Wukong

Serverless DAG Engine

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Serverless Computing

- Emerging cloud computing platform based on the composition of fine-grained user-defined functions
- Service provider is responsible for provisioning, scaling, and managing resources
- Pay-per-use pricing model with fine granularity

AWS Lambda

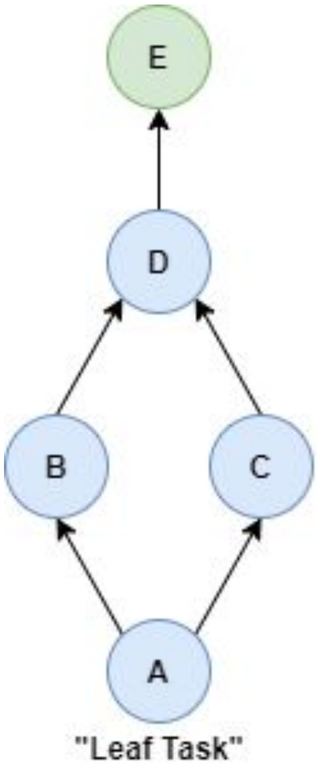
- Amazon Web Service's FaaS offering
- Can vary serverless function memory size between 128 - 3008MB
- Can vary execution time between 3 seconds - 15 minutes
- Cost:
  - $0.0000002 per request
  - $0.00001667 per GB second
- Supports JS, Go, Python, Ruby, Java, C#, and Powersh

Background - DAG Scheduling

- Data analytics applications can be modeled as a **d**irected **a**cyclic **g**raph (**DAG**) based workflow

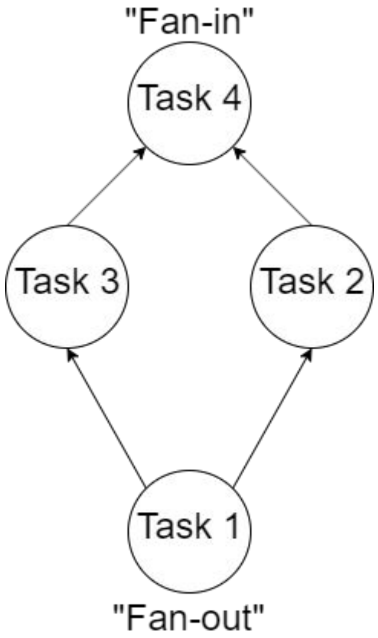
- **Nodes** represent **computations** or "**tasks**"
    - Computations can be executed by a processor.
    - May require reading/writing shared memory.

- **Edges** represent **dependencies between tasks.**
    - Nodes can only be executed after their immediate predecessors have been executed.



Background - DAG Scheduling

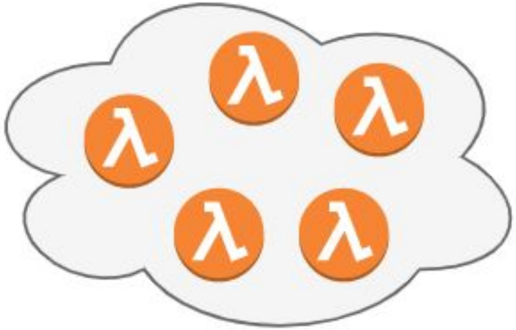
- DAG workflows well-suited for serverless computing (or Functions-as-a-Service)
    - **Auto-scaling** accommodates **short** tasks and **bursty** workloads
    - Workloads with short tasks can take advantage of **fine-grained pricing** used by FaaS providers.
        - **In general, pay-per-use pricing keeps cost of short tasks low.**



From Serverful to Serverless (Pt. 1)

- Serverful focuses on load balancing and cluster utilization
  - Bounded resources, unlimited time
  - User explicitly allocates tasks to processors
  - Servers managed by the user

- Serverless platforms provide a nearly unbounded amount of ephemeral resources
  - Bounded time, unlimited resources
  - Cloud provider automatically allocates serverless functions to VMs
  - Servers managed by the service provider



From Serverful to Serverless (Pt. 2)

- Assumptions of traditional serverful schedulers do not necessarily hold.

- A hypothetical serverless DAG scheduler may not necessarily care about traditional “scheduling”-related metrics and constraints (e.g., load balancing, cluster utilization).

- Individual tasks can be executed anywhere in the serverless data center (which is essentially managed by the serverless provider).

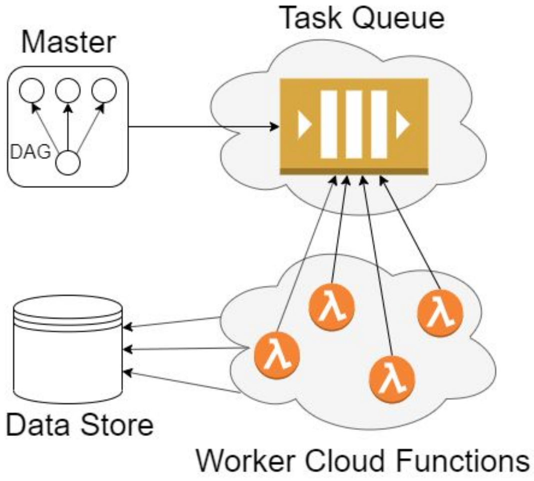
AWS Lambda Constraints

- Lambda function invocation currently takes 50ms on average
- Outbound-only network connectivity
- Relatively low network bandwidth
- Execution time limits (900 seconds)
- Lack of quality-of-service (QoS) control, leading to stragglers
    - e.g., cold starts

Existing Parallel Frameworks Using Serverless Computing

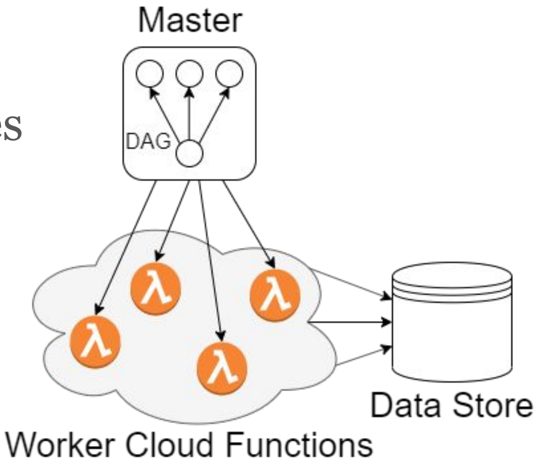
- PyWren [SoCC'17]
  - Parallelize existing Python code with AWS Lambda
- Numpywren
  - System for linear algebra built atop PyWren
- ExCamera [NSDI'17]
  - Allows users to edit, transform, and encode videos using fine-grained serverless functions
- gg [ATC'19]
  - Framework and command-line tools to execute "everyday applications" within cloud functions

Typical Approaches



- Approach 1: Queue-based Master-Worker
  - Master submits ready tasks to a queue
  - Workers are cloud functions that process tasks in parallel, e.g., Numpywren
  - **Drawbacks**: cannot exploit data locality as easily; reading from queue could become a bottleneck

- Approach 2: Centralized scheduler directly invokes cloud functions to process ready tasks, e.g., ExCamera
  - **Drawback**: centralized scheduler can become a bottleneck for system



Wukong solves these drawbacks.

Wukong

- **Approach**

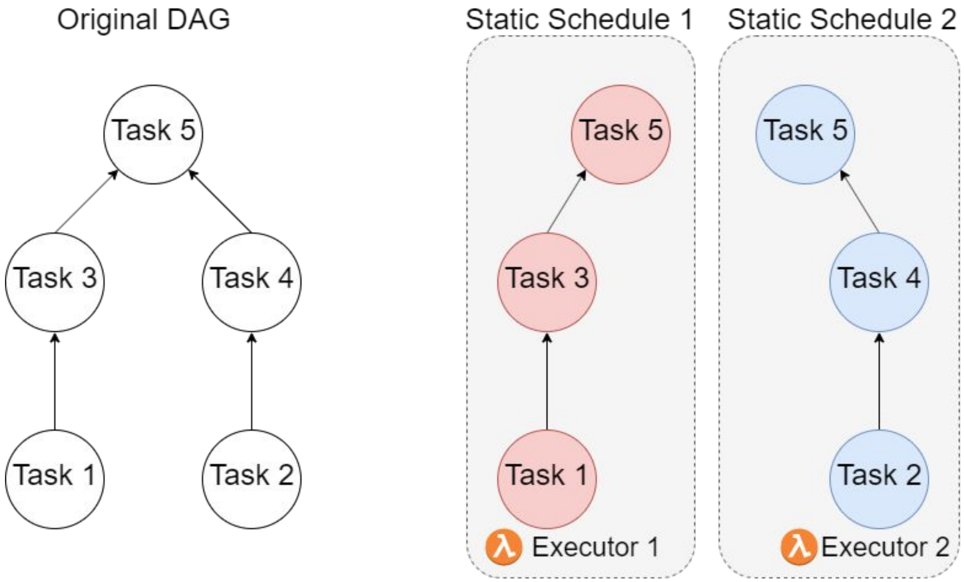
- Architecture
  - Static Scheduler
  - Task Executors
  - Storage Cluster

- Evaluation

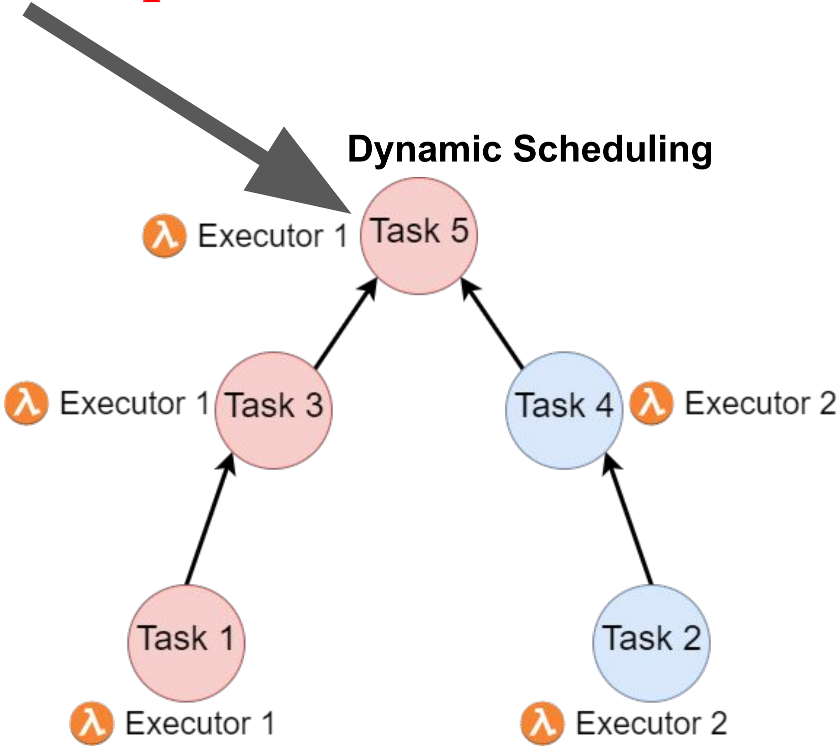
Task executors cooperate here!

