MinFlow: High-performance and Cost-efficient Data Passing for I/O-intensive Stateful Serverless Analytics

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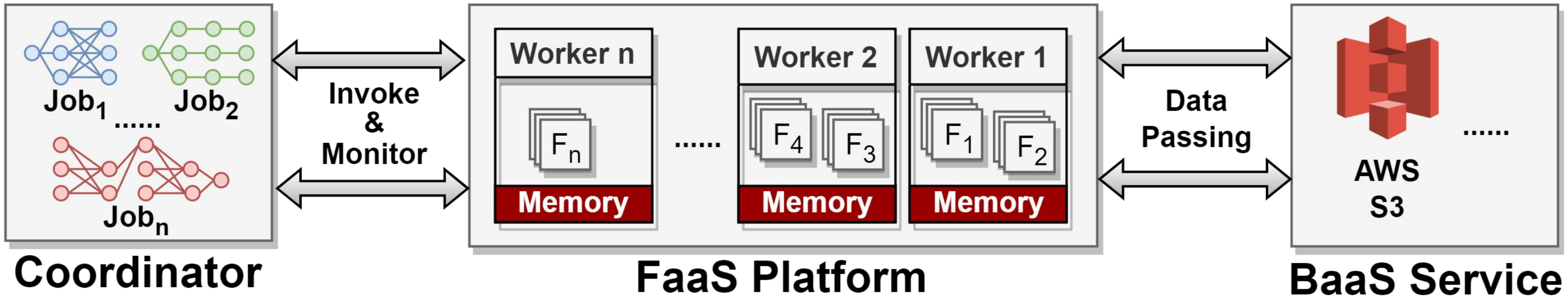
Background

- Serverless computing benefits
  - Low operational overhead
  - Fine-grained "pay-as-you-go" billing (1ms)
  - Fast scaling (<1s)

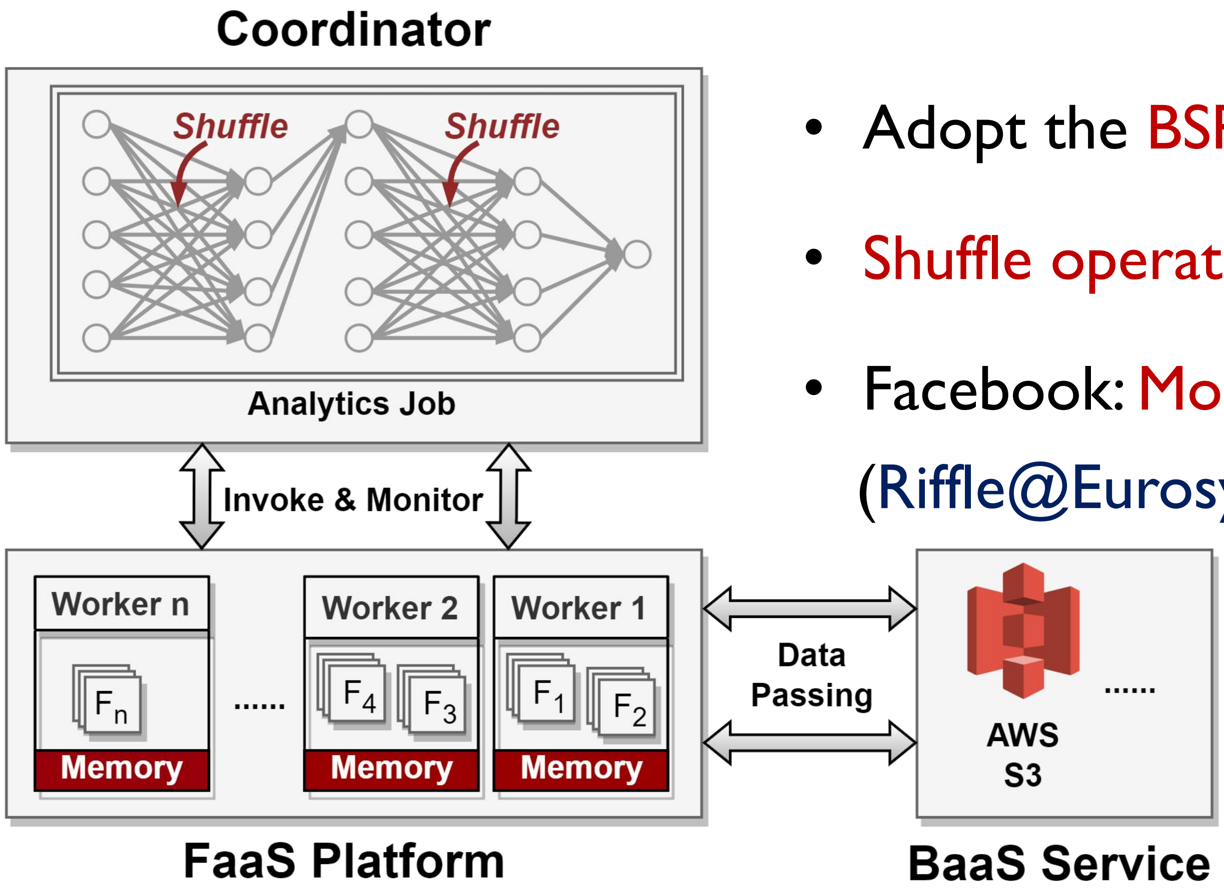
AWS Lambda
Google Cloud Functions
Azure Functions
IBM Cloud Functions

