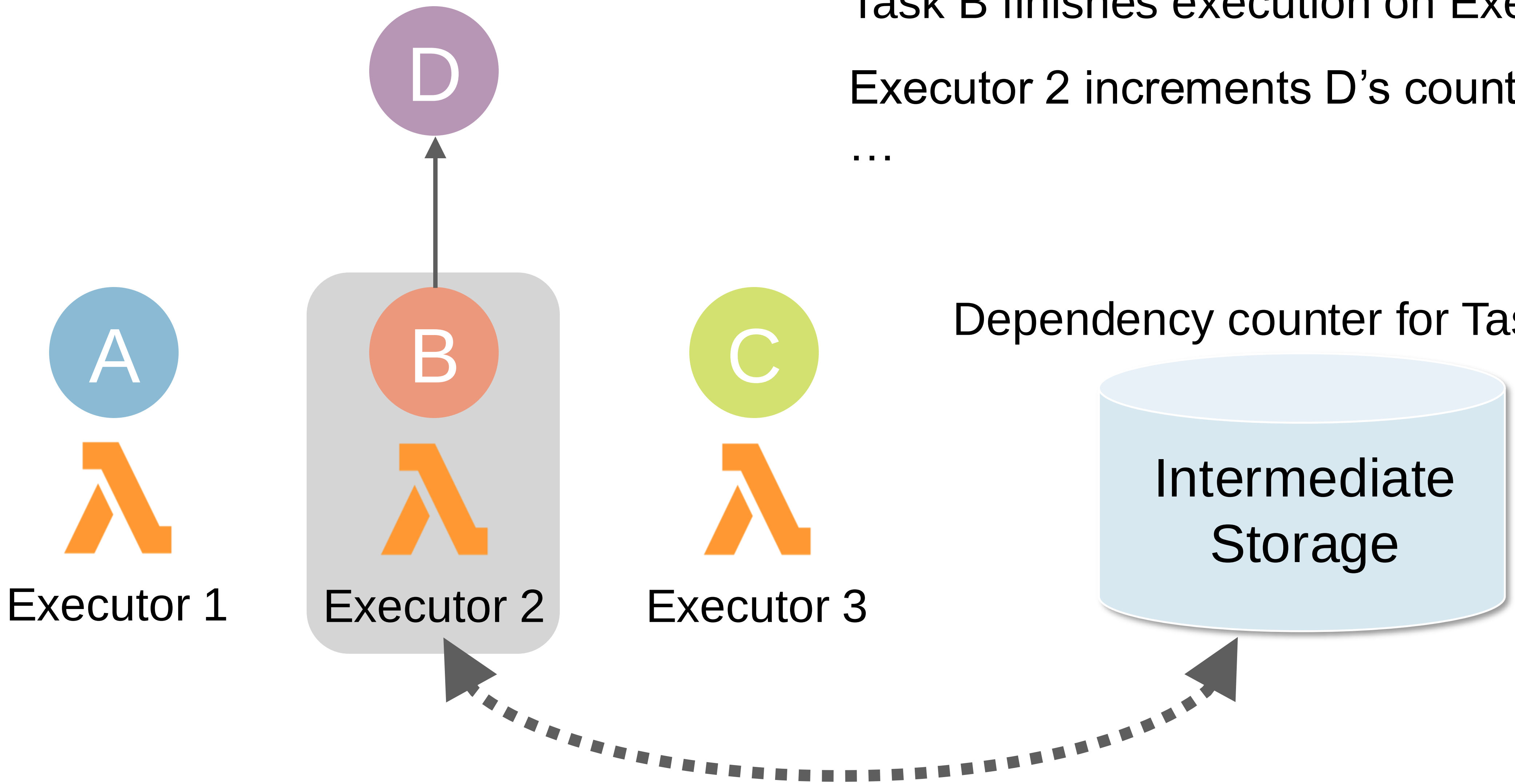


Handling fan-in

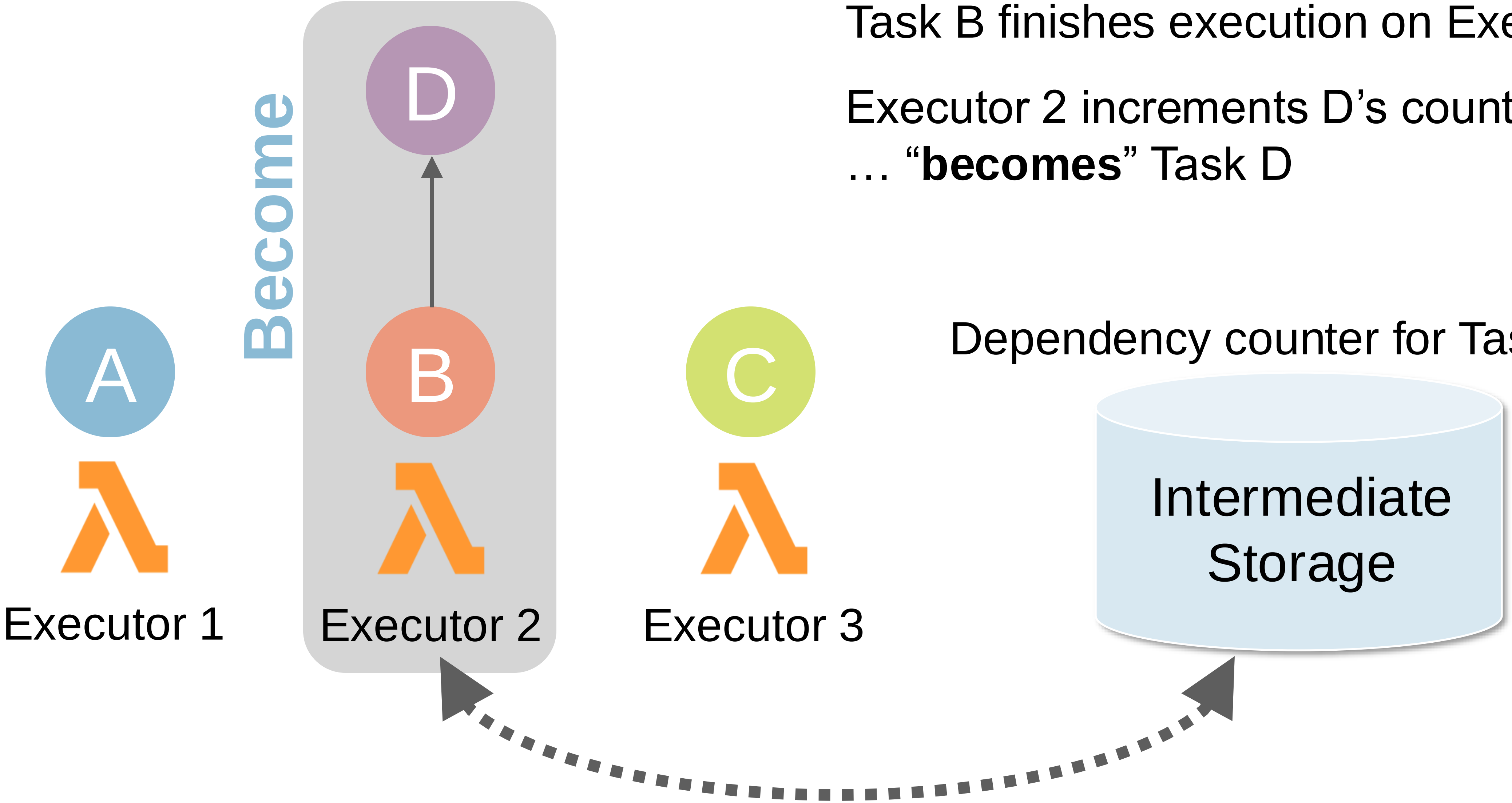
Task B finishes execution on Executor 2