Our Approach - Wukong

Static Scheduling



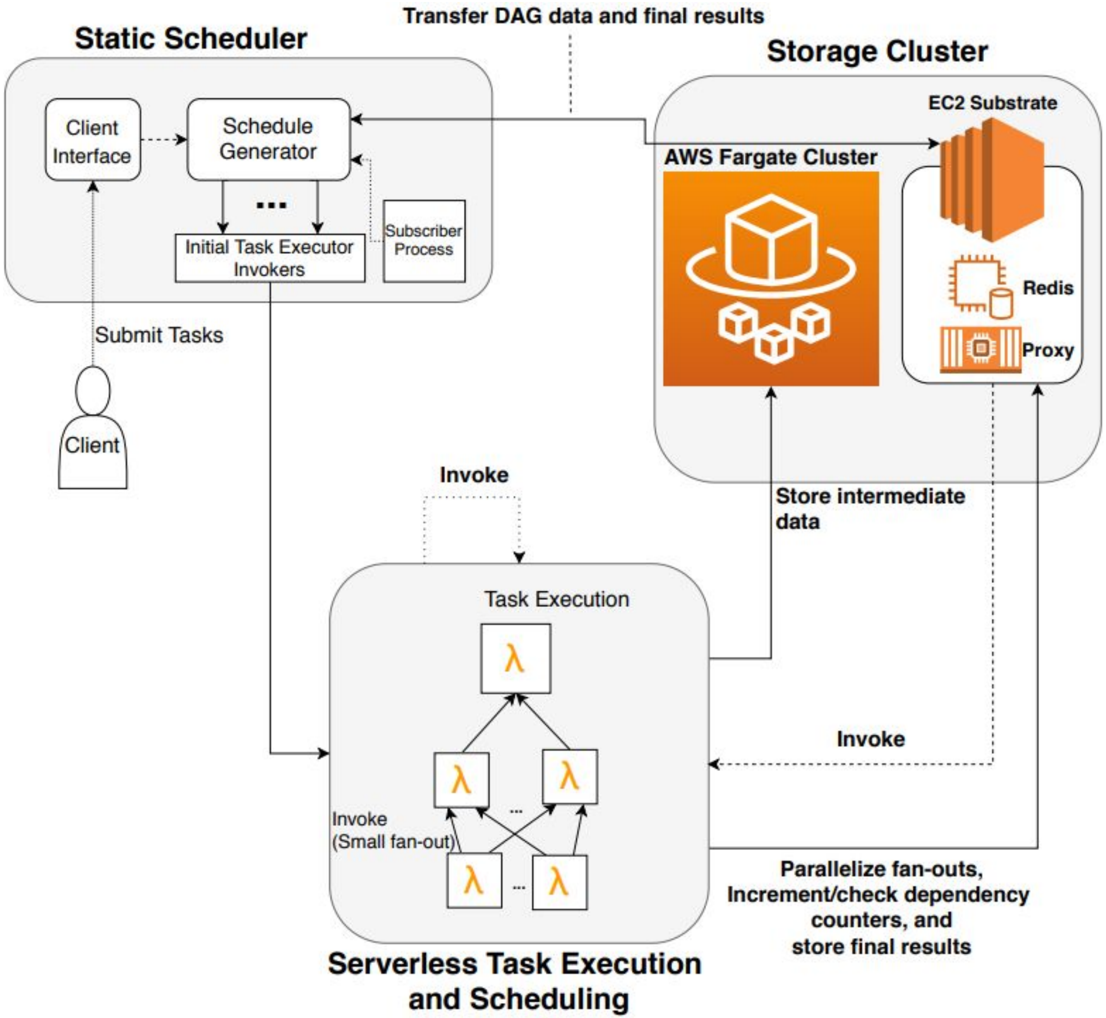
Dynamic Scheduling



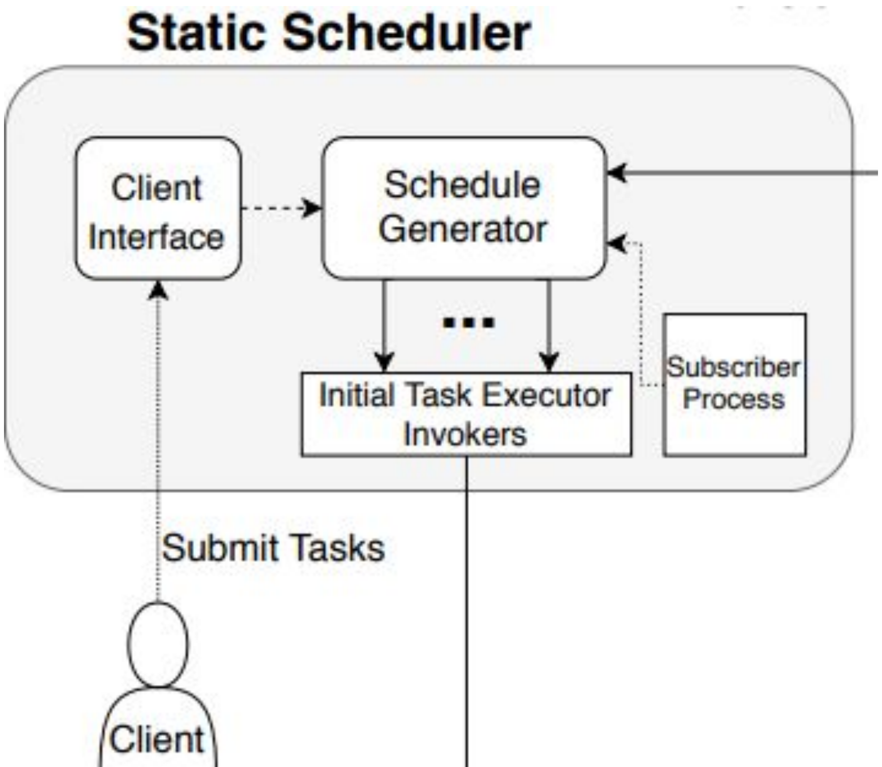
- Statically partition DAG into sub-DAGs
    - Assign each partition to a Lambda function
- Decentralized, cooperative scheduling
    - Lambda functions coordinate with each other to execute overlapping sections of assigned sub-DAGs

Wukong

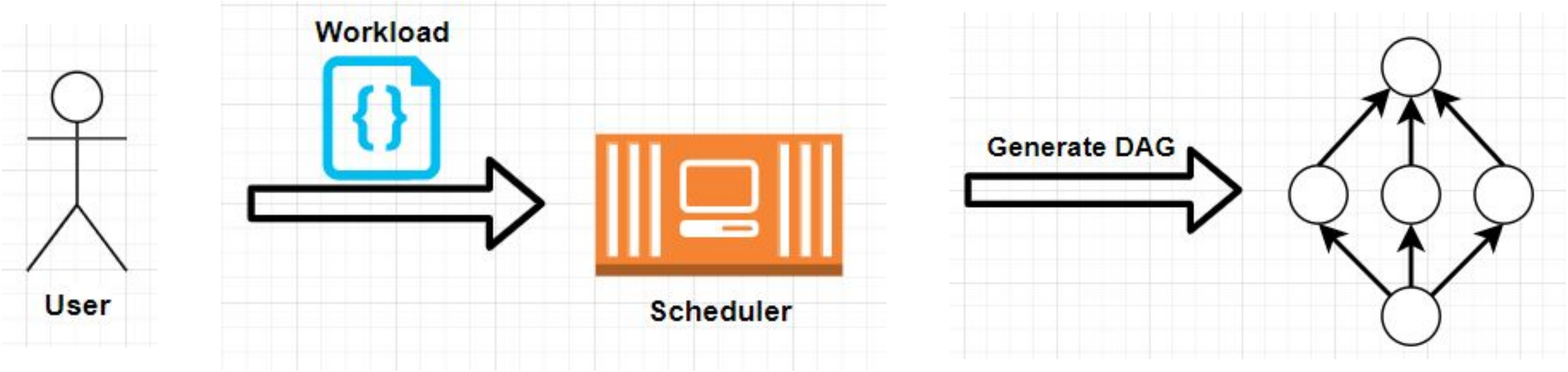
- Approach
- **Architecture**
  - **Static Scheduler**
  - **Task Executors**
  - **Storage Cluster**
- Evaluation


Transfer DAG data and final results
Static Scheduler
Storage Cluster
Client Interface
Schedule Generator
EC2 Substrate
AWS Fargate Cluster
Subscriber Process
Initial Task Executor Invokers
Redis
Proxy
Submit Tasks
Client
Invoke
Store intermediate data
Task Execution
Invoke
Invoke (Small fan-out)
Parallelize fan-outs, Increment/check dependency counters, and store final results
Serverless Task Execution and Scheduling

Static Scheduler



- Partitions DAG into sub-DAG using a depth-first search (DFS) from each leaf node.
- Assigns sub-DAGs to executors
- Returns final results back to client.



(1) User submits a workload to the Scheduler

(2) Scheduler uses Dask to generate a DAG from the workload.

(3) Scheduler performs pre-processing on the newly-generated DAG.

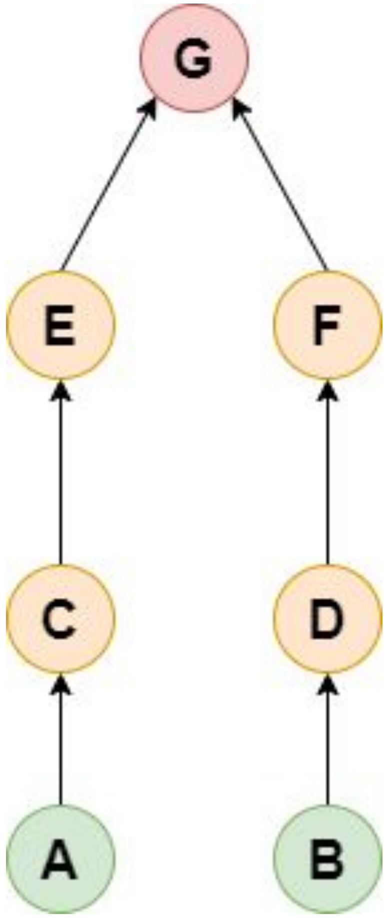
(4) Scheduler assigns static schedules to serverless task executors.

