In Search of a Fast and Efficient Serverless DAG Engine

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Serverless Computing

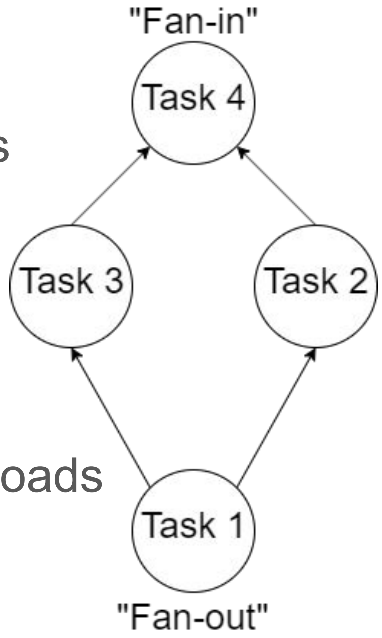
- Emerging cloud computing platform based on the composition of fine-grained user-defined functions

- Service provider is responsible for provisioning, scaling, and managing resources

- Pay-per-use pricing model with fine granularity

Background

- Data analytics applications can be modeled as a directed acyclic graph (DAG) based workflow
  - Nodes: fine-grained tasks
  - Edges: dependencies between tasks, often large fan-outs
- DAG workflows well-suited for serverless computing (or Functions-as-a-Service)
  - Auto-scaling accommodates short tasks and bursty workloads
  - Pay-per-use keeps the cost of short tasks low



From Serverful to Serverless

- 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

AWS Lambda Constraints

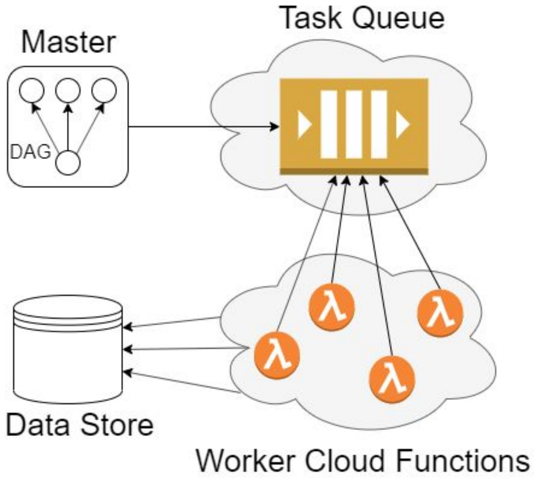
- Lambda function invocation currently take 50ms on average
- Outbound-only network connectivity
- Relatively low network bandwidth
- Execution time limits (900 seconds)
- Lack of quality-of-service (QoS) control, leading to stragglers
    - e.g., cold starts

Existing Parallel Frameworks Using Serverless Computing

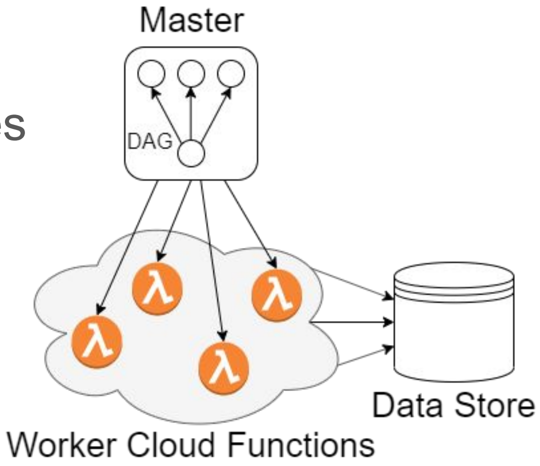
- PyWren [SoCC'17]
  - Parallelize existing Python code with AWS Lambda
- Numpywren
  - System for linear algebra built atop PyWren
- ExCamera [NSDI'17]
  - System which allows users to edit, transform, and encode videos using fine-grained serverless functions
- gg [ATC'19]
  - Framework and command-line 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 could become a bottleneck for system



Wukong solves these drawbacks.

Wukong

- **Approach**

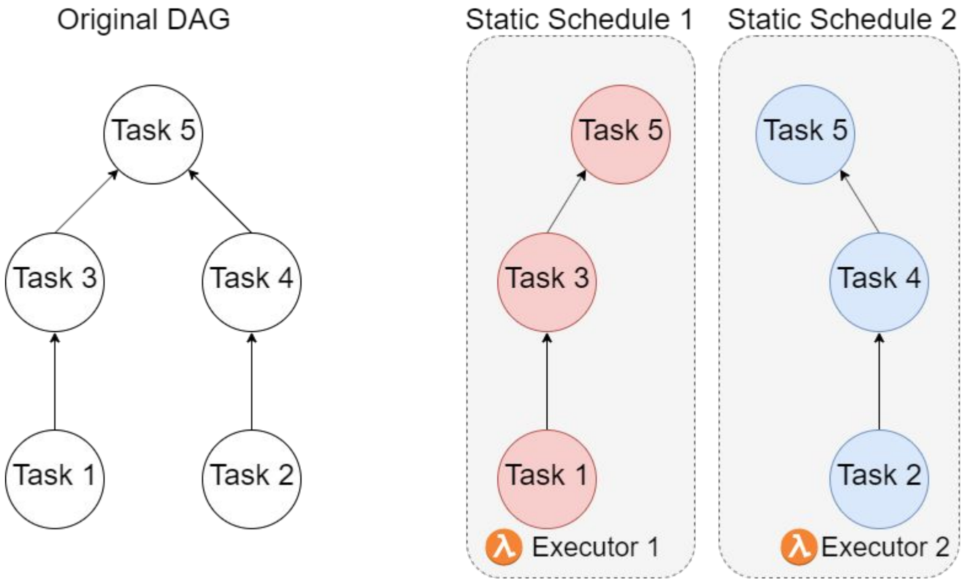
- Architecture
  - Static Scheduler
  - Task Executors
  - Storage Manager