- Serverless computing framework
  - Separate computation and storage
  - FaaS: containerized functions; BaaS: cloud storage (typically S3)



Background

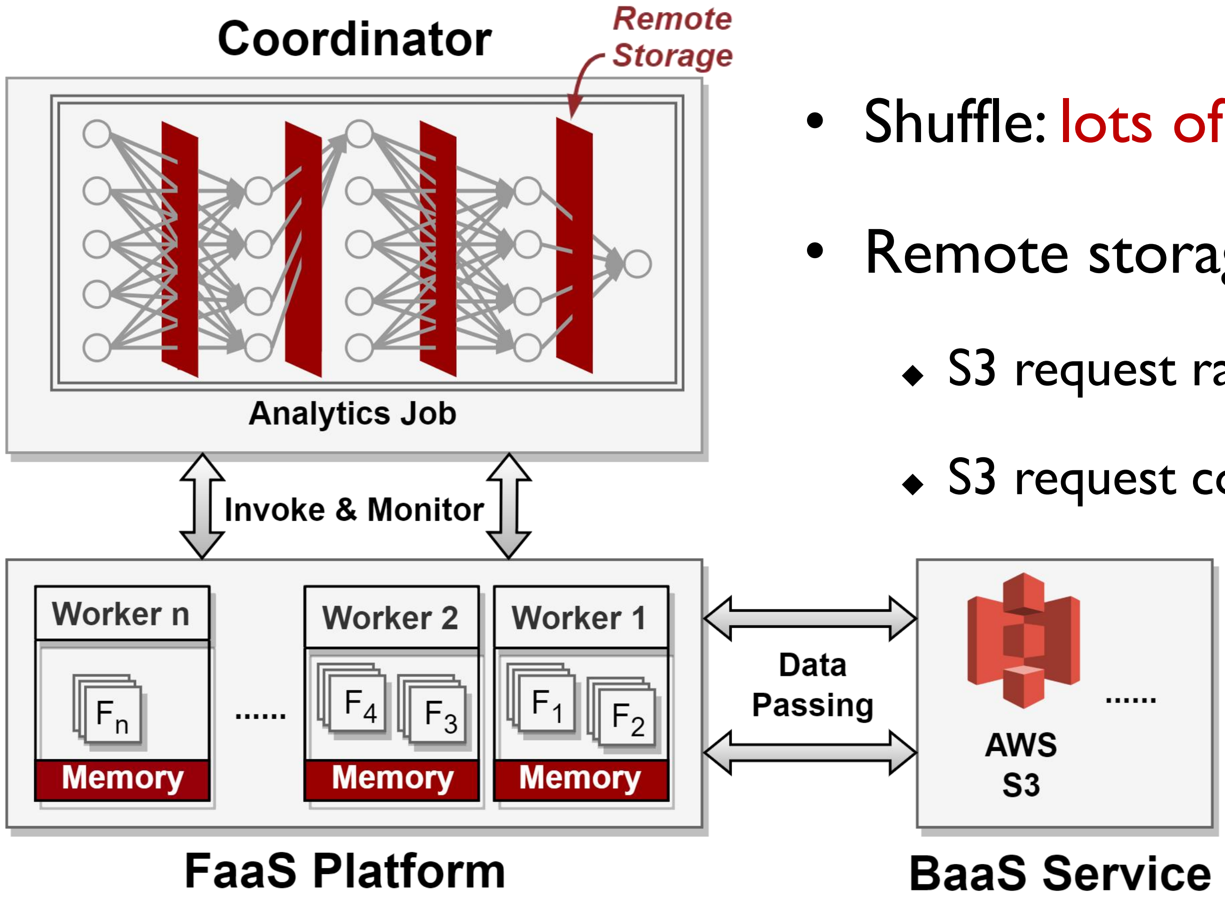
➢ Data analytics is a critical class of applications



- Adopt the BSP model
- Shuffle operation: all-to-all connection
- Facebook: More than 50% involve at least one shuffle (Riffle@Eurosys'18)