DAG Pre-processing Stage

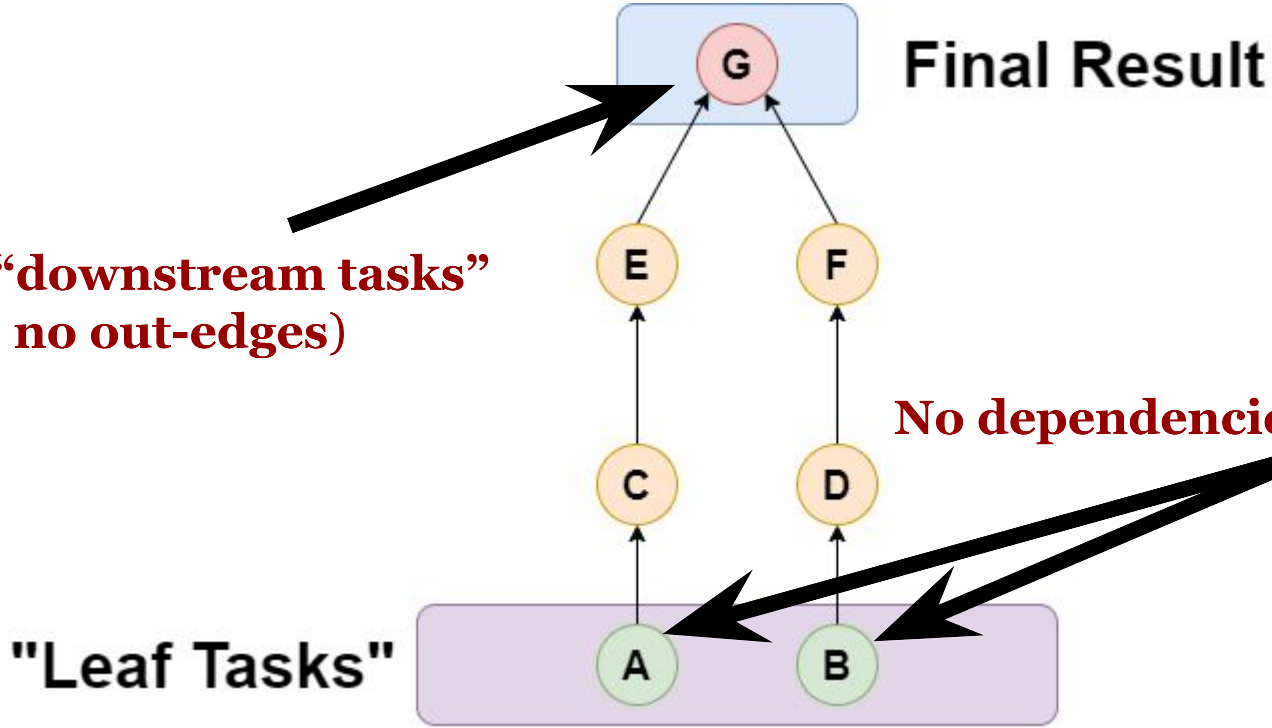
1. Generate DAG from user-submitted workload.

2. Iterate over generated tasks to find “**leaf tasks**”, or the tasks with **no dependencies** (i.e., in-edges), and “**final results**”, or tasks with no “**downstream tasks**” (i.e., out-edges).

3. Perform a series of **depth-first searches** beginning at each “leaf task” to partition DAG into a series of “**static schedules**”.



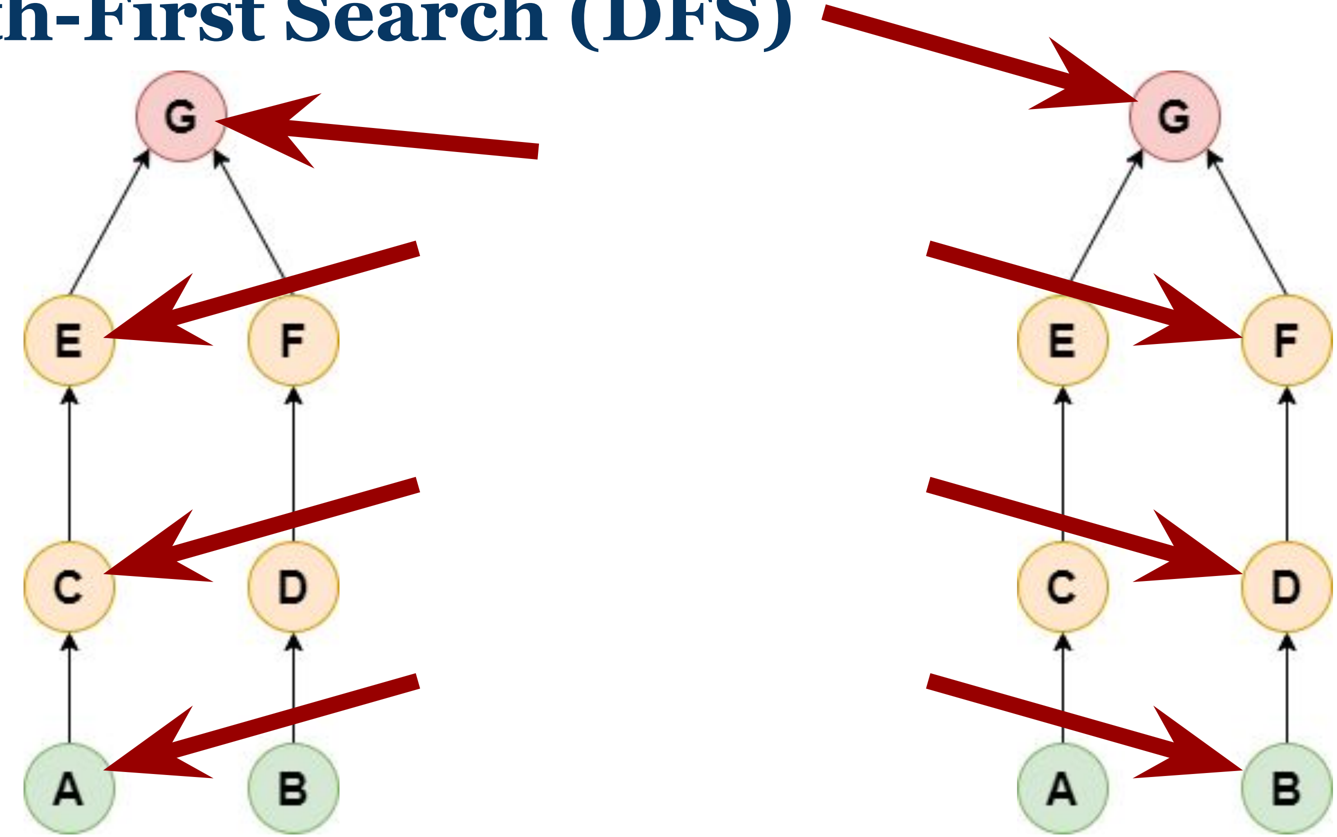
Identifying "**Leaf Tasks**" and **Final Results**



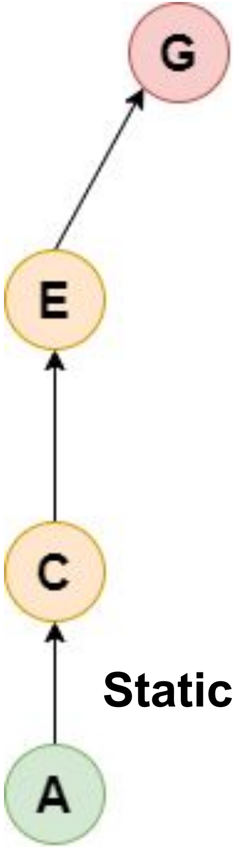
No "downstream tasks"
(i.e., **no out-edges**)

No dependencies (i.e., **no in-edges**)

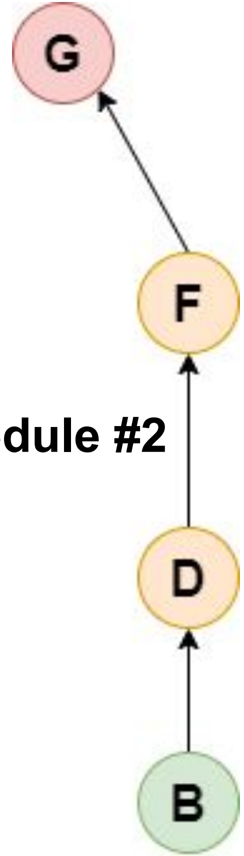
Depth-First Search (DFS)



Two Static Schedules



Static Schedule #1



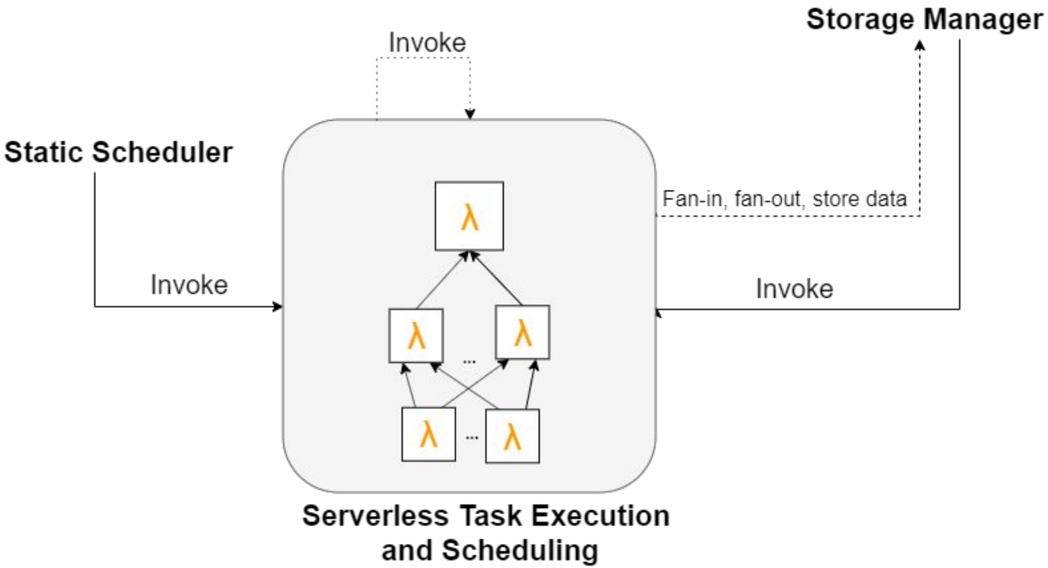
Static Schedule #2

Post-DAG Preprocessing Steps

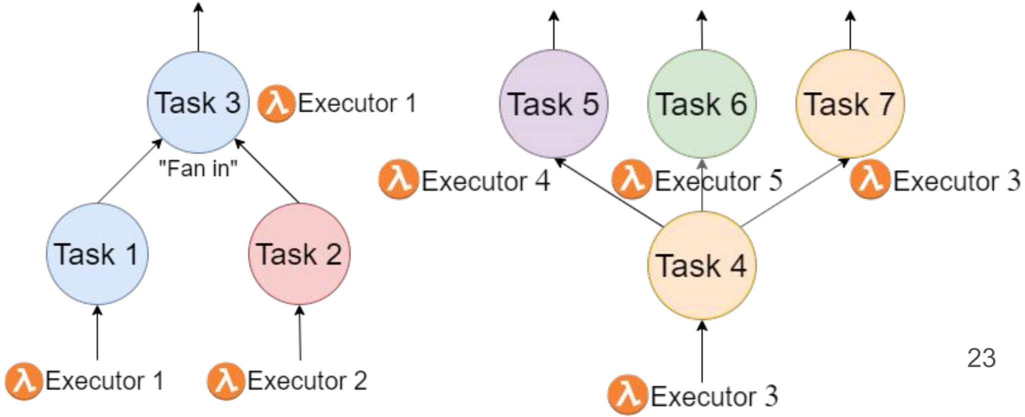
- Once the DFS has been completed, the Static Scheduler will serialize each of the static schedules and store them in the Key-Value Store (Redis).