- Evaluation

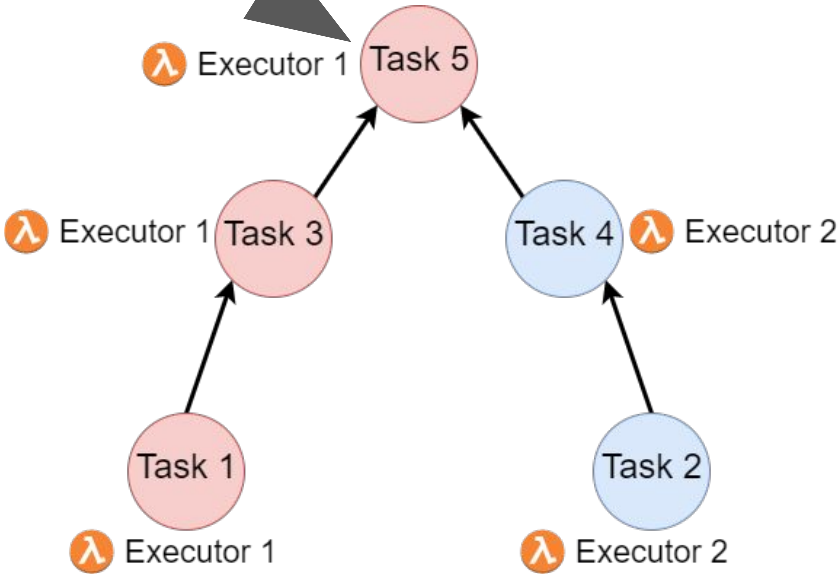
Task executors cooperate here!

Our Approach - Wukong

Static Scheduling



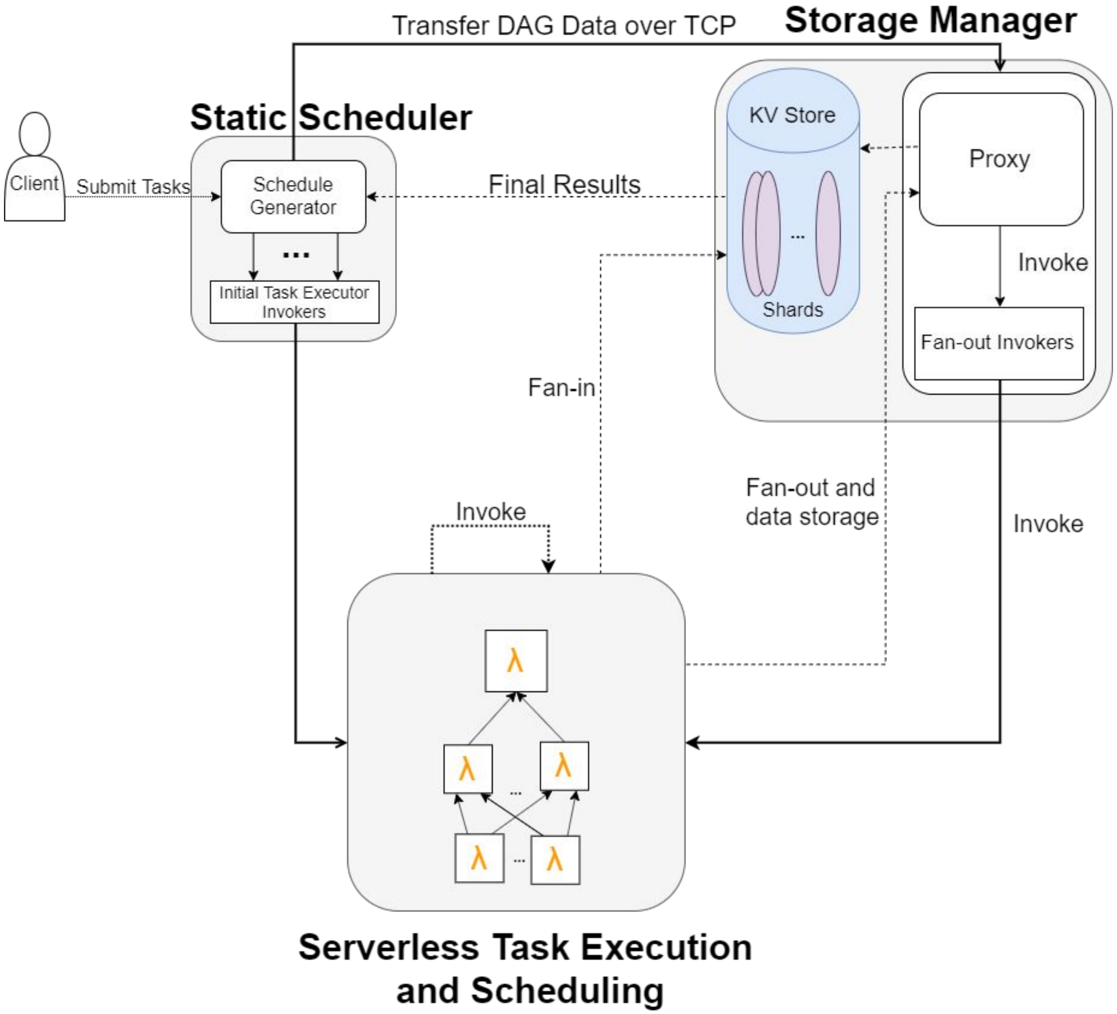
Dynamic Scheduling



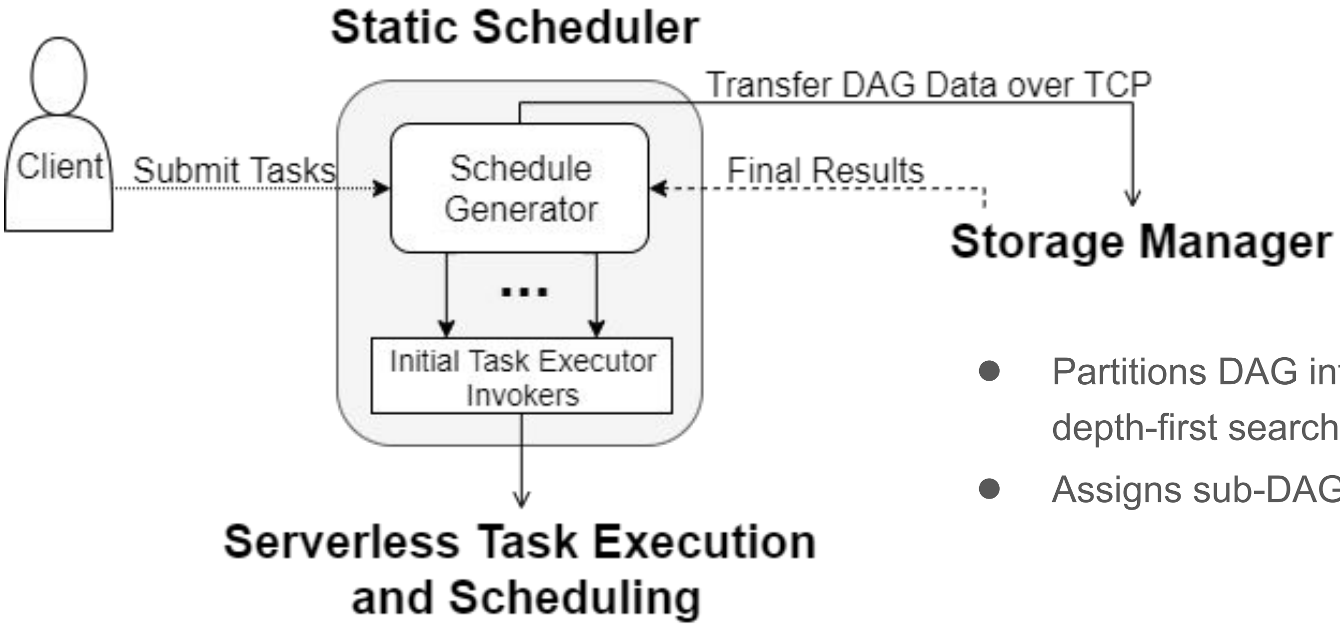
- Statically partition DAG into sub-DAGs
    - Assign each partition to a Lambda function
- Decentralized, cooperative scheduling
    - Lambda functions coordinate with each other to execute overlapping sections of assigned sub-DAGs