Executor 2 increments D’s counter and …

Dependency counter for Task D: **3**



Handling fan-in

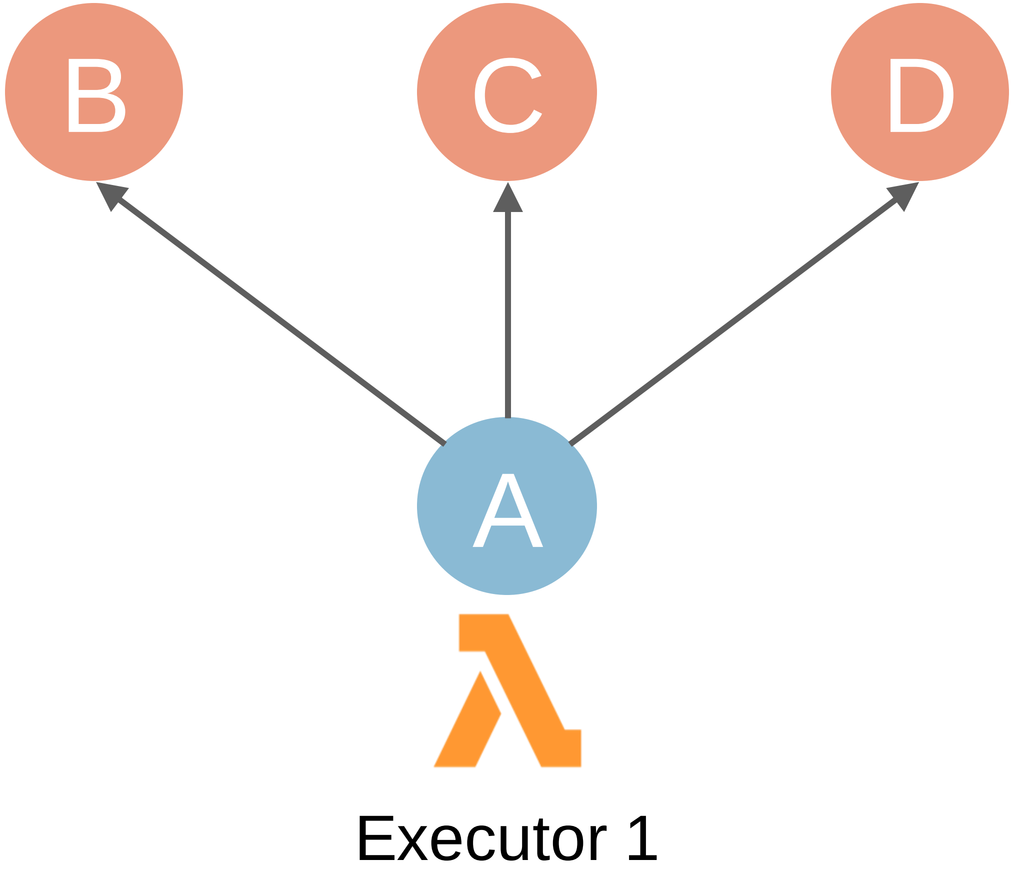