Background

➢ Serverless computing passes data via remote storage



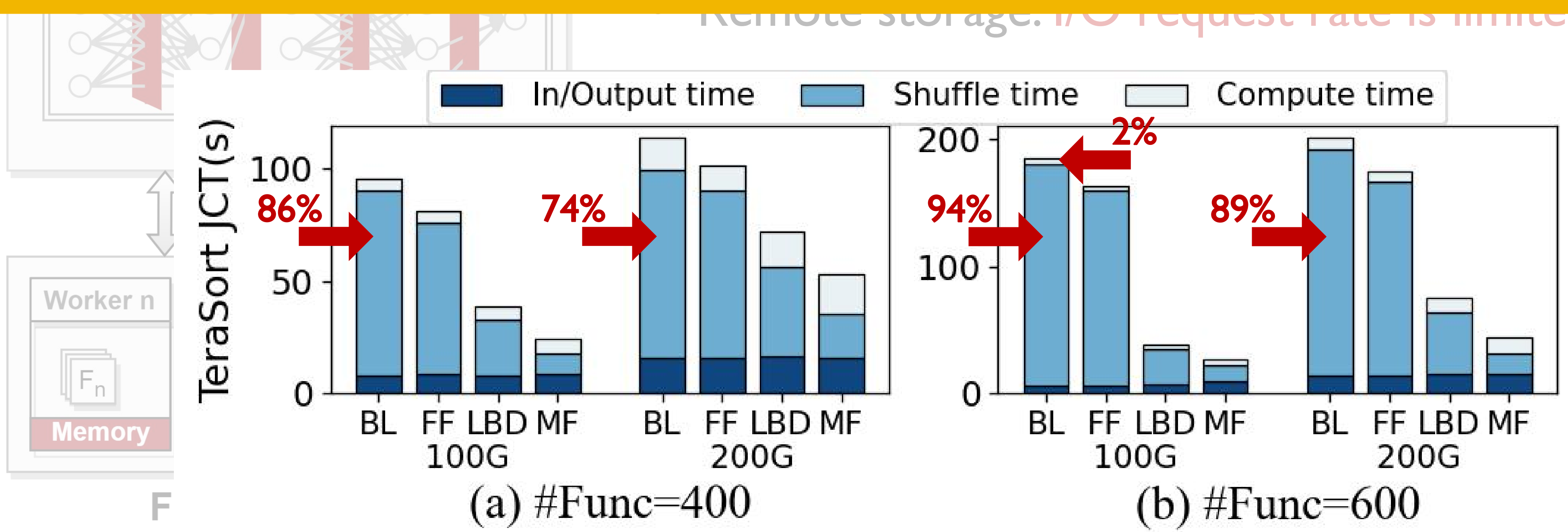
- Shuffle: lots of read/write requests
- Remote storage: I/O request rate is limited
  - S3 request rate: 3.5k and 5.5k req/s for writes and reads
  - S3 request cost: 0.005/0.0004 USD$ per 1k PUTs/GETs

Background

- Serverless computing passes data via remote storage

Data passing severely impedes the elasticity and economy of serverless analytics

Remote storage: I/O request rate is limited



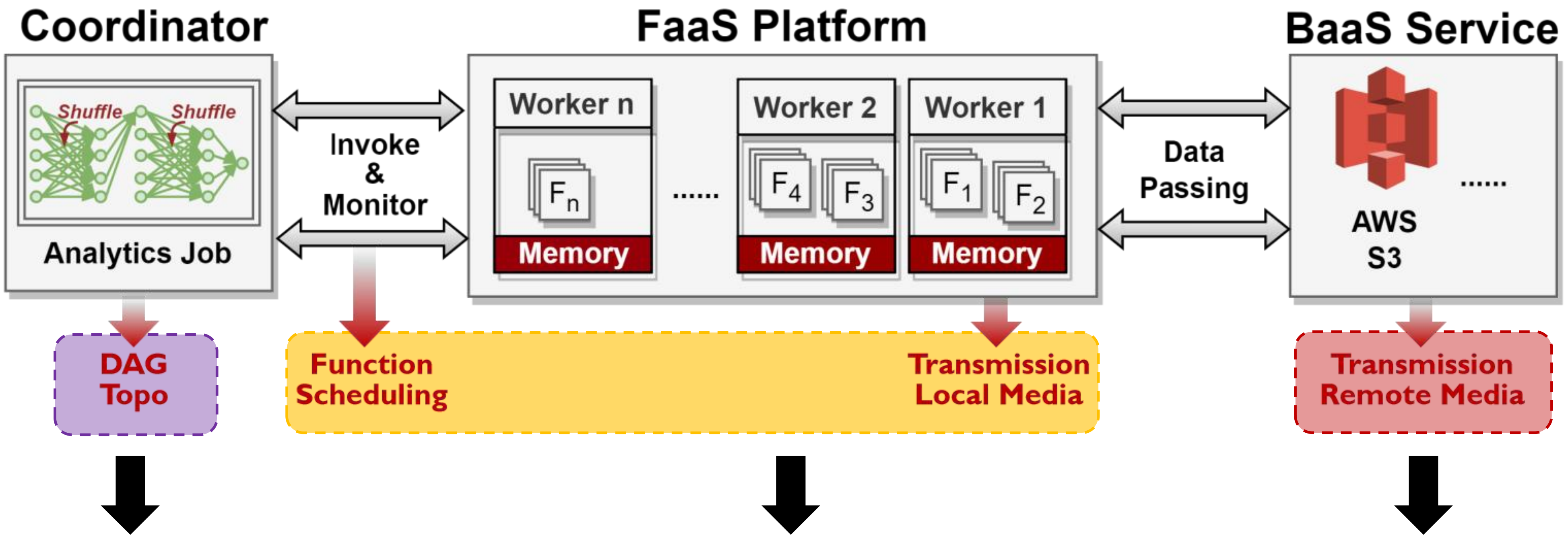
ınd reads

Ts/GETs

Key Issues

➢ How to improve the efficiency of data passing?