- After storing the static schedules, the Static Scheduler will invoke a AWS Lambda Task Executor for each leaf task.
    - If the static schedule is < 256 kB in size, then the Scheduler will send the static Schedule to the Task Executor via the invocation payload.
    - If the static schedule is > 256 kB in size, then the Scheduler will simply pass the Redis key of the static schedule. The Task Executor will retrieve the static schedule once it begins execution.

Executors



- Decentralized, cooperating schedulers
- Schedule and execute tasks in assigned sub-DAGs
- Cooperate on scheduling tasks contained in two or more sub-DAGs



AWS Fargate

- “Serverless compute engine” for containers

- Works with Amazon Elastic Container Service (ECS) and Amazon Elastic Kubernetes Servers (EKS)

- AWS Fargate is responsible for provisioning and managing the servers; user just specifies resource allocation.

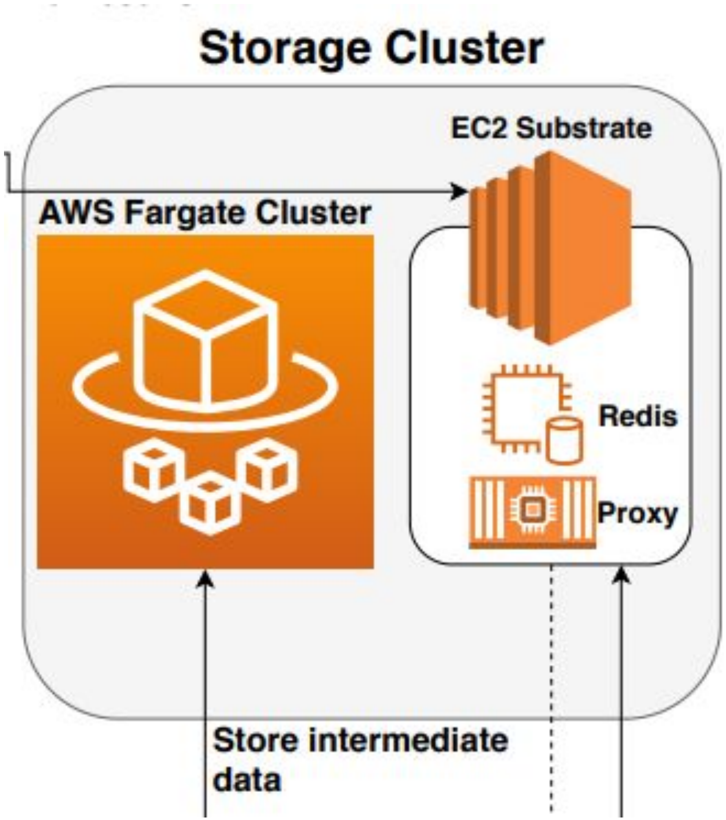
- Relatively inexpensive

Storage Cluster

- Performs storage operations on behalf of Executors and Static Scheduler

- Uses AWS Fargate cluster for intermediate data storage.

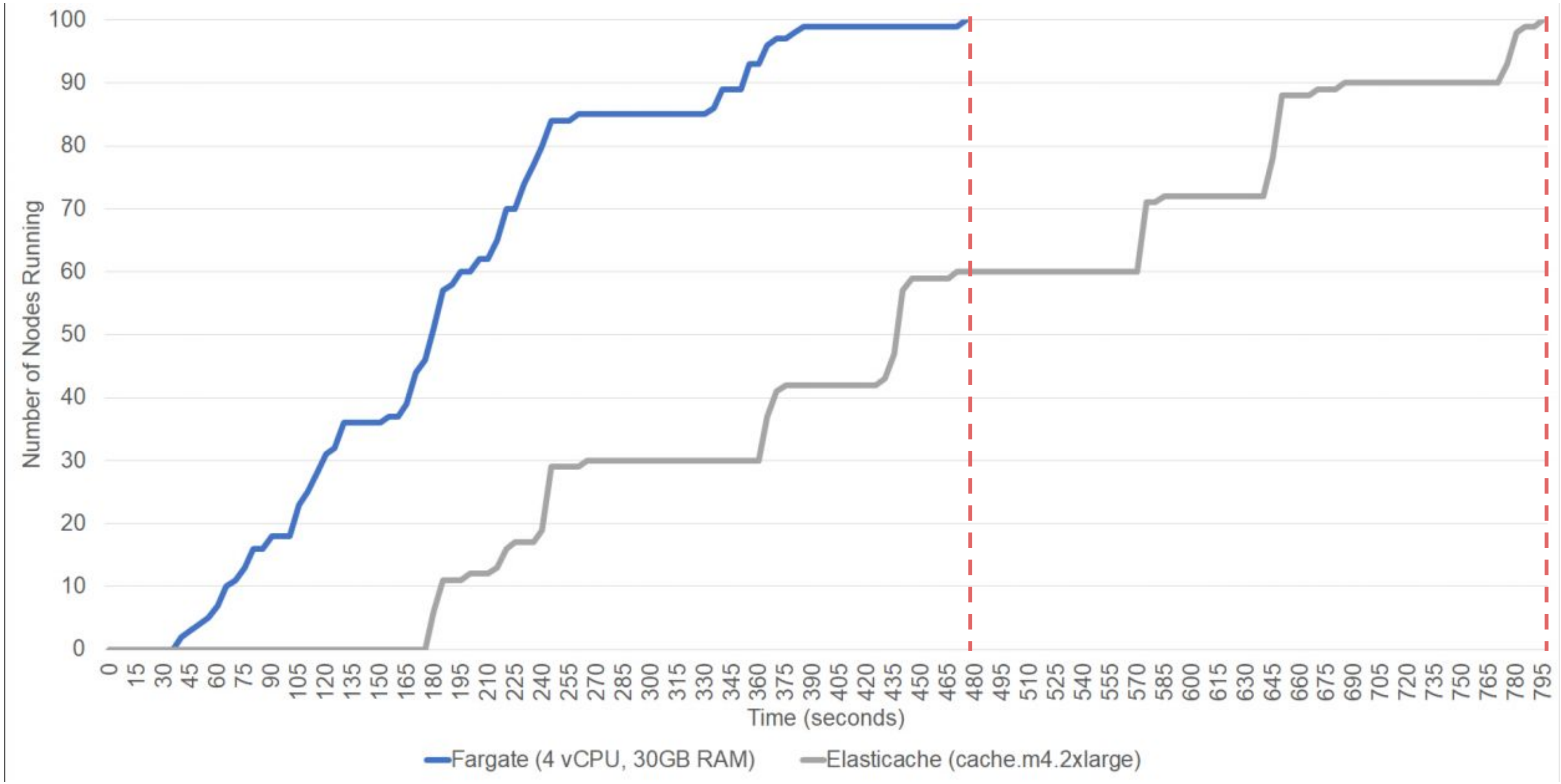
- Use additional, separate Redis instance running on EC2 for dependency counters and static schedule storage.



Storage Cluster - Cost Effectiveness

- Fargate Storage Cluster is **64.8%** cheaper than hosting an equivalent cluster on EC2 and **79.4%** cheaper than hosting the same number of Redis instances on AWS ElastiCache.

Storage Cluster Elasticity



Wukong

- Approach
- Architecture
  - Static Scheduler
  - Task Executors
  - Storage Manager
- **Evaluation**

Experimental Goals

- Identify and describe the factors influencing performance and scalability

- Compare WUKONG against Dask
  - Can WUKONG achieve performance comparable to Dask `distributed` executing on general-purpose VMs, given the inherent limitations of AWS Lambda?

Experimental Setup

- Compare against Dask `distributed`.
  - 11-node EC2 cluster of `r5.4xlarge` VMs
- Wukong Static Scheduler, KV Store, and KV Store Proxy running on `r5n.16xlarge` EC2 VMs.
- Task Executor allocated 3GB memory with timeout set to two minutes.

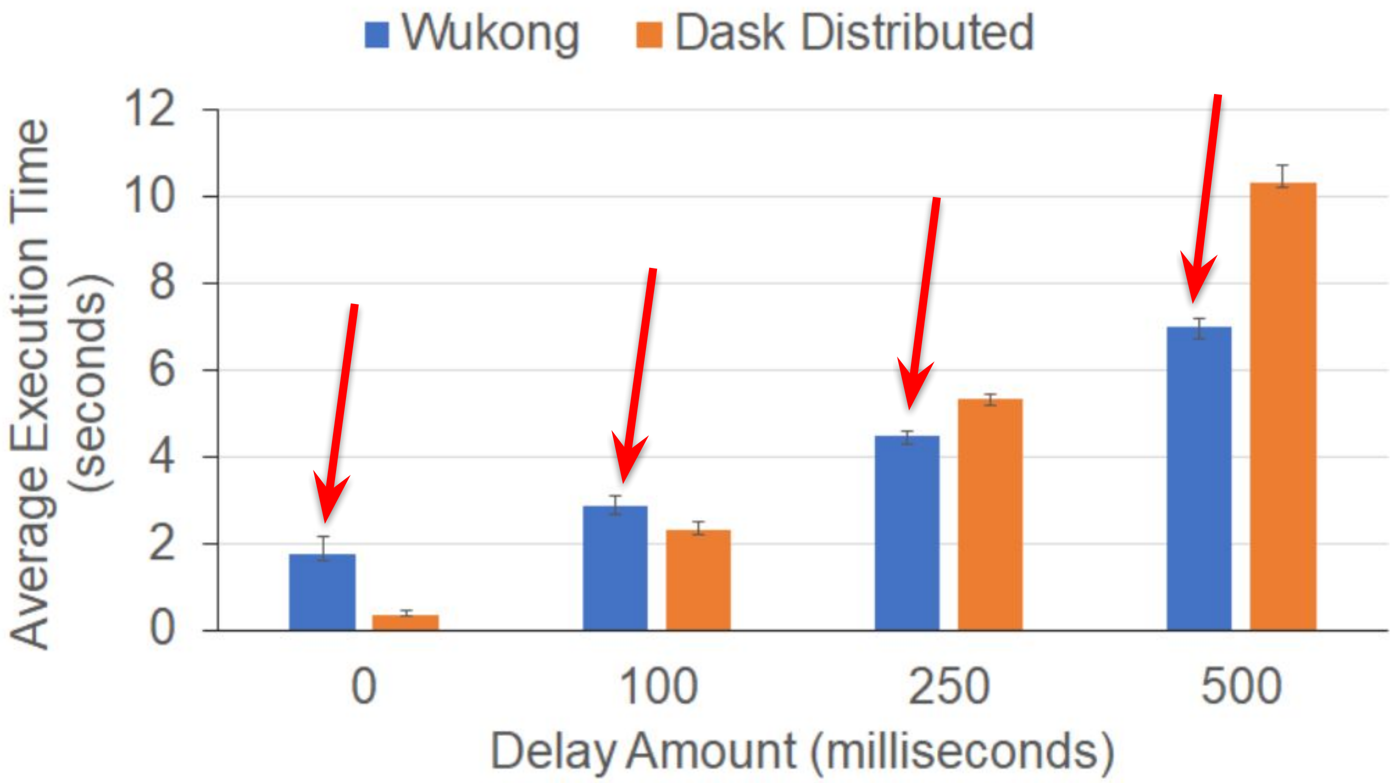
Four DAG Applications

- Microbenchmark
  - **Tree Reduction**: repeatedly add adjacent elements of an array until a single value remains