Task B finishes execution on Executor 2

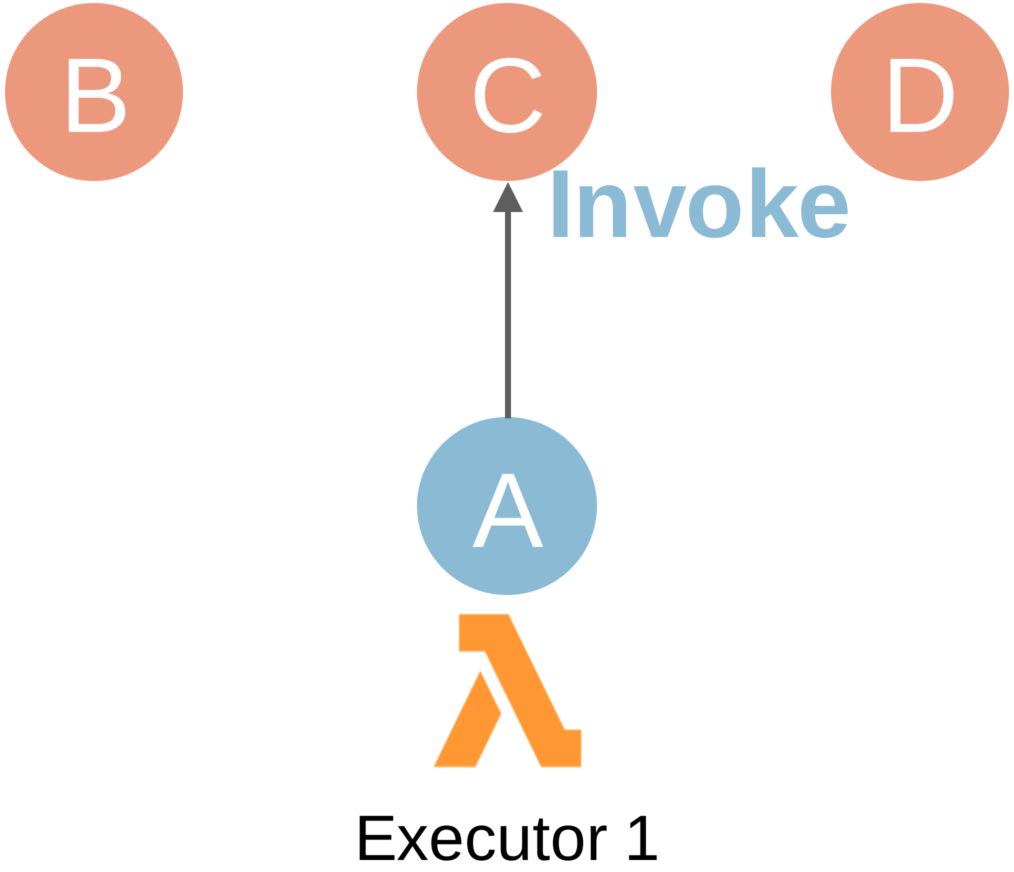
Executor 2 increments D’s counter and … “**becomes**” Task D