- **DAG topology**, **function scheduling**, and **transmission media**



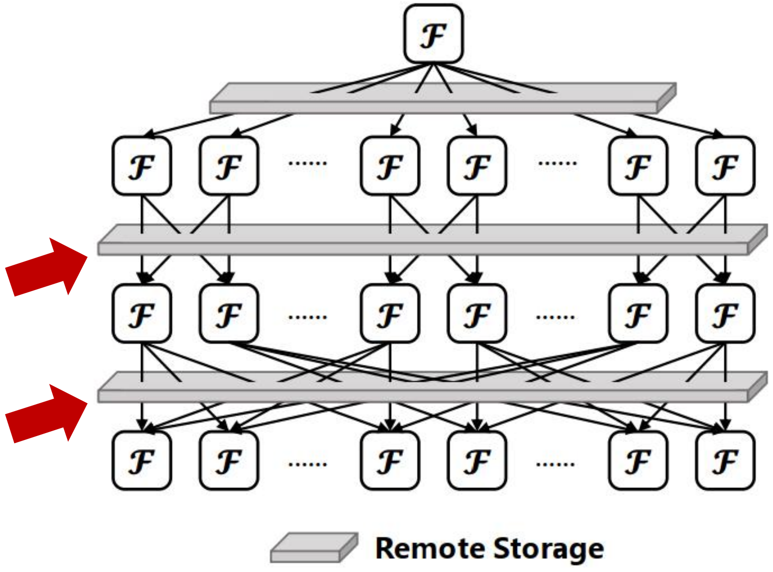
How to optimize the topology to reduce data passing requests?

How to decide the function scheduling plan to leverage over-provisioned local memory?

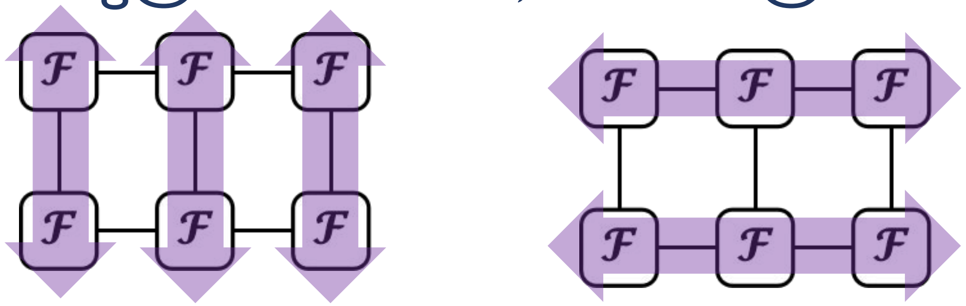
How to build the high-performance and cost-effcient remote storage?

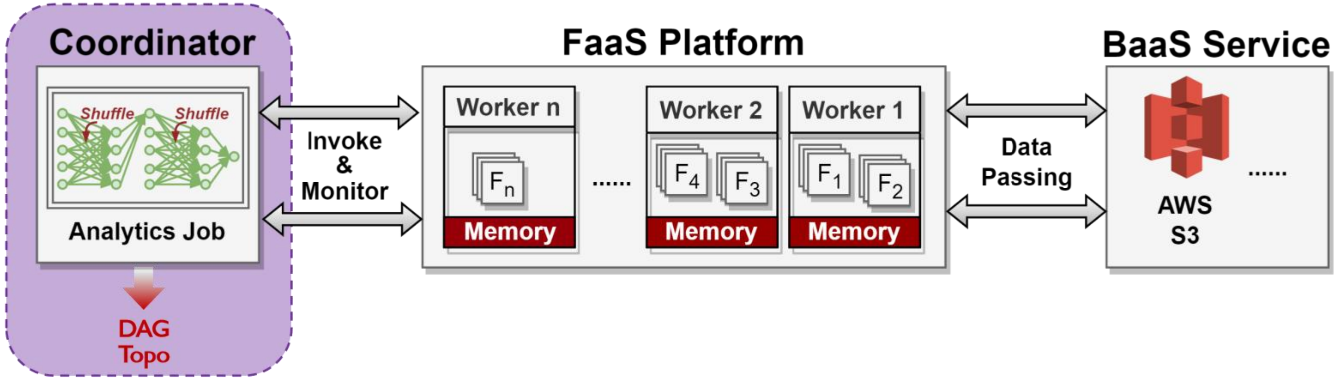
Existing Designs

➢ Two-level Shuffle



- Use mesh-based two-level Shuffle to decrease the number of data passing requests
- Starling@SIGMOD'20,Lambada@SIGMOD'20