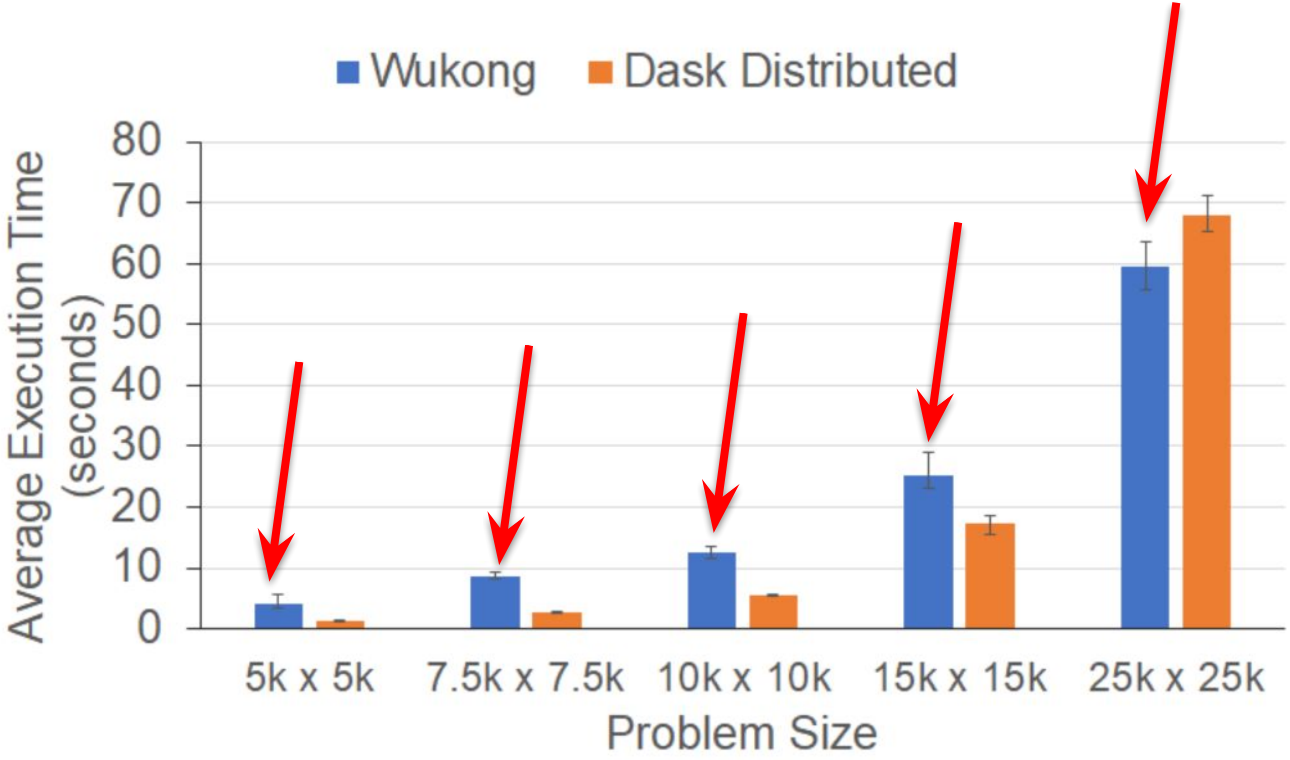
- Linear Algebra
  - **General Matrix Multiplication (GEMM)**
    - 5,000 × 5,000 through 25,000 × 25,000
  - **Singular Value Decomposition (SVD)**
    - $n \times n$ matrix and a tall-and-skinny matrix, varying sizes

- Machine Learning
  - **Support Vector Classification (SVC)**
    - 100,000 - 8,192,000 samples

Microbenchmark - Tree Reduction with Delays

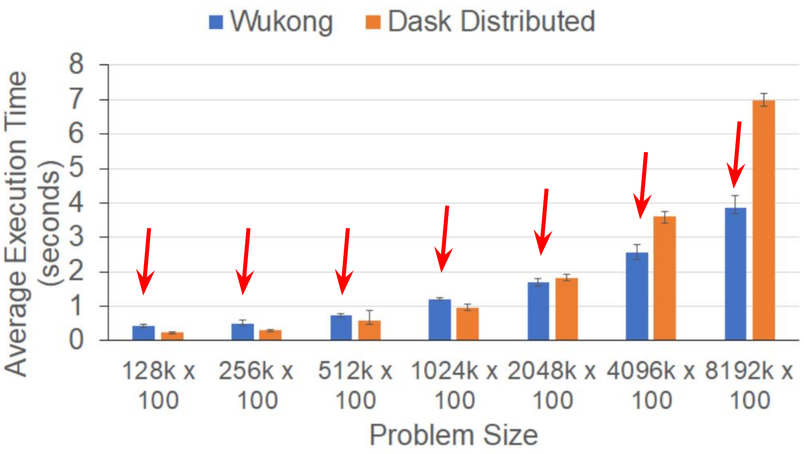


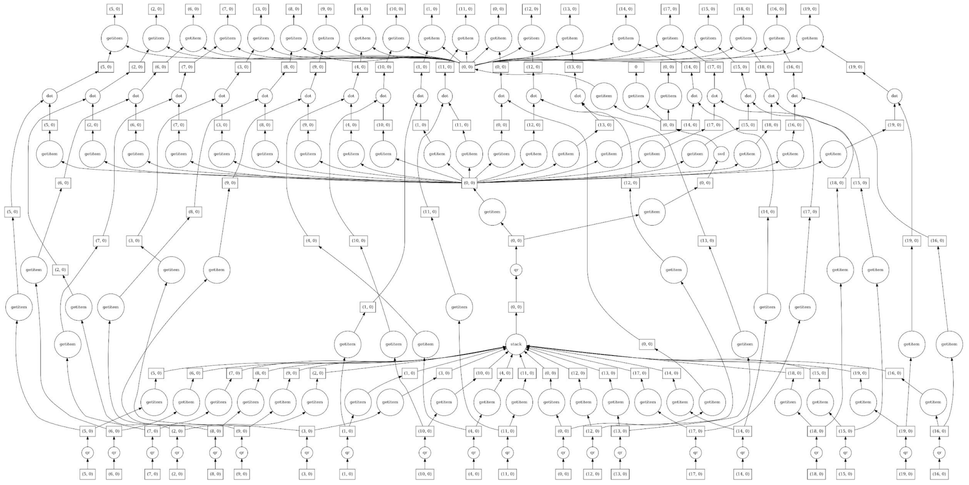
General Matrix Multiplication (GEMM) -- Dask



Singular Value Decomposition (SVD) - “Tall and Skinny”

SVD tall-and-skinny

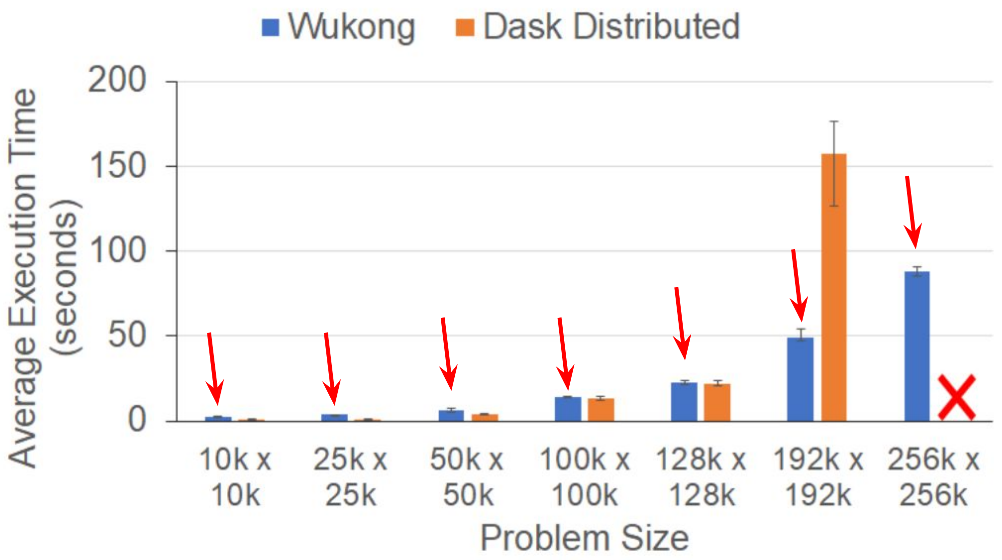


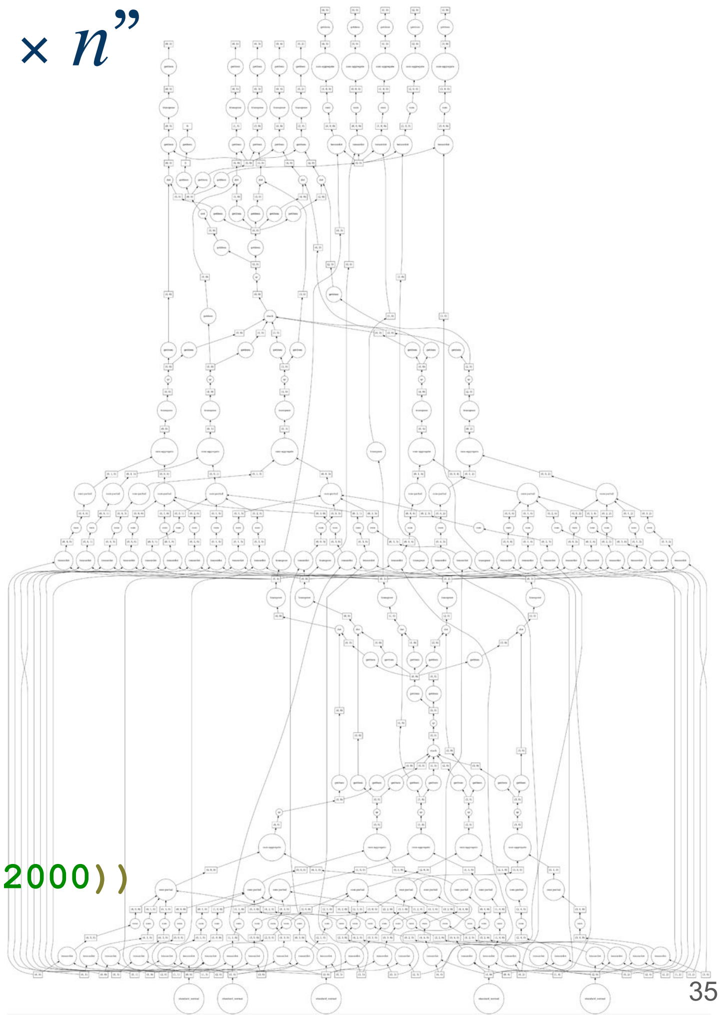


```
X = da.random.random((200000, 100), chunks=(10000, 100))
u, s, v = da.linalg.svd(X)
v.compute() # Begin execution
```