Dependency counter for Task D: **3**

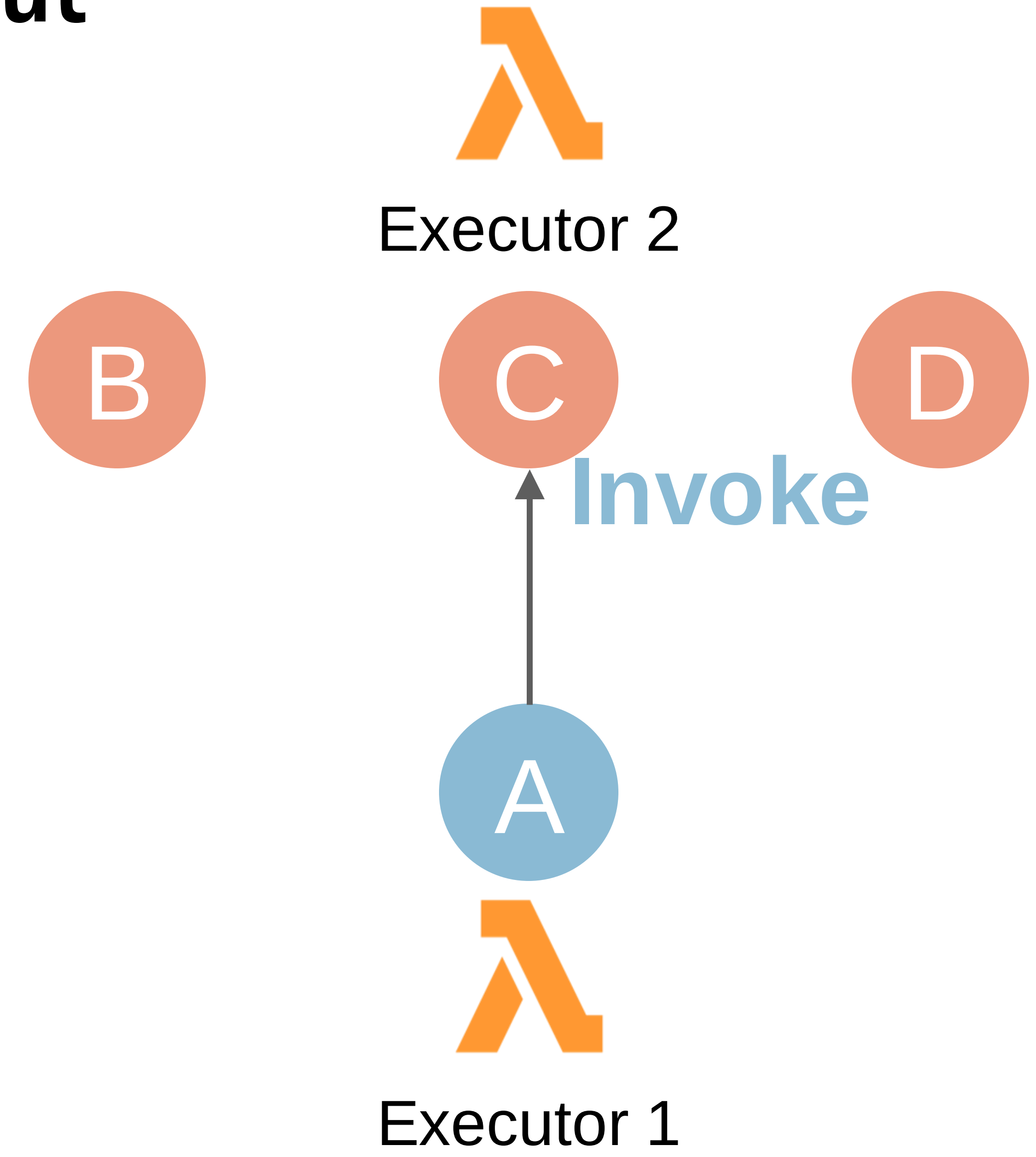
Handling fan-out



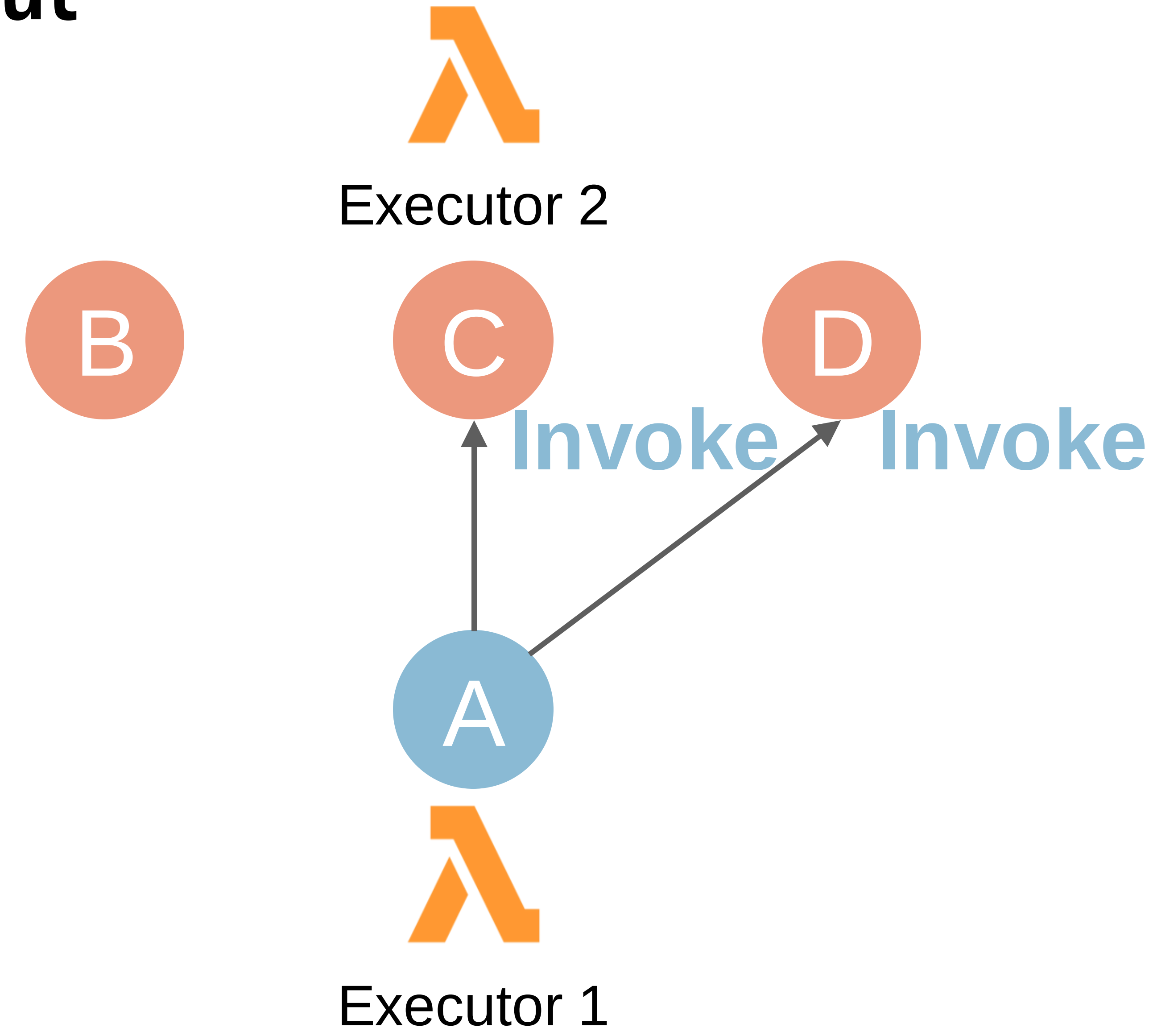
Handling fan-out