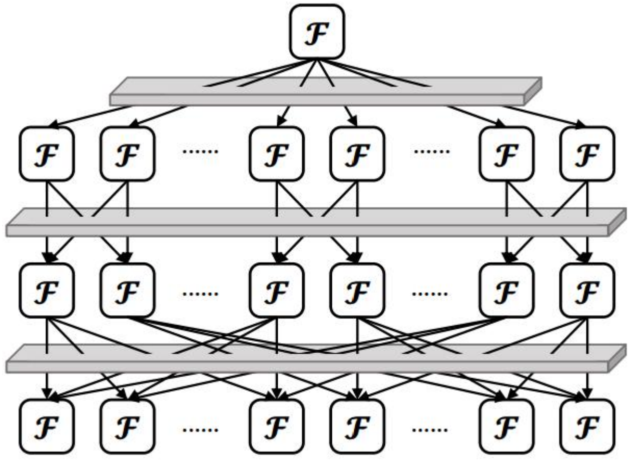
How to optimize the topology to reduce data passing requests?

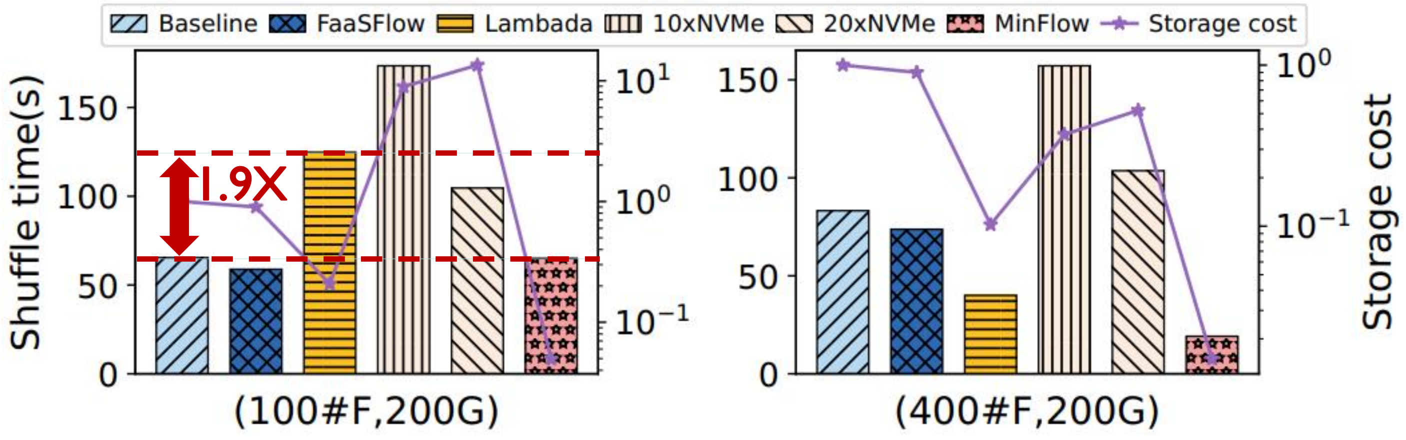
Existing Designs

- Two-level Shuffle
  - Use mesh-based two-level Shuffle to decrease the number of data passing requests (Starling@SIGMOD'20,Lambada@SIGMOD'20)

Limitations:

I. Bring about multiplied extra data volume due to the additional level
II. Cannot extend to a general multi-level network algorithm