Singular Value Decomposition - “$n \times n$”

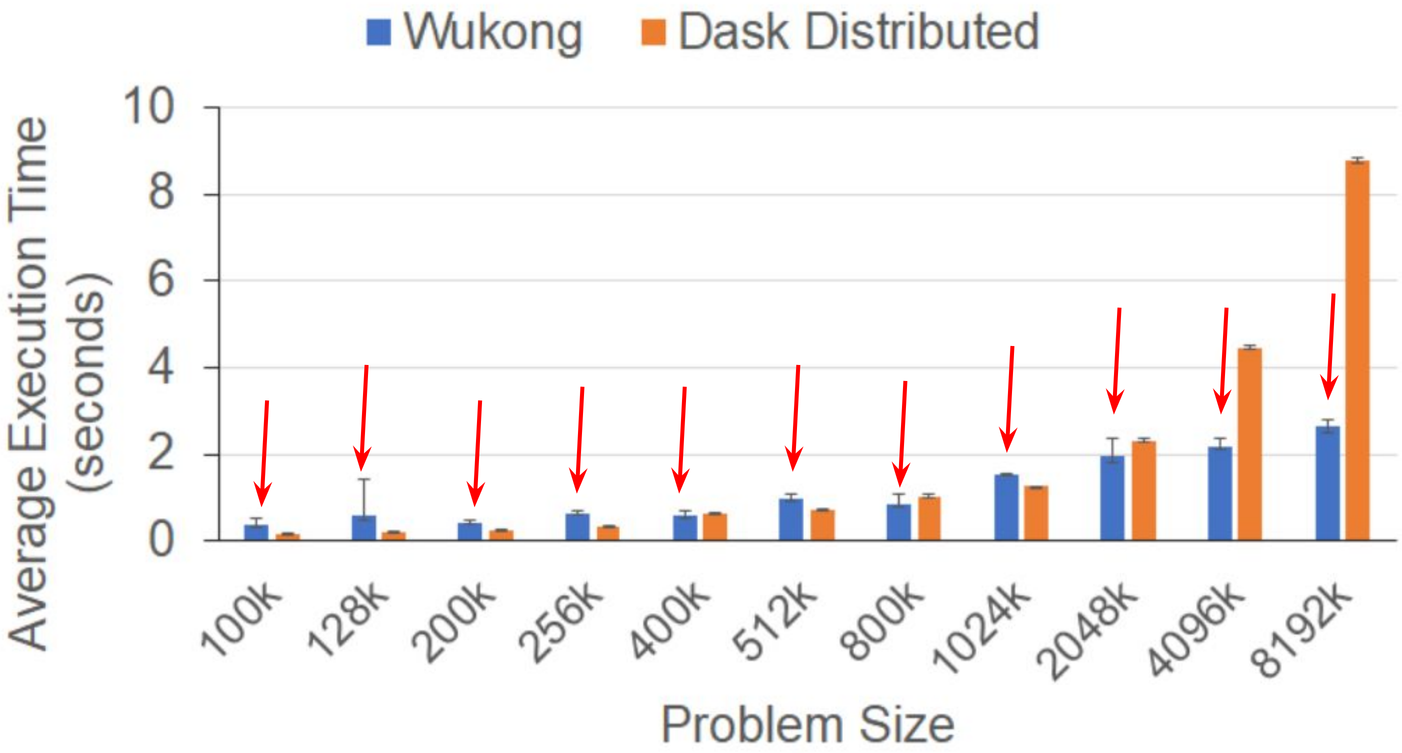
SVD-Compressed (rank 5) $n \times n$





```
X = da.random.random((10000, 10000), chunks=(2000, 2000))
u, s, v = da.linalg.svd_compressed(X, k=5)
v.compute() # Begin execution
```

Support Vector Classification (SVC)



Scalability - Strong & Weak Scaling

- **Weak Scaling:**
  - **Both** the **number of workers** and the **problem size** are **increased**.
    - **Keep amount of work per worker fixed, add more workers. Does performance improve?**
  - **Usually relevant for memory-bound tasks.**

- **Strong Scaling:**
  - The number of workers is **increased** while the problem size **remains constant**.
    - **Keep problem size fixed, but add more workers. Does performance improve?**
  - **Usually relevant for CPU-bound tasks.**

Scalability of Wukong (ABC)