Wukong

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

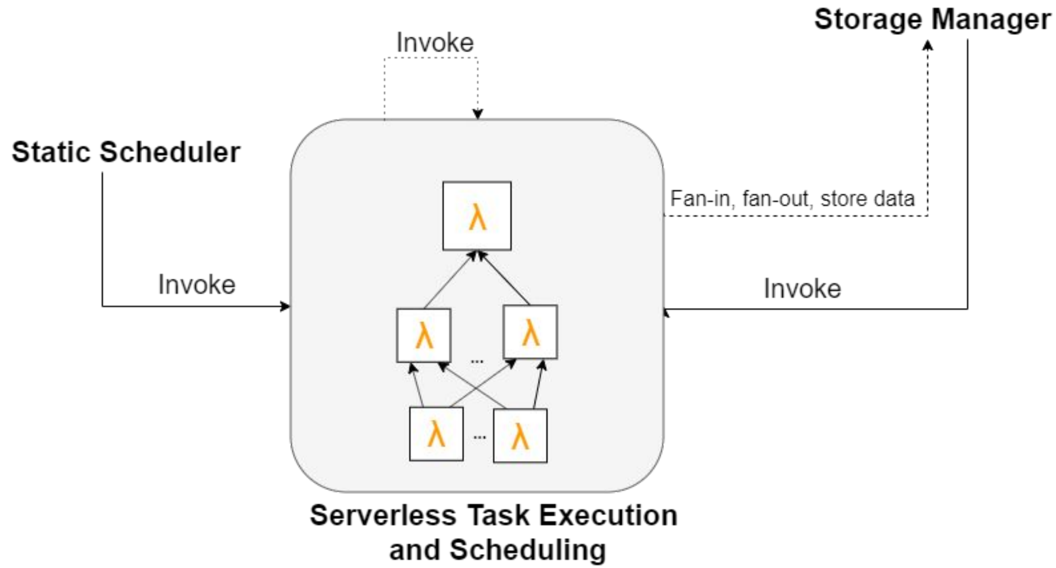

Transfer DAG Data over TCP
Storage Manager
Static Scheduler
Client
Submit Tasks
Schedule Generator
Initial Task Executor Invokers
Final Results
KV Store
Shards
Proxy
Invoke
Fan-out Invokers
Fan-in
Fan-out and data storage
Invoke
Invoke
λ
Serverless Task Execution and Scheduling

Static Scheduler

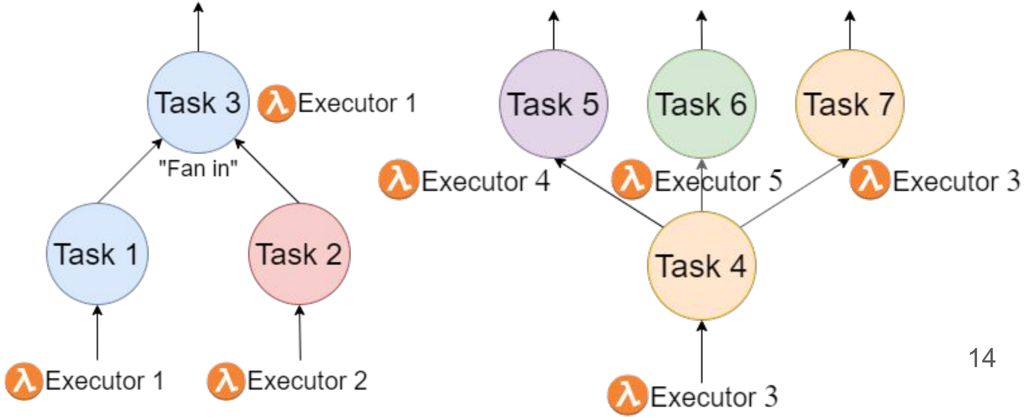


- Partitions DAG into sub-DAG using a depth-first search (DFS) from each leaf node.
- Assigns sub-DAGs to executors