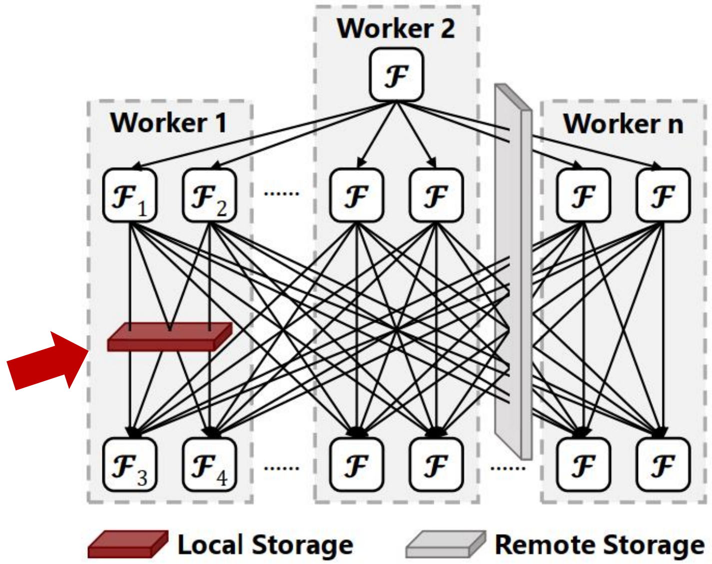




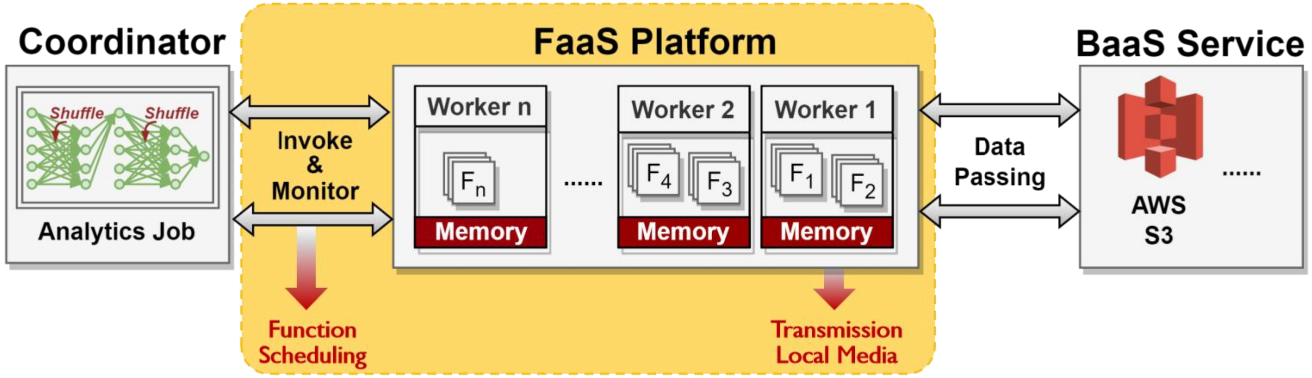
TeraSort Shuffle Time under Different Configurations

Existing Designs

➢ Shuffle via intra-worker memory



- Reclaim over-provisioned memory in workers to localize intra-worker traffic
- Wukong@SoCC'20,FaaSFlow@ASPLOS'22



How to decide the function scheduling plan to leverage over-provisioned local memory?

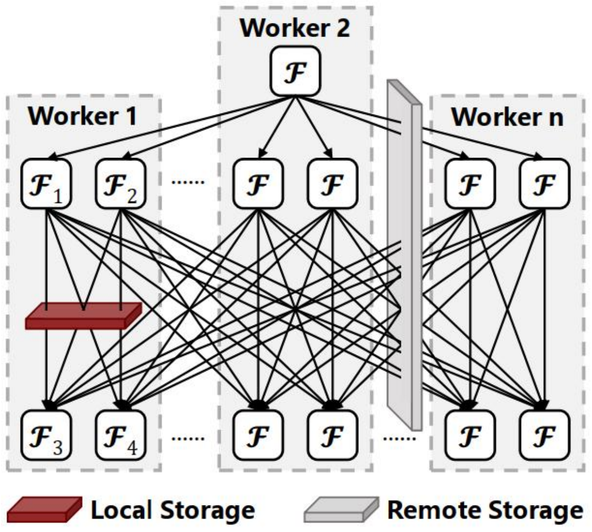
Existing Designs

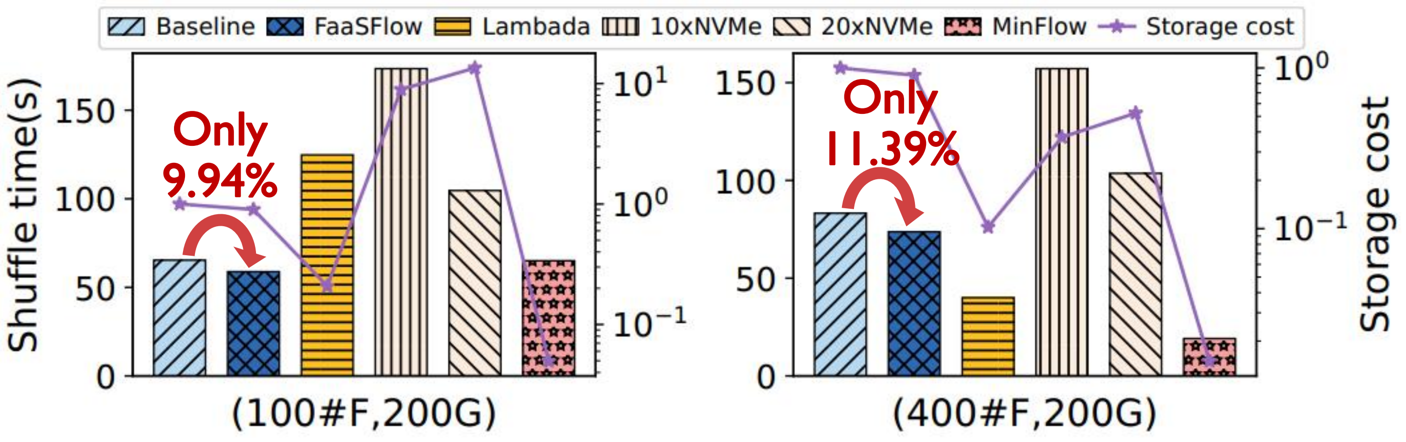
- Shuffle via intra-worker memory
  - Reclaim over-provisioned memory in workers to localize intra-worker traffic (Wukong@SoCC'20,FaaSFlow@ASPLOS'22)