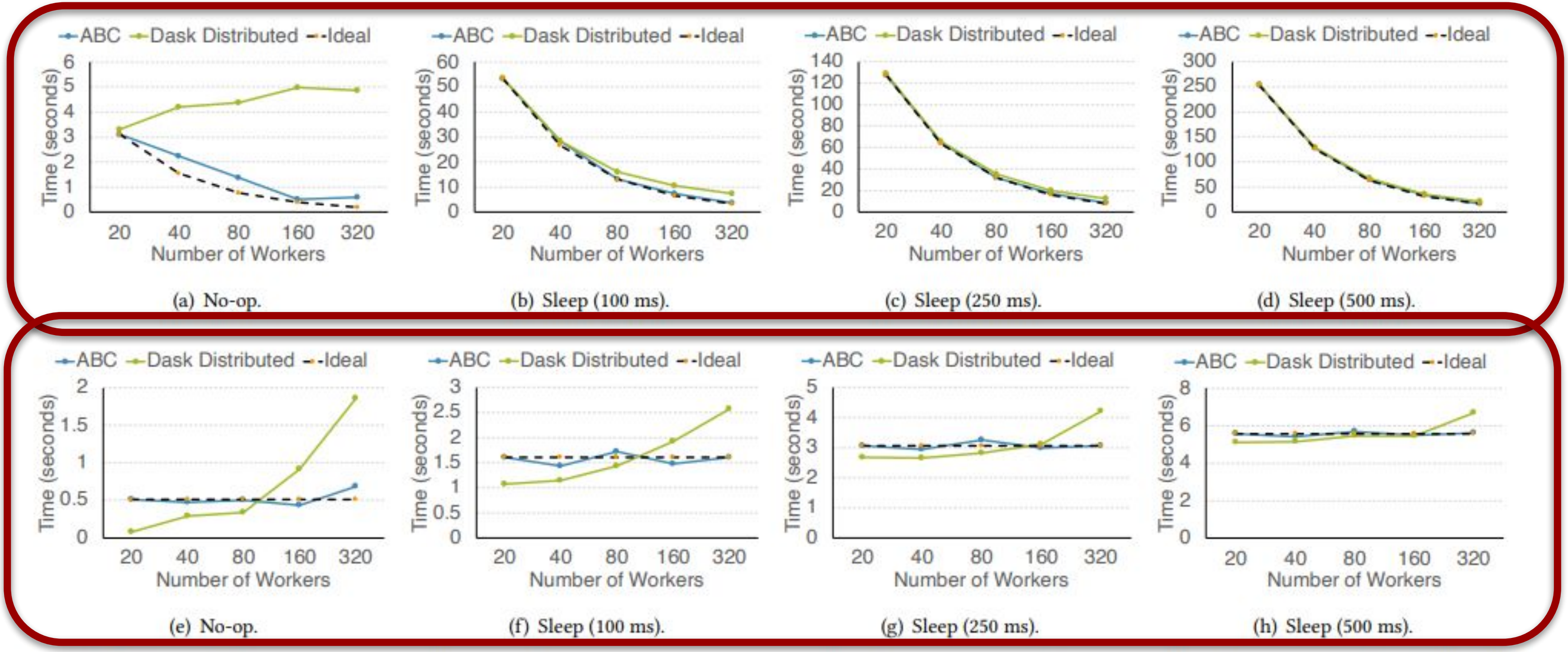
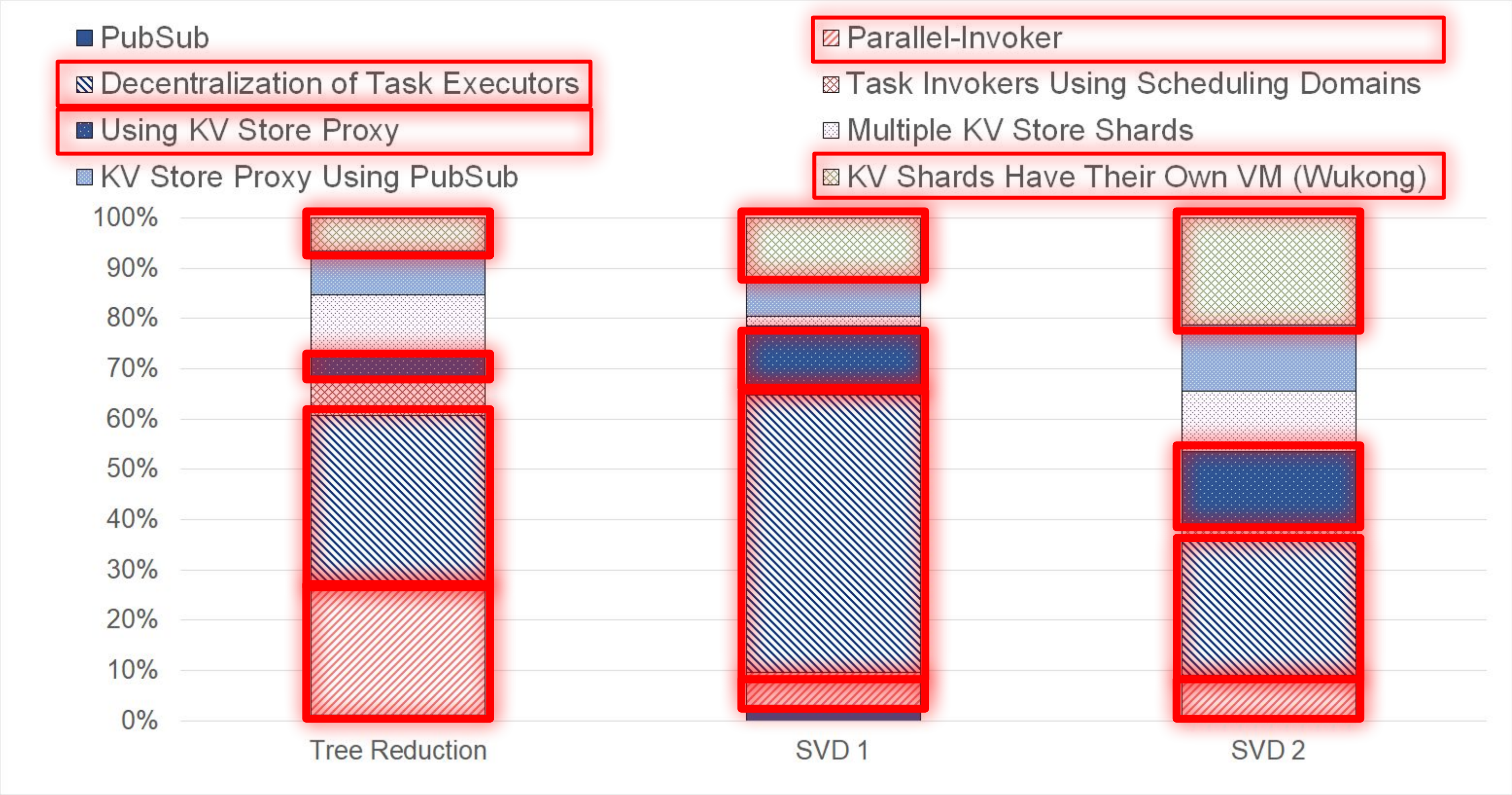
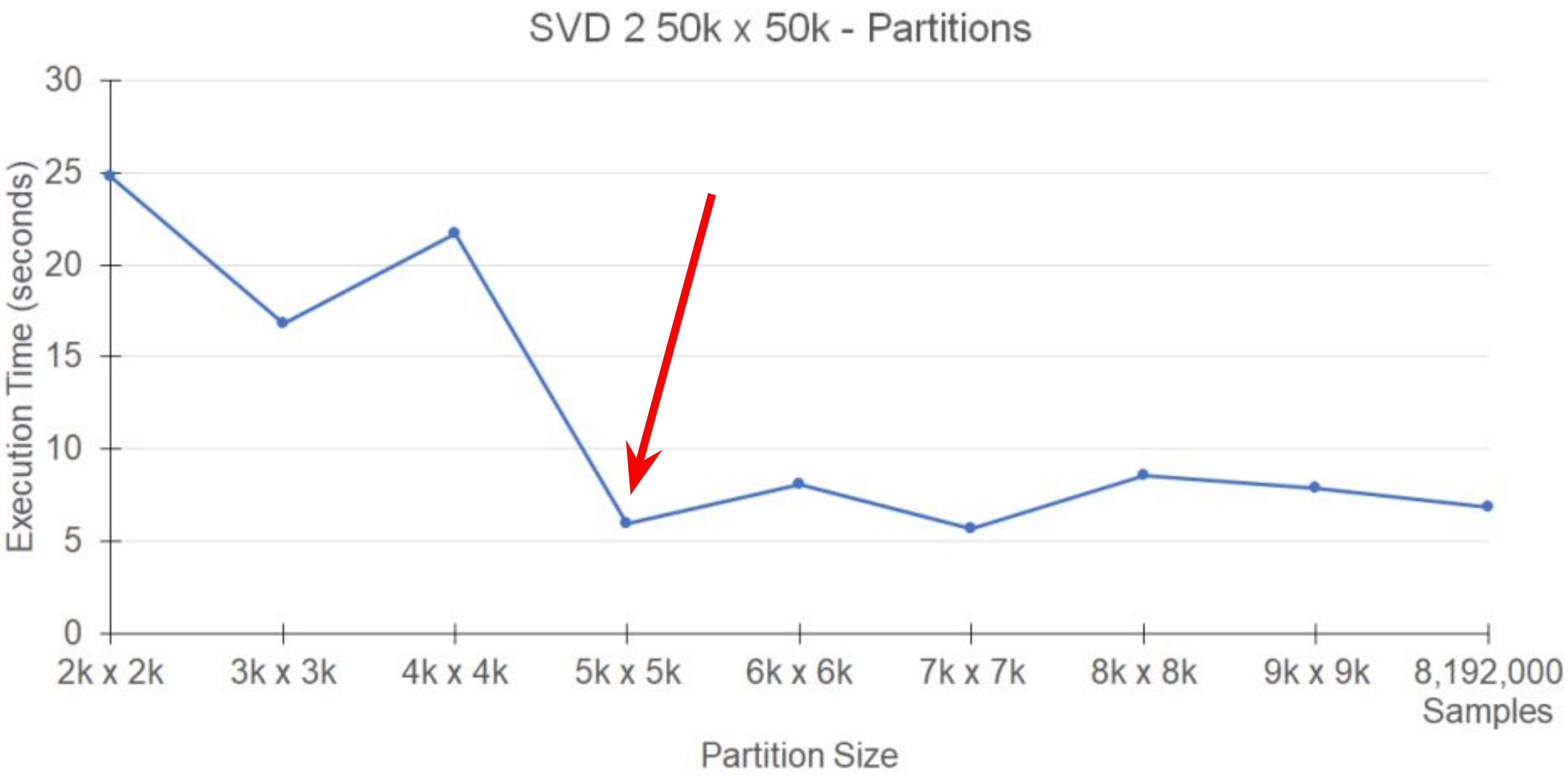


Figure 13: Strong scaling vs. weak scaling. Figure 13(a)–13(d) – strong scaling: time (Y-axis) to execute 10, 000 tasks over N workers (X-axis). Figure 13(e)–13(h) – weak scaling: time to execute 10 tasks per worker. For each row, plots are for (from left to right) tasks of 0, 100, 250, and 500 ms.

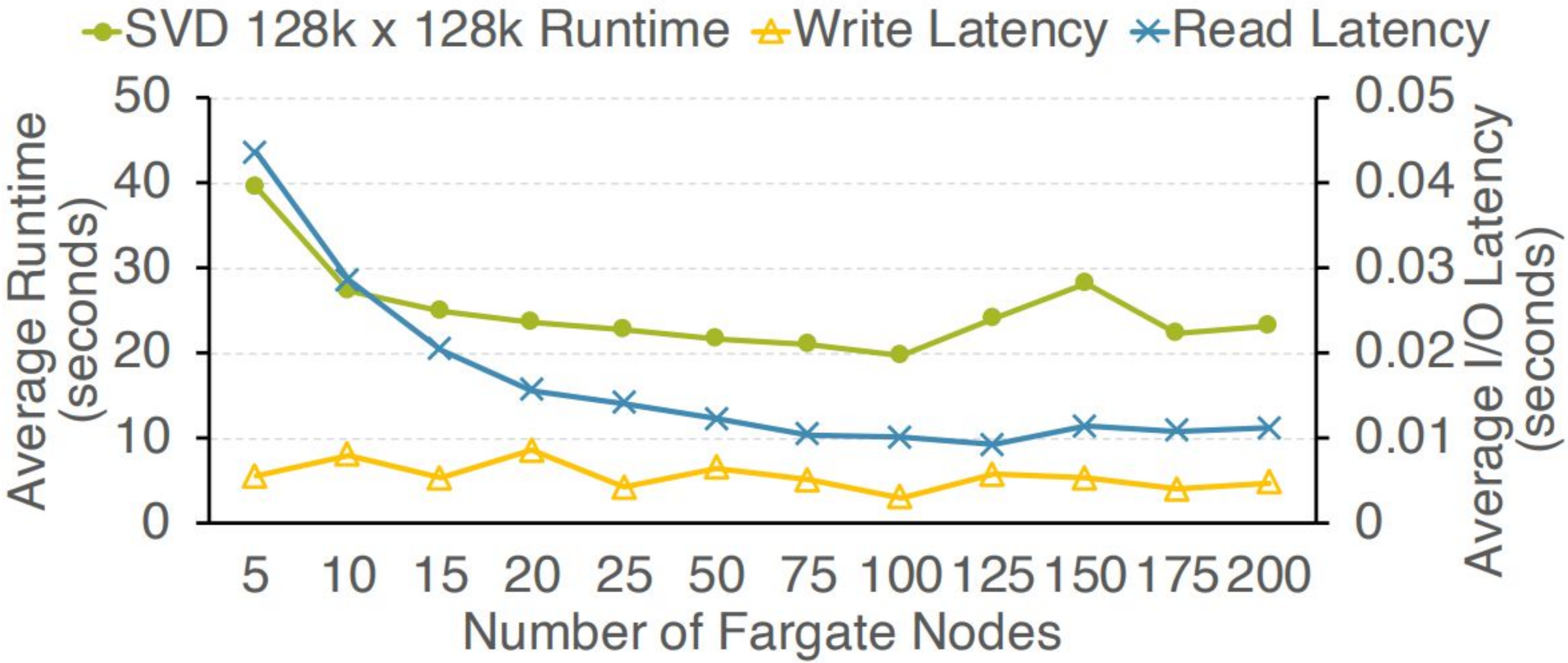
Factors Influencing Performance of Wukong