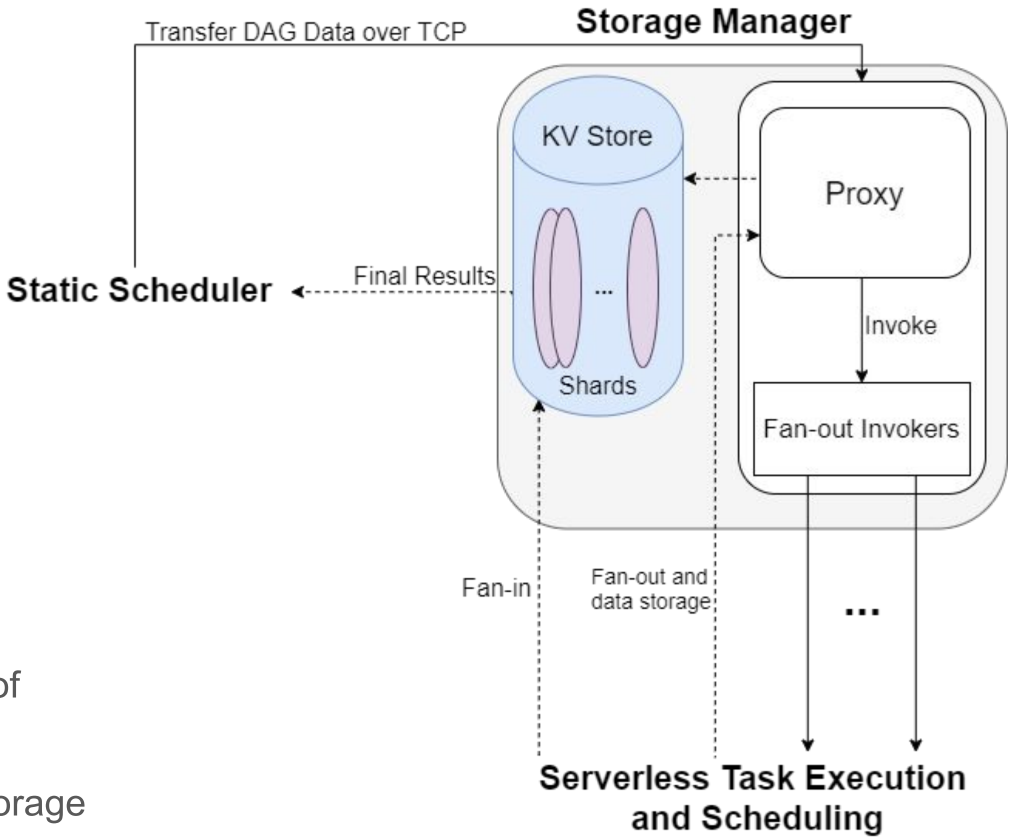
Executors



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



Storage Manager



- Performs storage operations on behalf of Executors and Static Scheduler
- Using KV Store for intermediate data storage

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` running on two different setups.
  - 5-node EC2 cluster of `t2.2xlarge` VMs
  - Laptop
    - Windows 7 64-bit
    - Intel Core i5-6200U CPU @ 2.30GHz
    - 8GB RAM

- Wukong Static Scheduler, KV Store, and KV Store Proxy running on `c5.18xlarge` EC2 VMs.

- Task Executor allocated 3GB memory with timeout set to two minutes.