Limitations:

I. Cross-worker traffic dominates and cannot be accelerated

II. Stragglers caused by slower remote storage

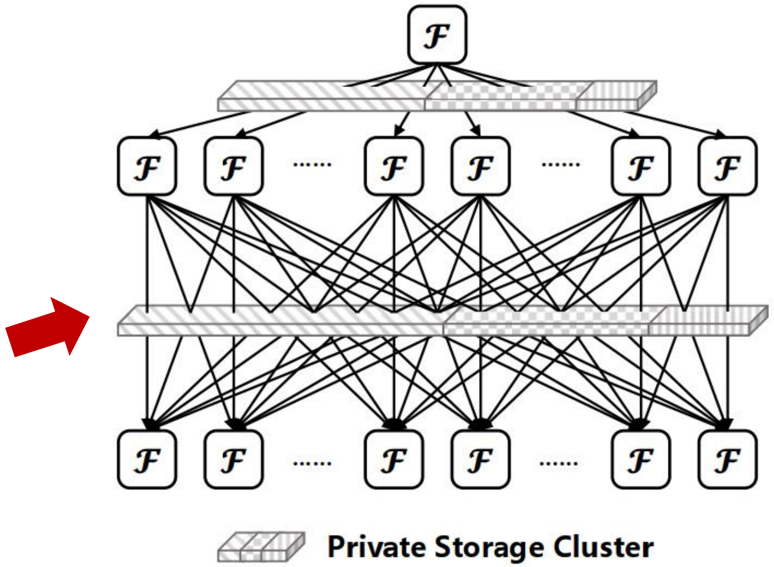




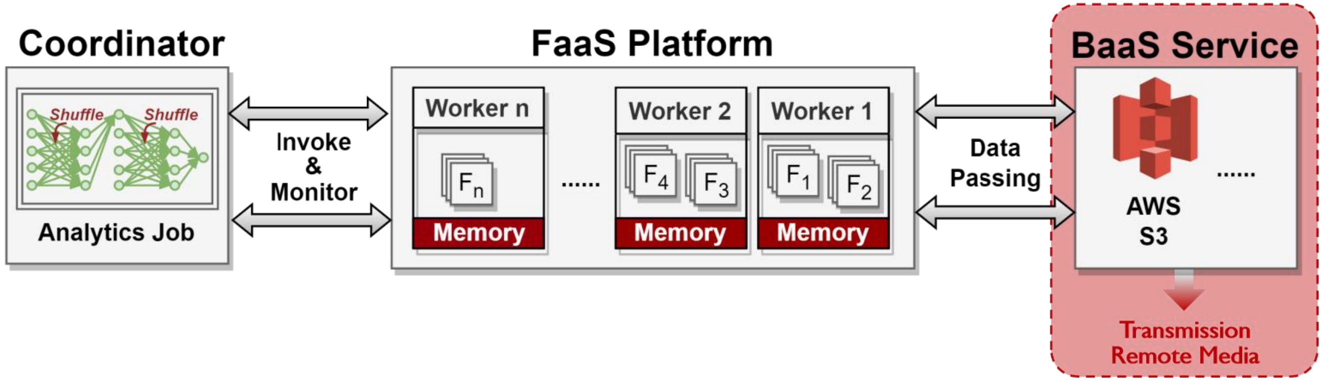
TeraSort Shuffle Time under Different Configurations

Existing Designs

➢ Shuffle via private storage



- Combine high-end and cheap remote storage media to achieve better trade-offs between performance and cost
- Pocket@OSDI'18, Locus@NSDI'19



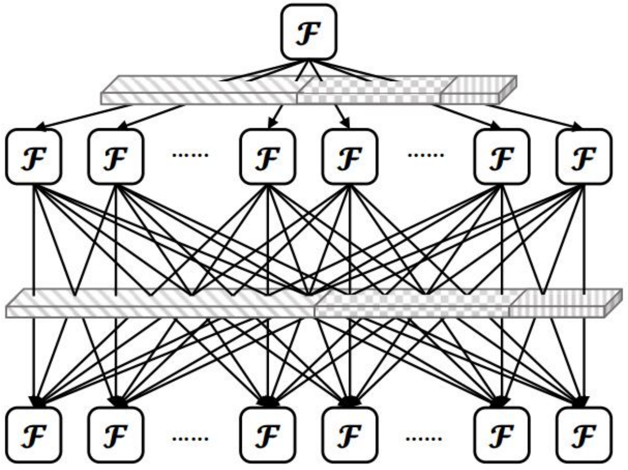
How to build the high-performance and cost-effcient remote storage?