Workload Parameters - Partition Size



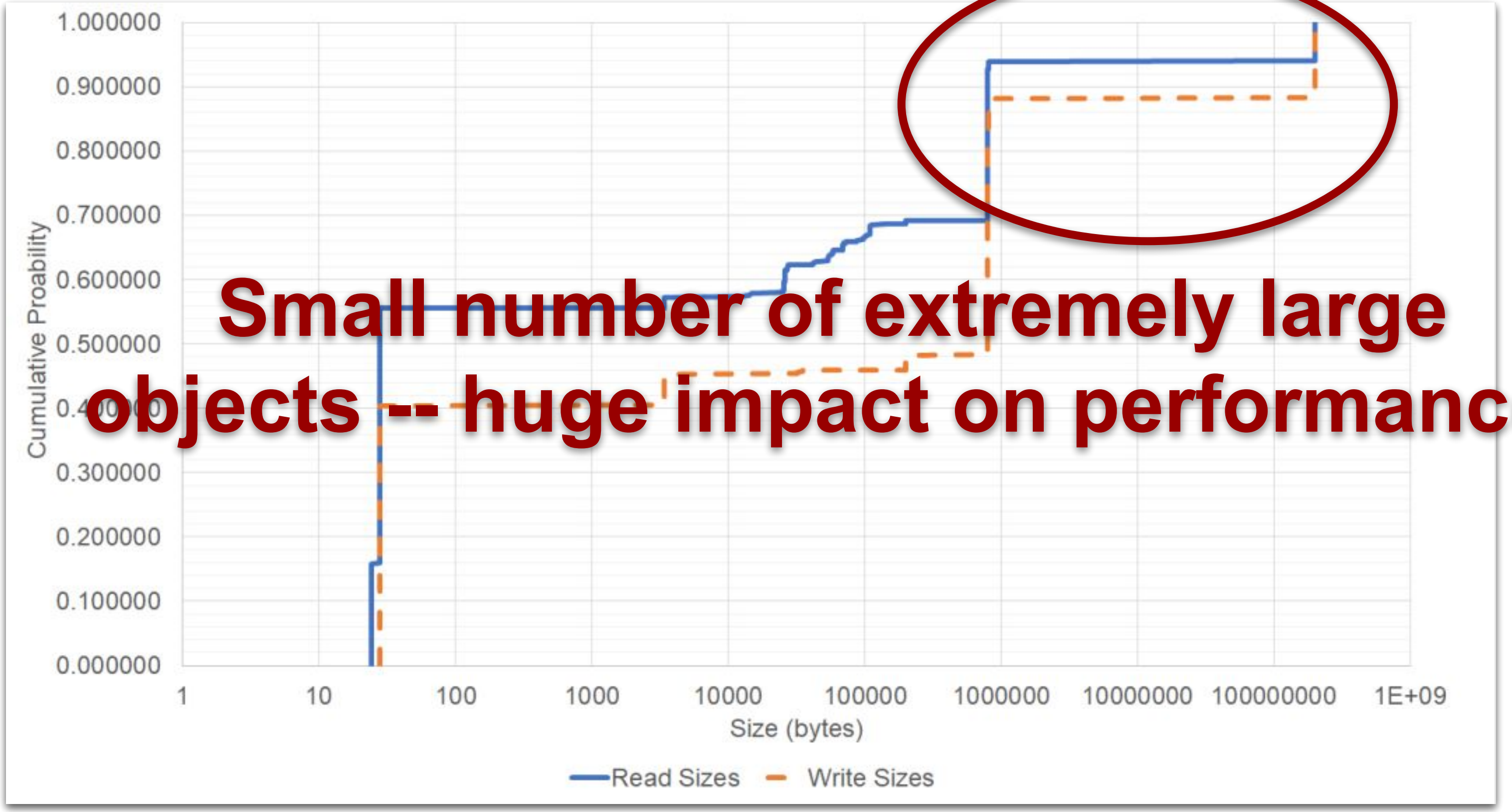
Workload Parameters - Fargate Cluster Size



Diagnosing Performance - Workload Characteristics

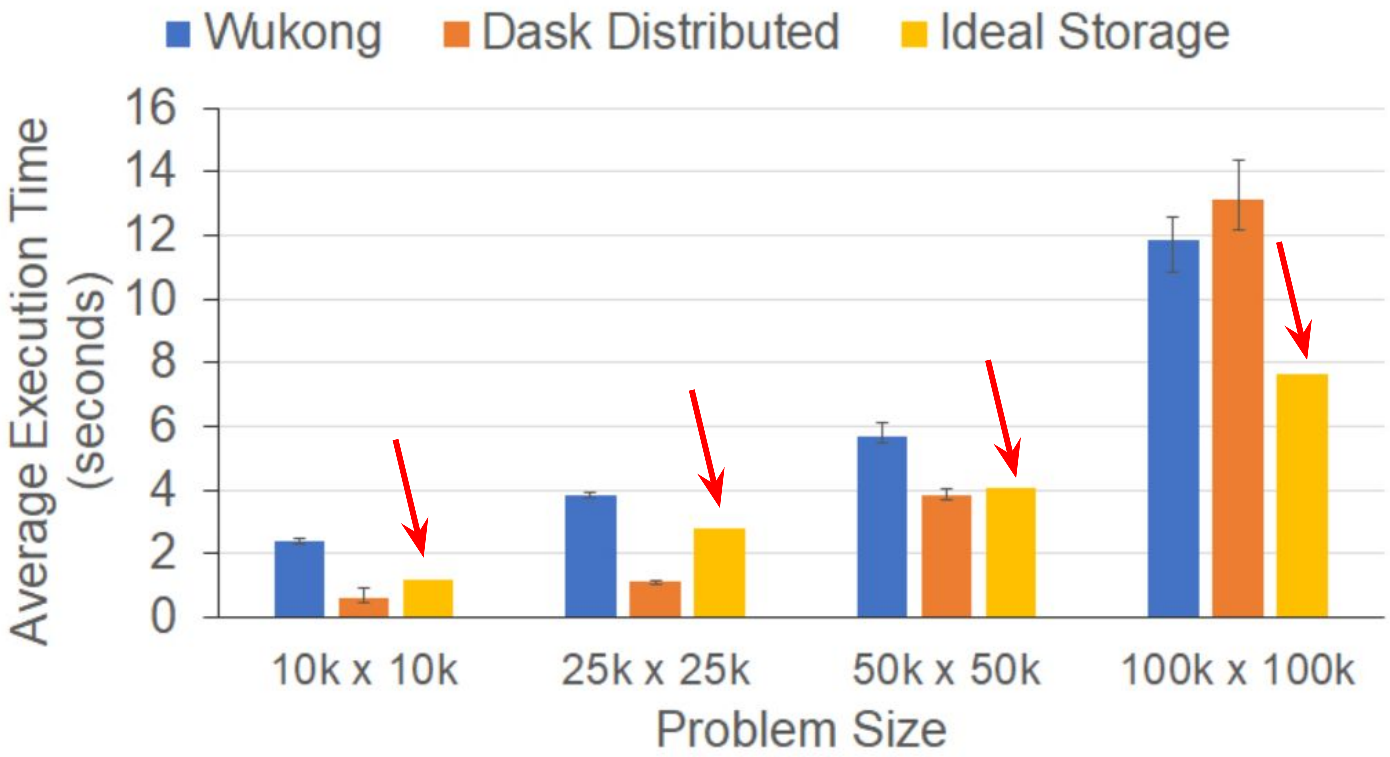
- How is the overall execution time divided up?
- What activities are being performed? Taking the longest?
- How can we optimize the common case?

Workload I/O Characteristics



Small number of extremely large objects -- huge impact on performance!

SVD 50k x 50k Performance with Ideal Storage




DATA

Task Clustering and Delayed I/O

- We developed new techniques to eliminate large-object I/O during execution.

- Task Clustering
  - After executing a task that produces “large” intermediate data, execute all immediate downstream tasks locally on the same Task Executor.

- Delayed I/O
  - If there are some downstream tasks which depend on the large intermediate data *but are not yet ready to execute due to some other missing data dependency*, place these tasks in a queue in keep retrying them until they’re ready.

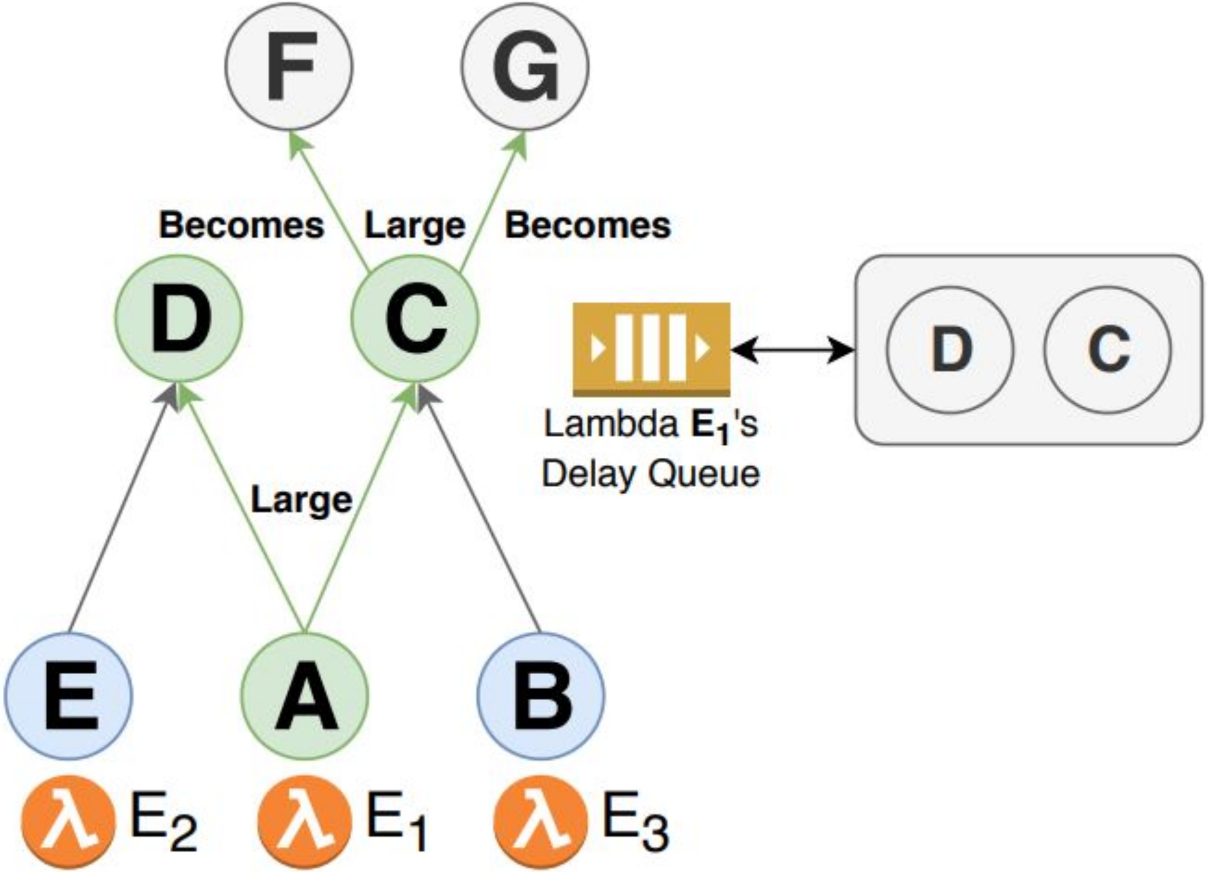


Figure 6: Task clustering and delay I/O.

How do task clustering and delayed I/O impact performance?

7.21x time spent invoking tasks

27.76x more I/O

Overall: 4.6x faster compared to baseline.

Do task clustering and delayed I/O impact cost?

- YES

- For SVD 50,000 x 50,000:
  - Task clustering + delayed I/O reduce workload cost by **65.23%** (from $0.04556 to $0.01584).

- For SVD 100,000 x 100,000:
  - Task clustering + delayed I/O reduce workload cost by **73.50%** (from $1.17 to $0.31).

Conclusion

- Serverless platform introduces unique challenges and opportunities
- Decentralization provides a large performance increase
  - Data locality and minimizing network overhead are also important to performance
- WUKONG achieves performance comparable to serverful Dask `distributed` running on general-purpose EC2 VMs.

Thank you!

Questions?

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GitHub: https://github.com/mason-leap-lab/Wuk