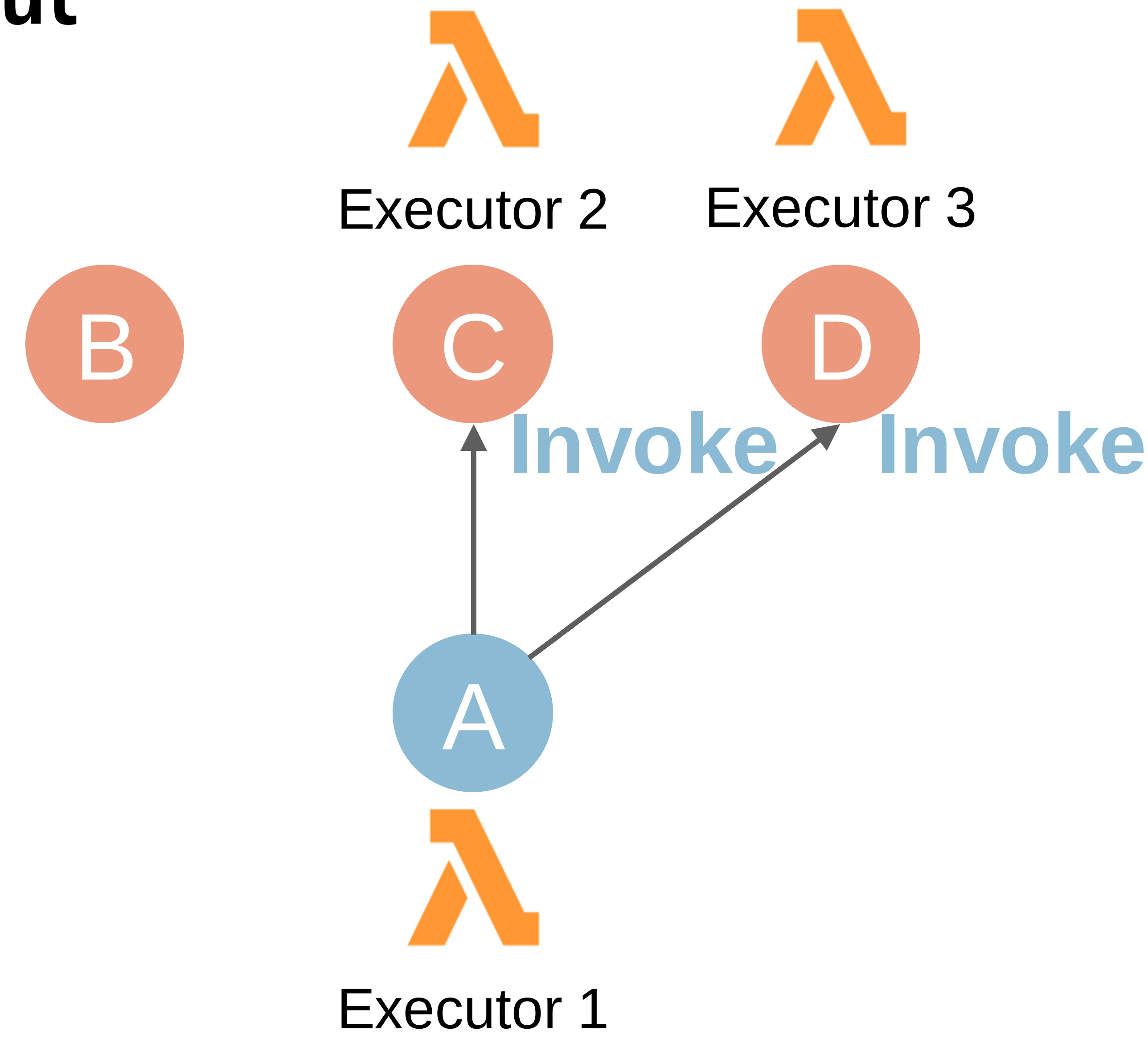
Handling fan-out



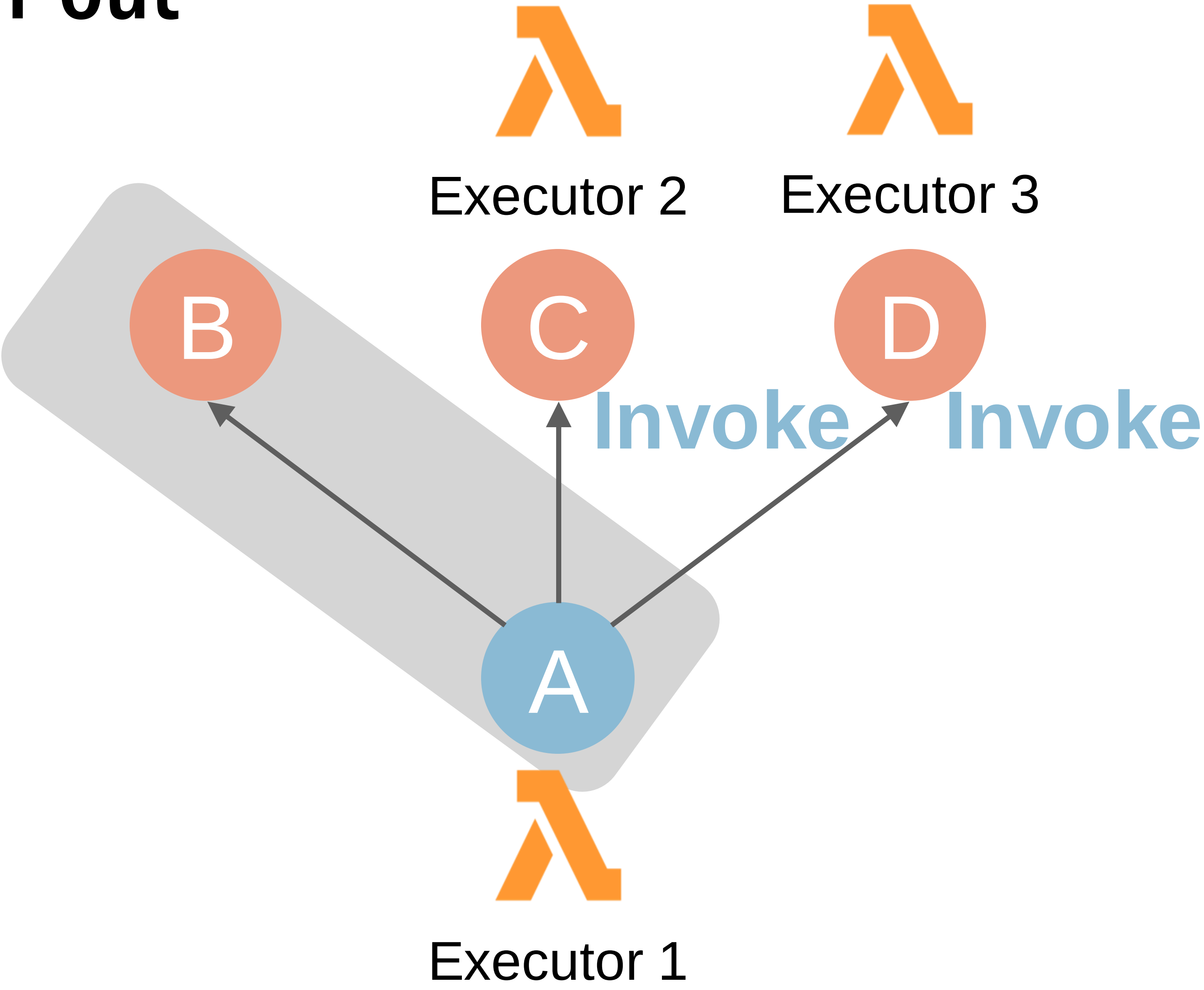
Handling fan-out



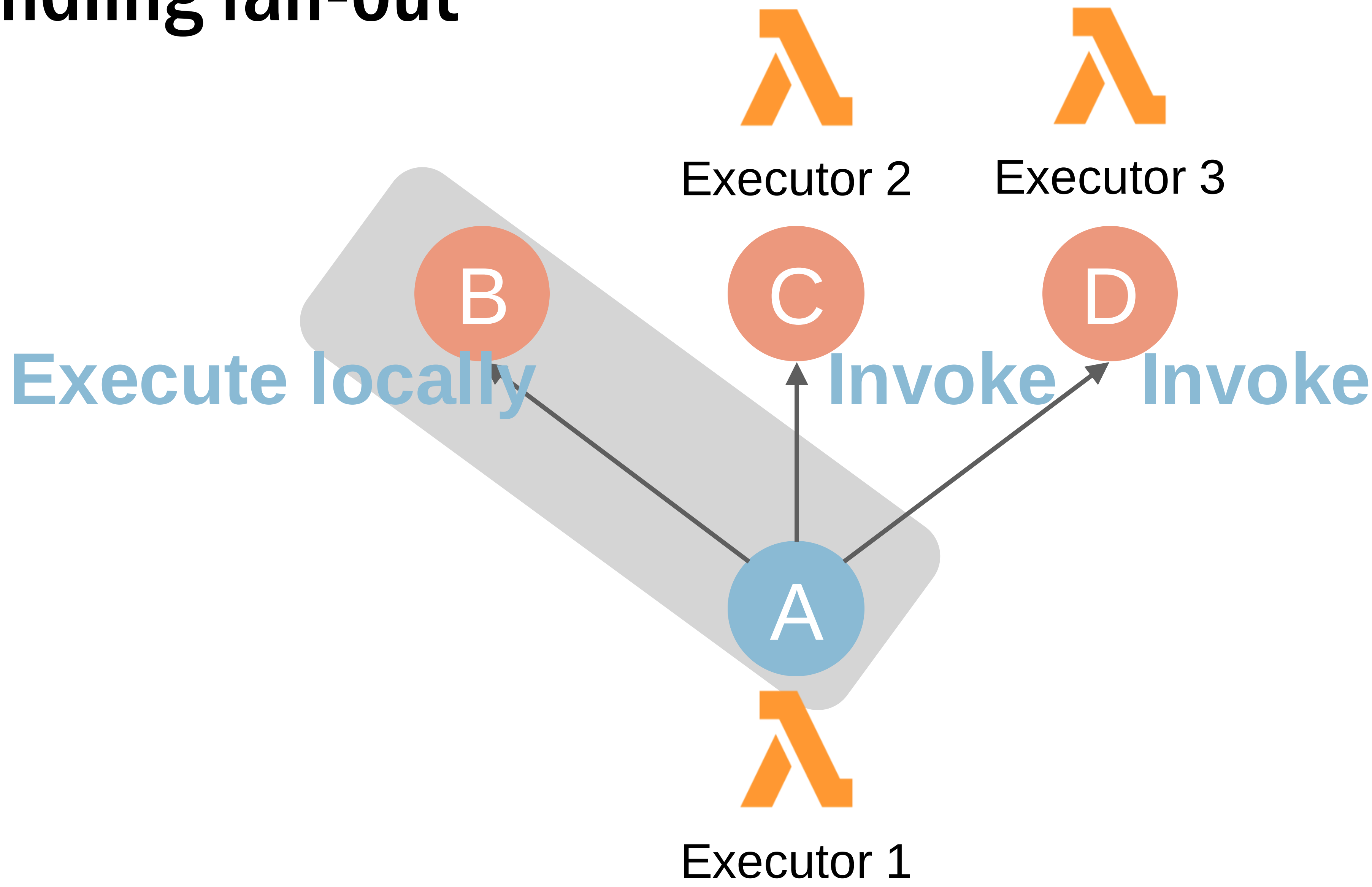