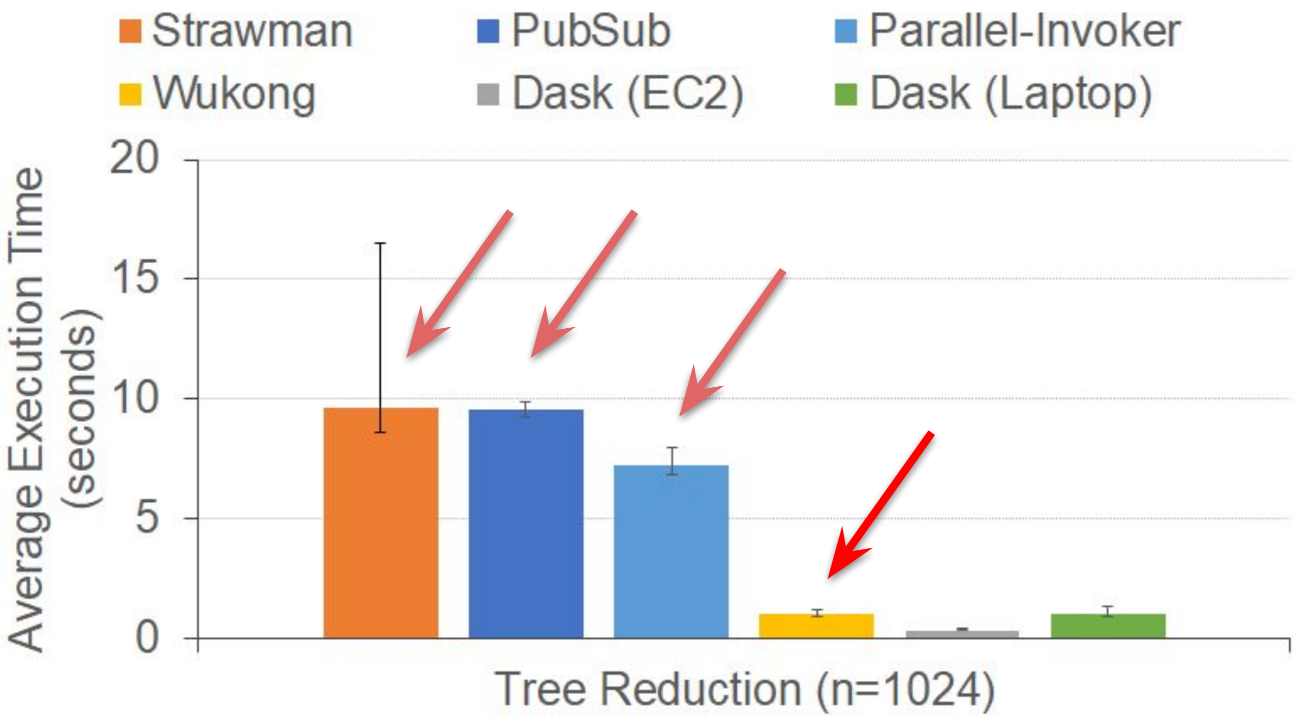
Four DAG Applications

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

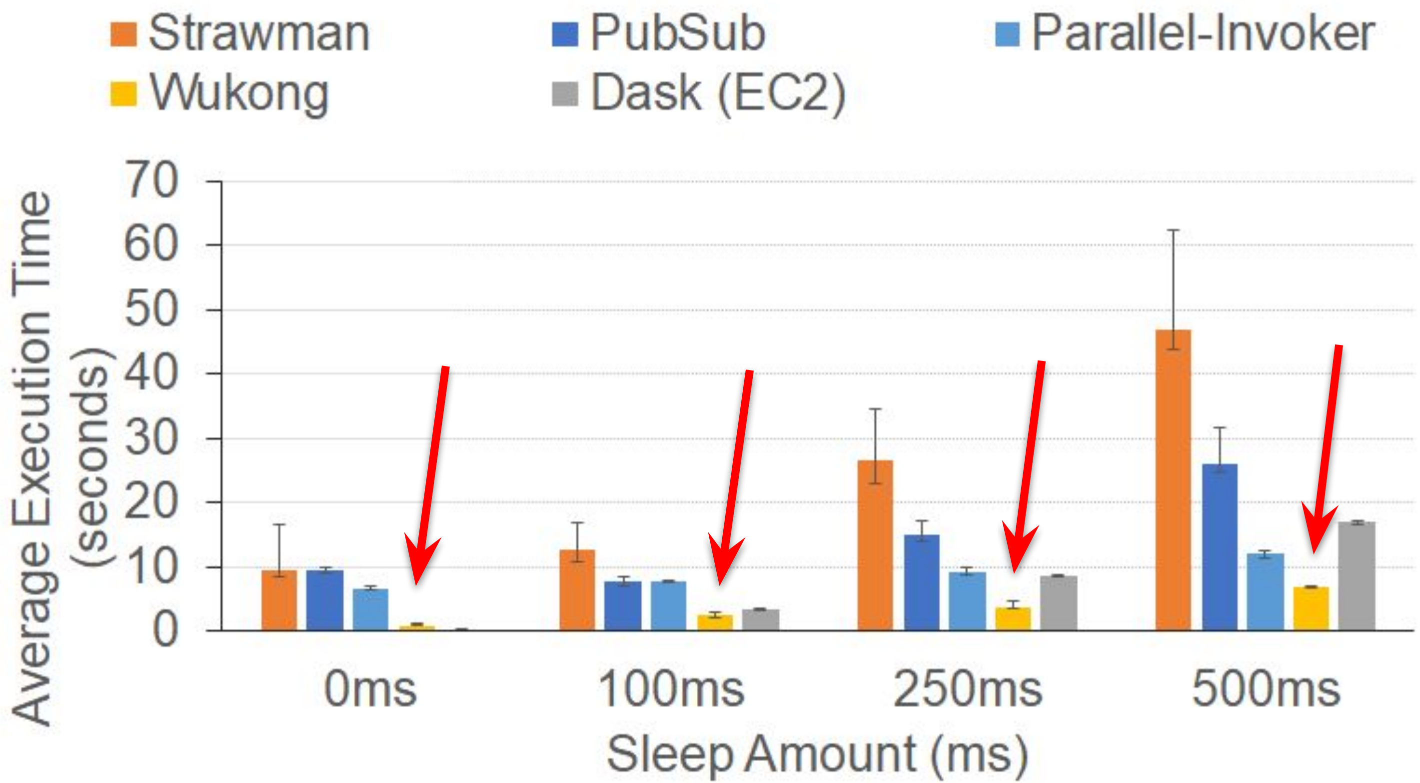
- Linear Algebra
  - **General Matrix Multiplication (GEMM)**
    - 10,000 × 10,000 and 25,000 × 25,000
  - **Singular Value Decomposition (SVD)**
    - $n \times n$ matrix and a tall-and-skinny matrix, varying sizes

- Machine Learning
  - **Support Vector Classification (SVC)**
    - 100,000 - 800,000 samples

Tree Reduction

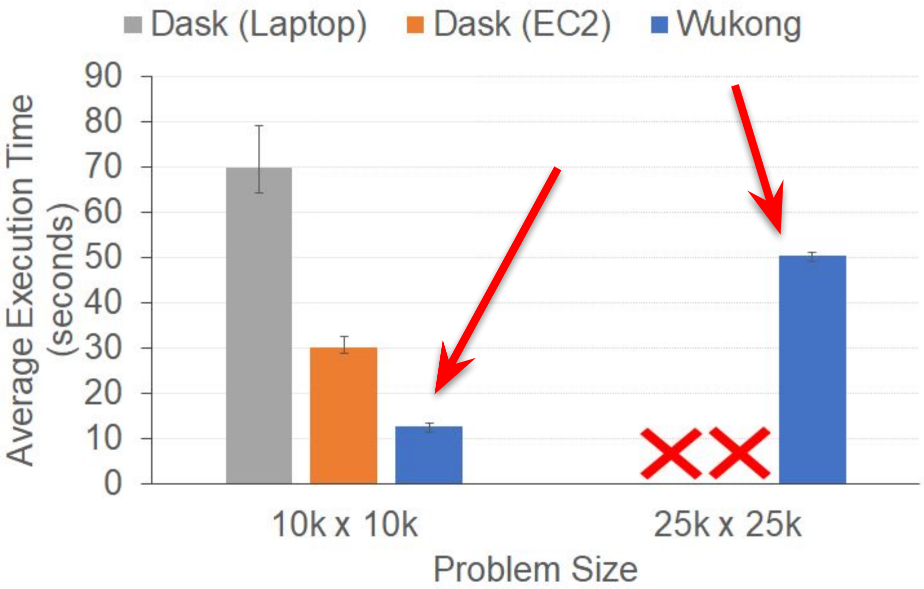


Tree Reduction with Delays

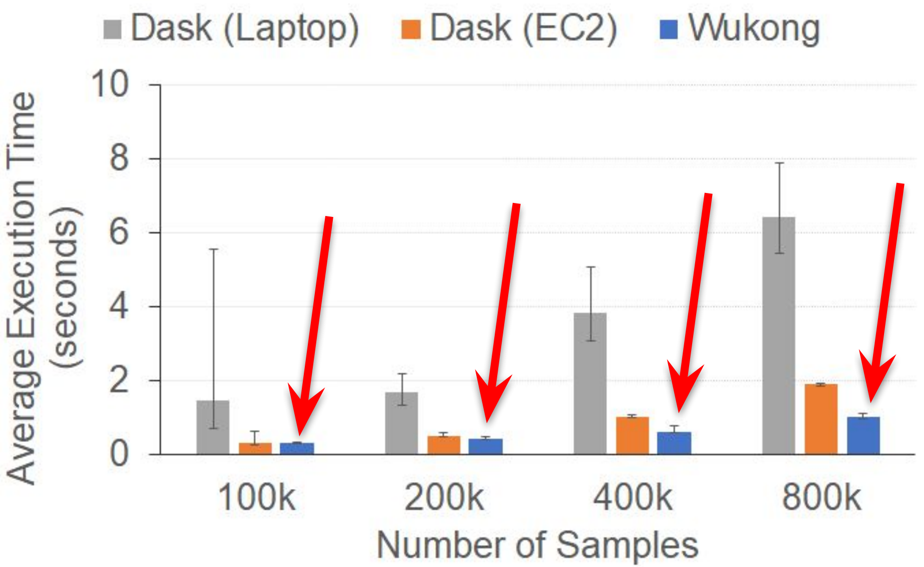


General Matrix Multiplication (GEMM) and Support Vector Classification (SVC)