Handling fan-out



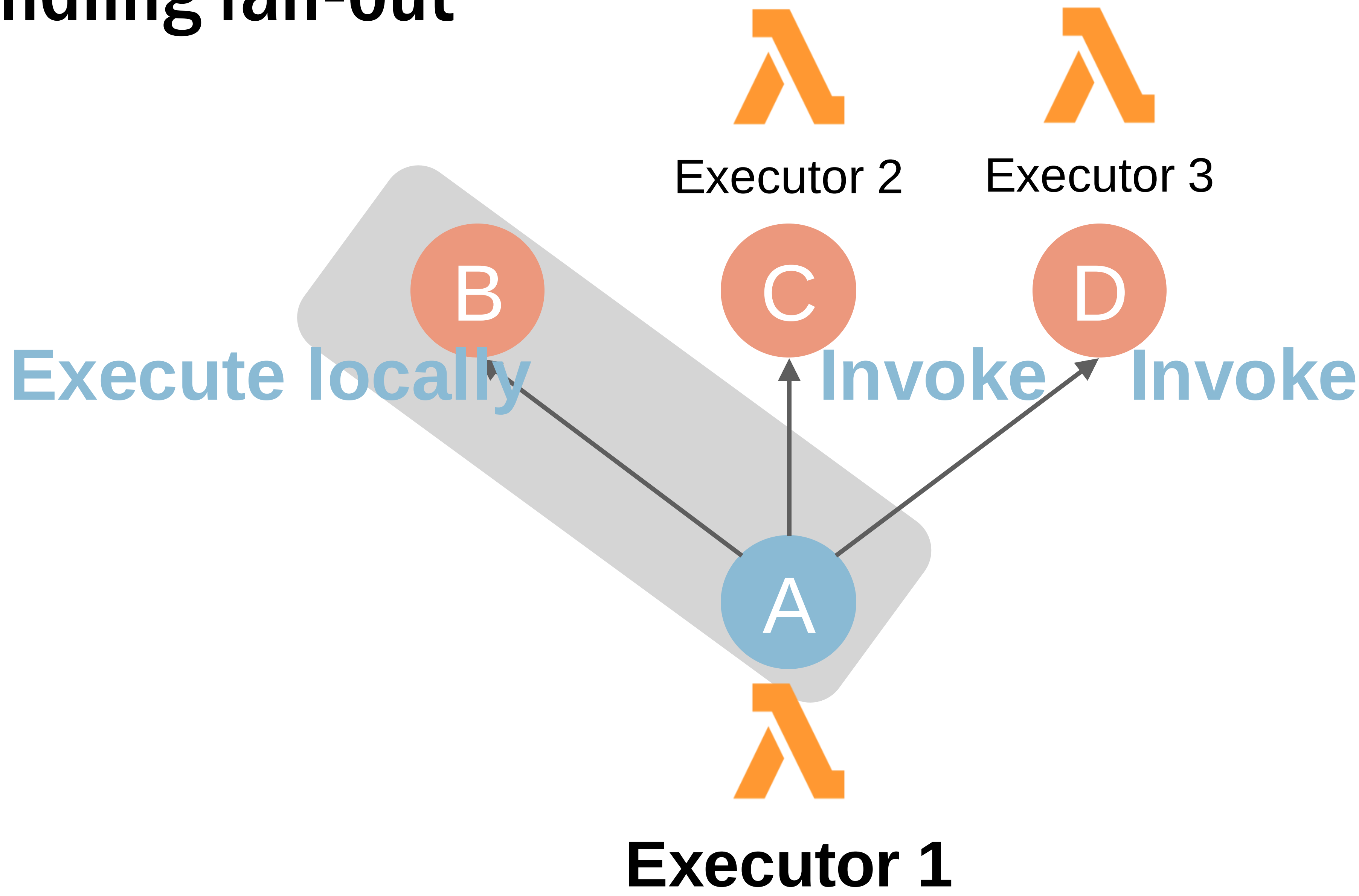
Handling fan-out



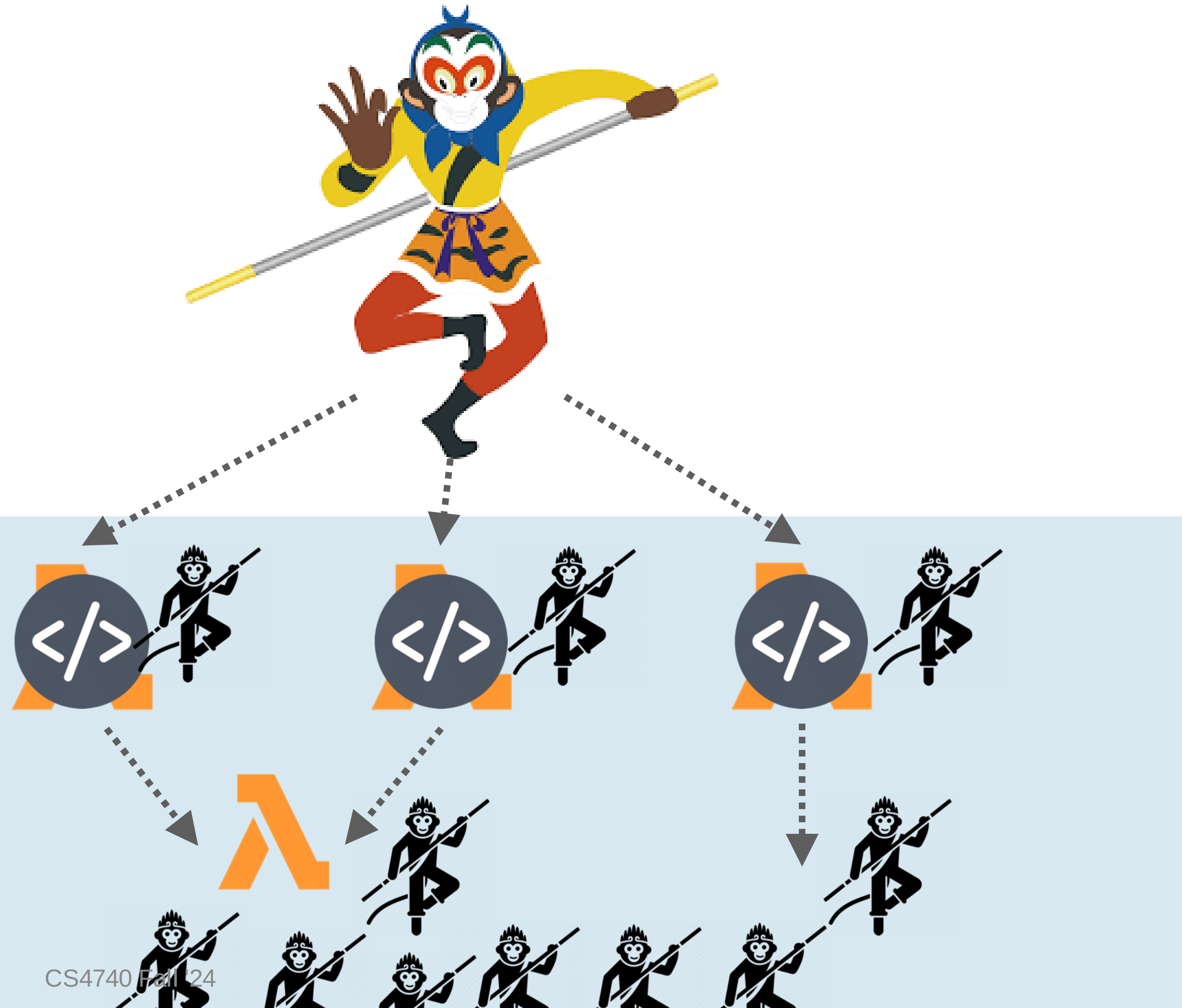
Handling fan-out



Handling fan-out



Wukong’s magic hairs vs. decentralized scheduling



Other optimizations in Wukong

Wukong uses several techniques to enhance **data locality**

Task clustering

Eliminate intermediate data transfer by executing tasks locally

Delayed I/O

Delay performing I/O until downstream tasks are ready

Then perform task clustering on those tasks