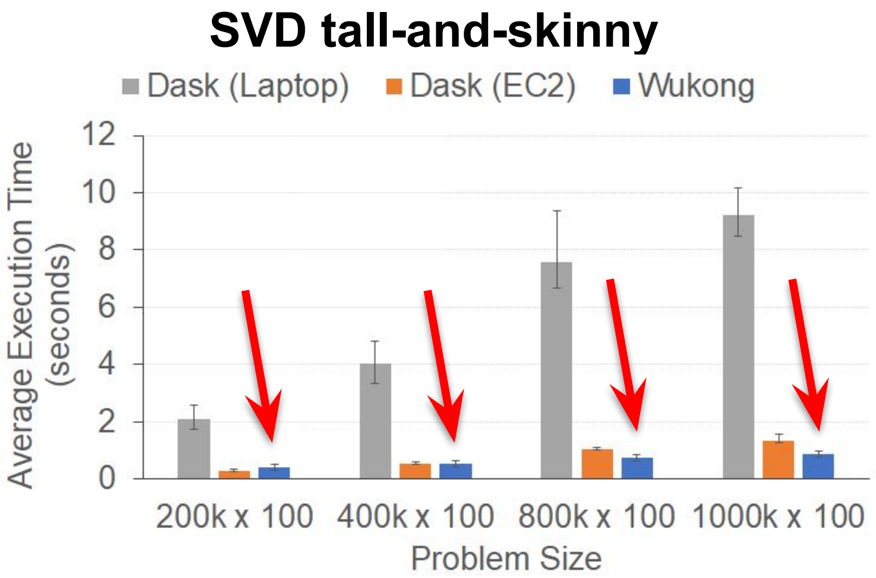
GEMM

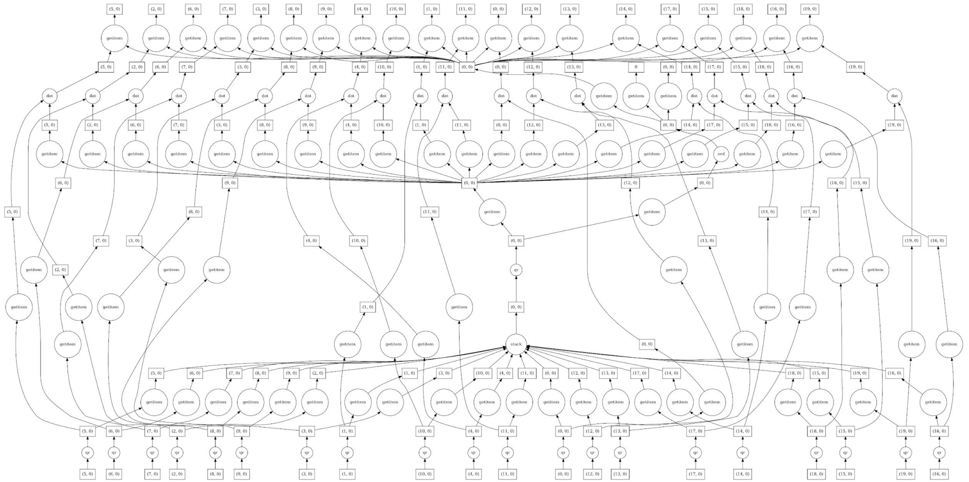


SVC



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

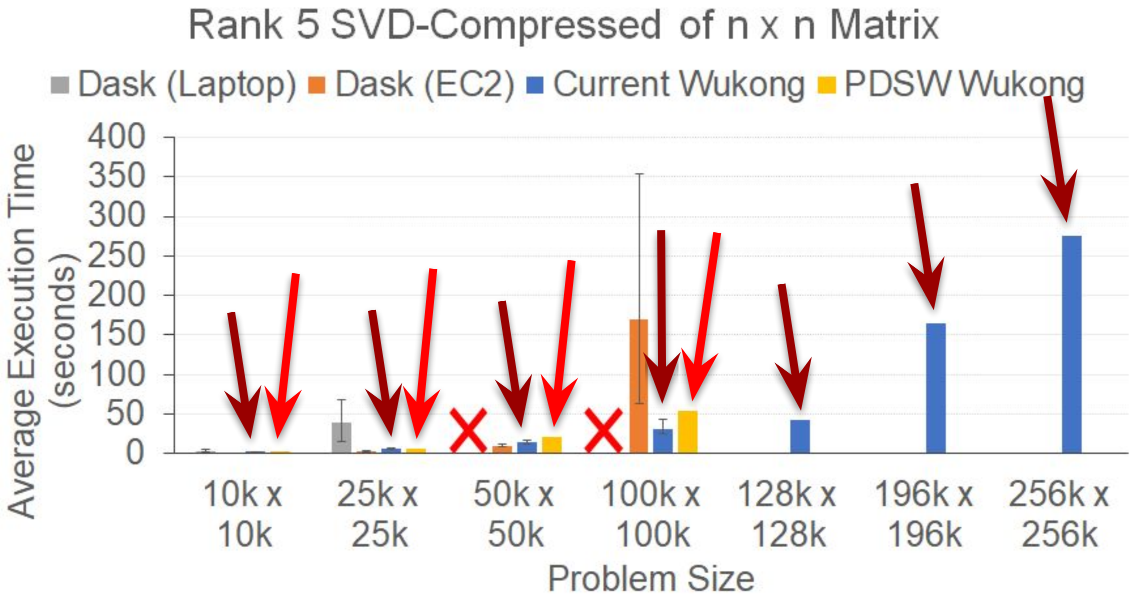




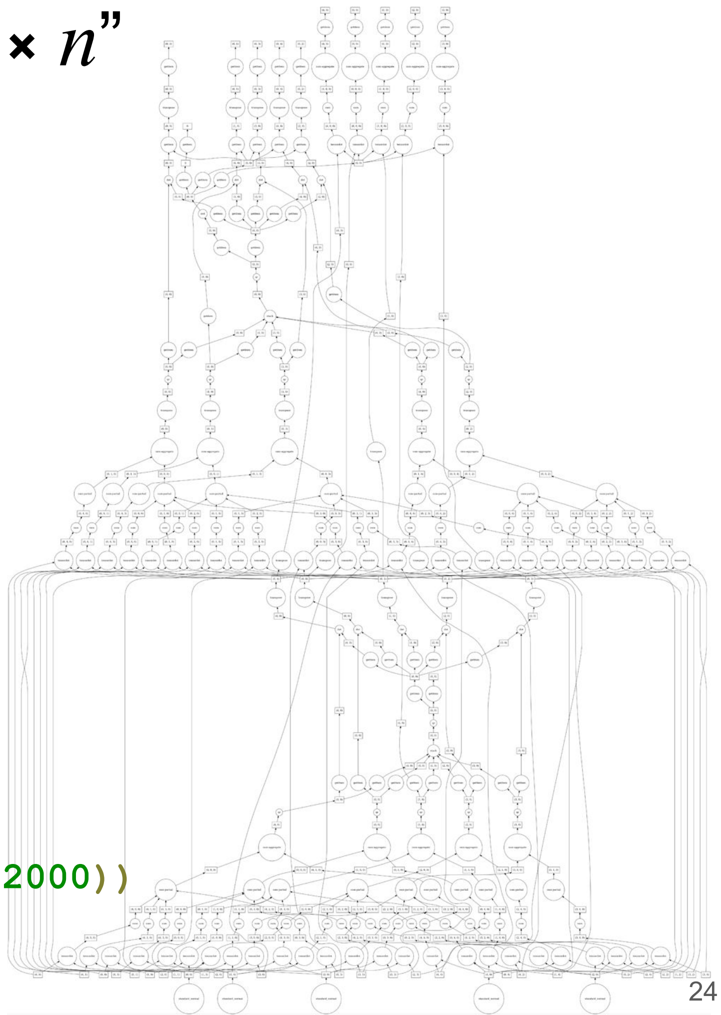
```
X = da.random.random((200000, 100), chunks=(10000, 100))
u, s, v = da.linalg.svd(X)
v.compute() # Begin execution
```

Singular Value Decomposition - "$n \times n$"

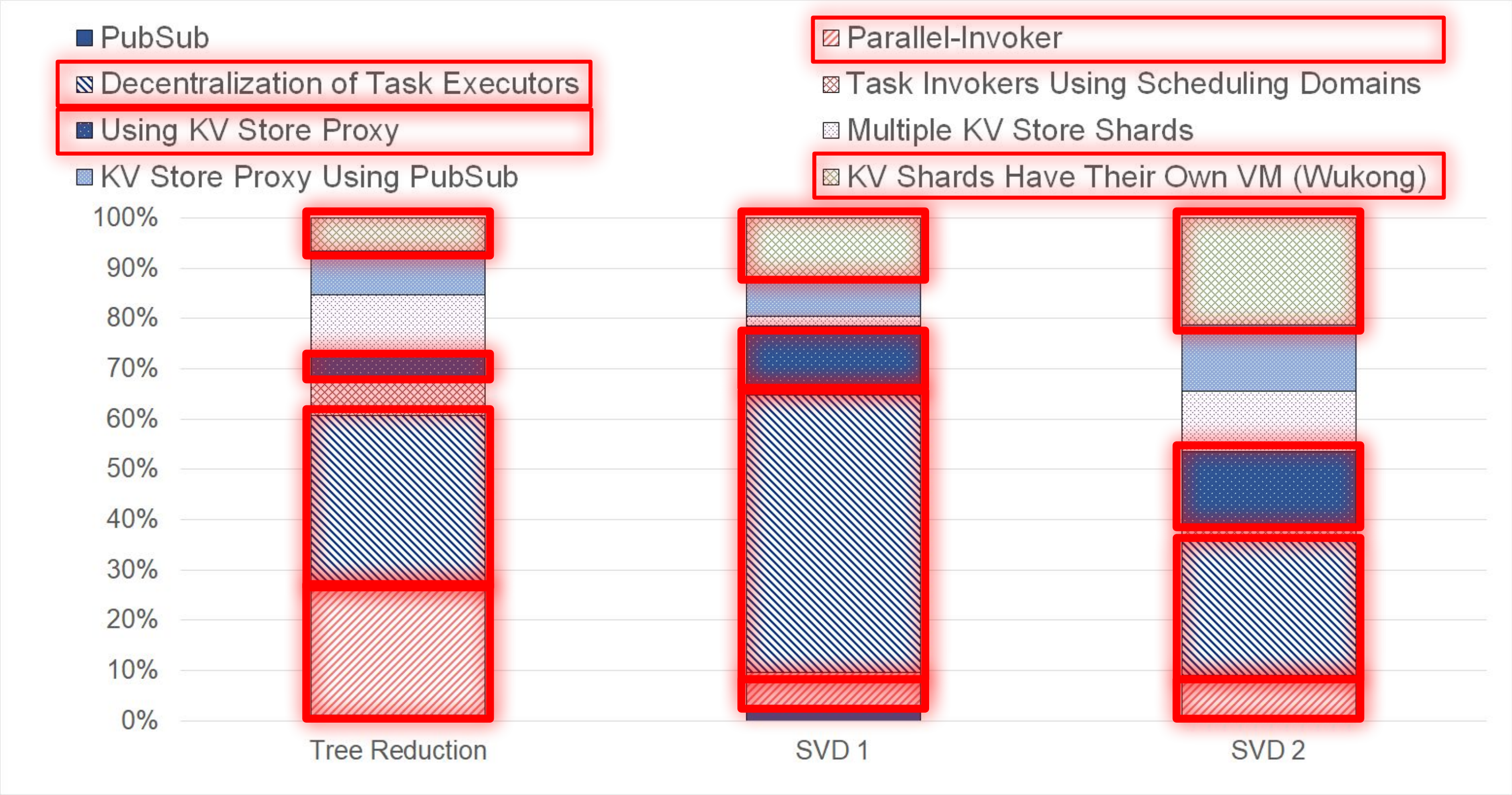
SVD-Compressed (rank 5) $n \times n$




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



Factors Influencing Performance



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
  - Improves performance by as much as 3.1x as problem size increases

Thank you!

Questions?

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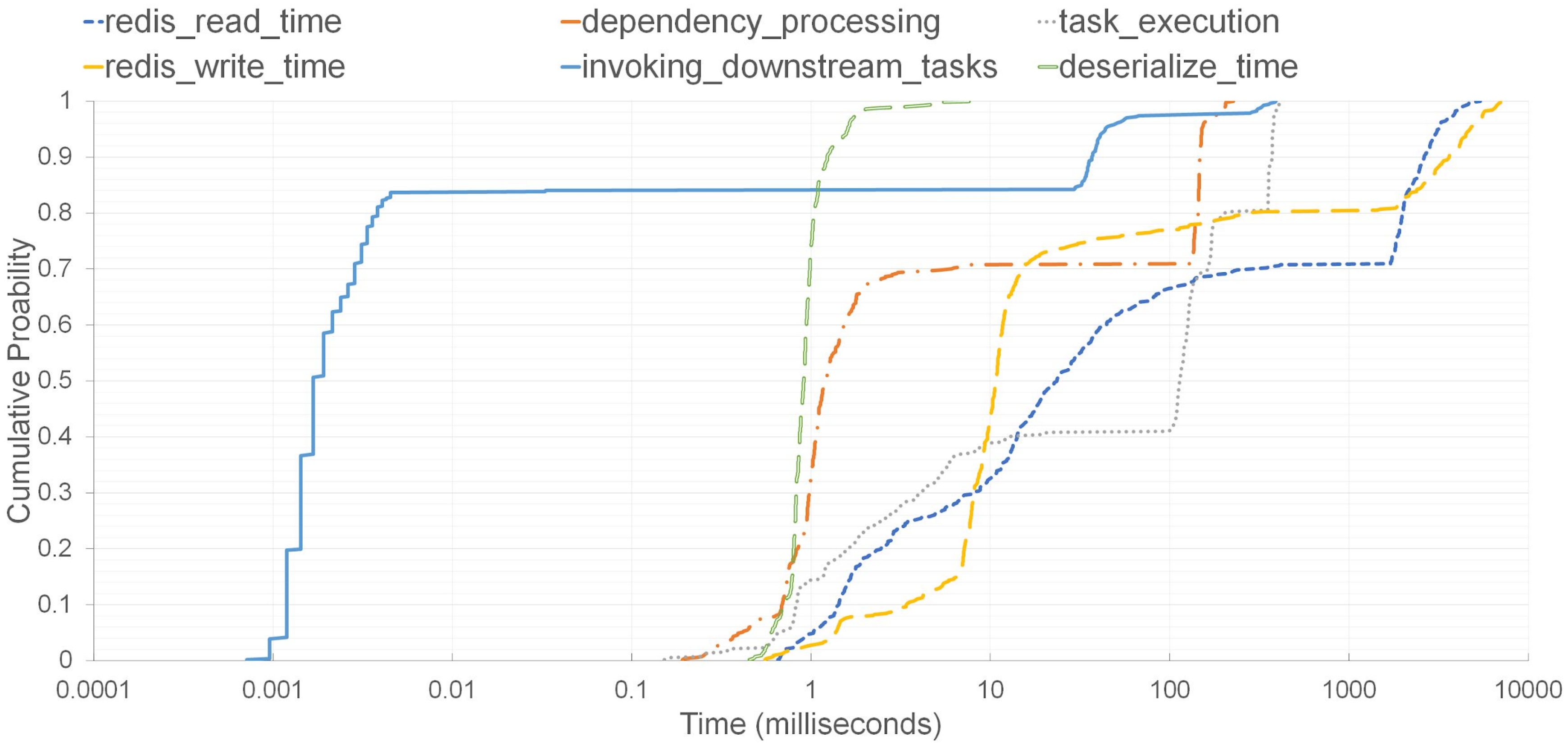
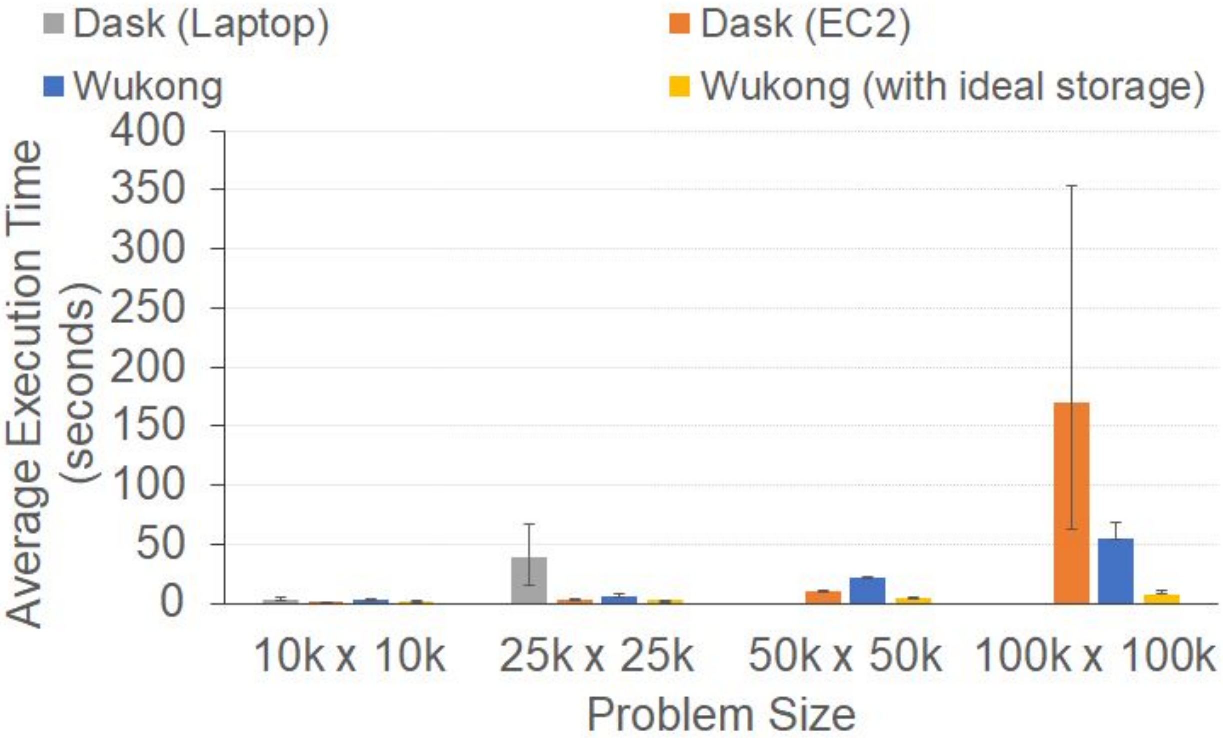
GitHub: https://github.com/mason-leap-lab/Wukong

SVD 50,000 × 50,000 CDF Plot



SVD $n \times n$ with "ideal storage"



SVD Phase #2	10k x 10k [2k x 2k]	25k x 25k [2k x 2k]	50k x 50k [5k x 5k]	100k x 100k [5k x 5k]	256k x 256k [5k x 5k]
NumPaths	95	565	345	1309	8376
NumTasks	172	800	507	1727	10509
NumLambdas	~84	~480	~295	~1082	8267 to 10511
LeafTasks	30	182	110	420	2756

SVD Phase #1	200k x 100 [10k x 100]
NumPaths	20
NumTasks	42
NumLambdas	~20
LeafTasks	20

Algorithm	ScaLAPACK (sec)	numpywren (sec)	Slow down
SVD	57,919	77,828	1.33x
QR	3,486	25,108	7.19x
GEMM	2,010	2,670	1.33x
Cholesky	2,417	3,100	1.28x

Table 1: A comparison of ScaLAPACK vs numpywren execution time across algorithms when run on a square matrix with N=256K