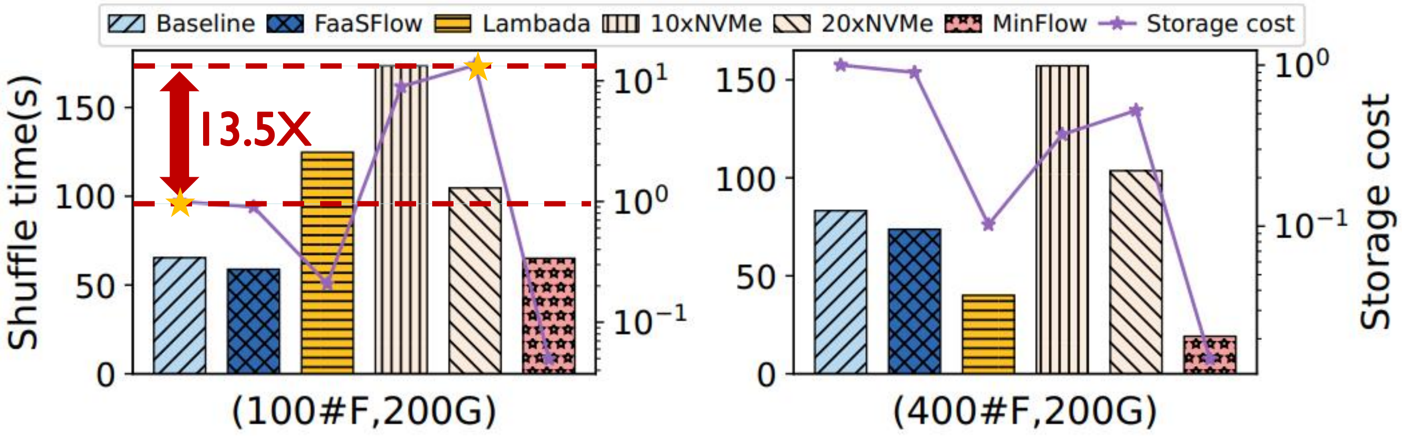
Existing Designs

- Shuffle via private storage
  - Combine high-end and cheap remote storage media to achieve better trade-offs between performance and cost (Pocket@OSDI'18, Locus@NSDI'19)

Limitations:

I. Entail high costs due to extra high-end storage
II. The network bandwidth of VMs is limited

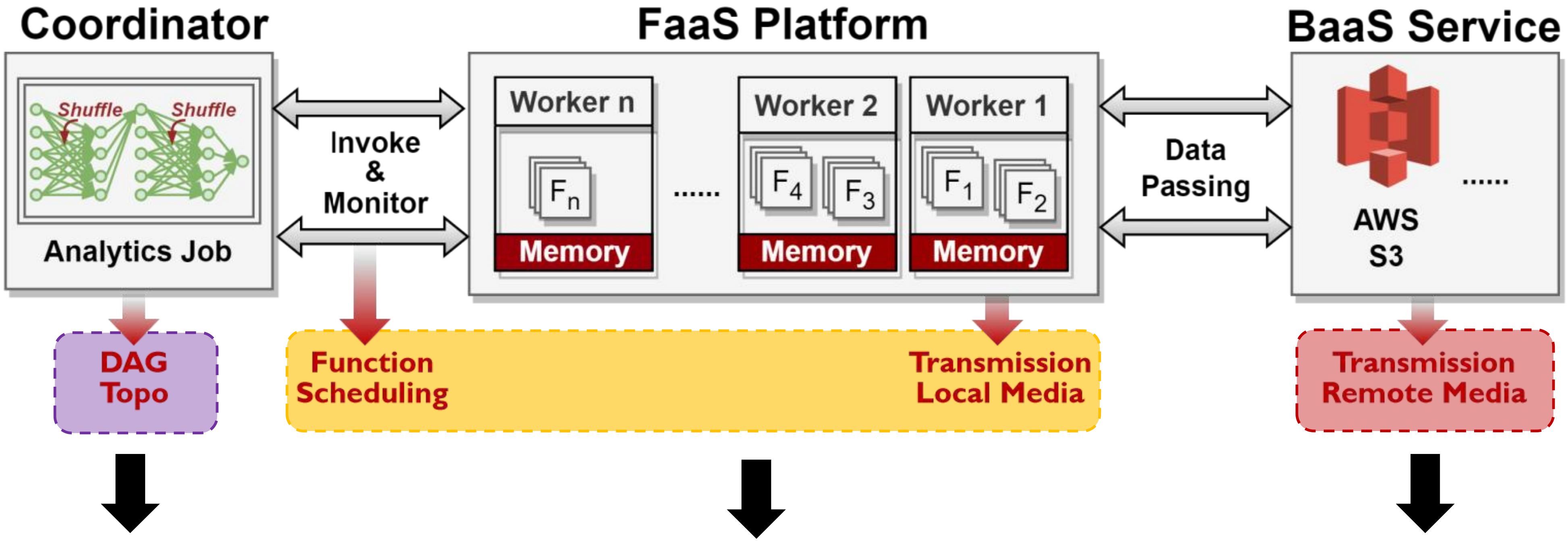




TeraSort Shuffle Time under Different Configurations

Motivation and Main Idea

- Existing approaches: independent optimizations in different components
  - performance/cost/ease-of-use degradation



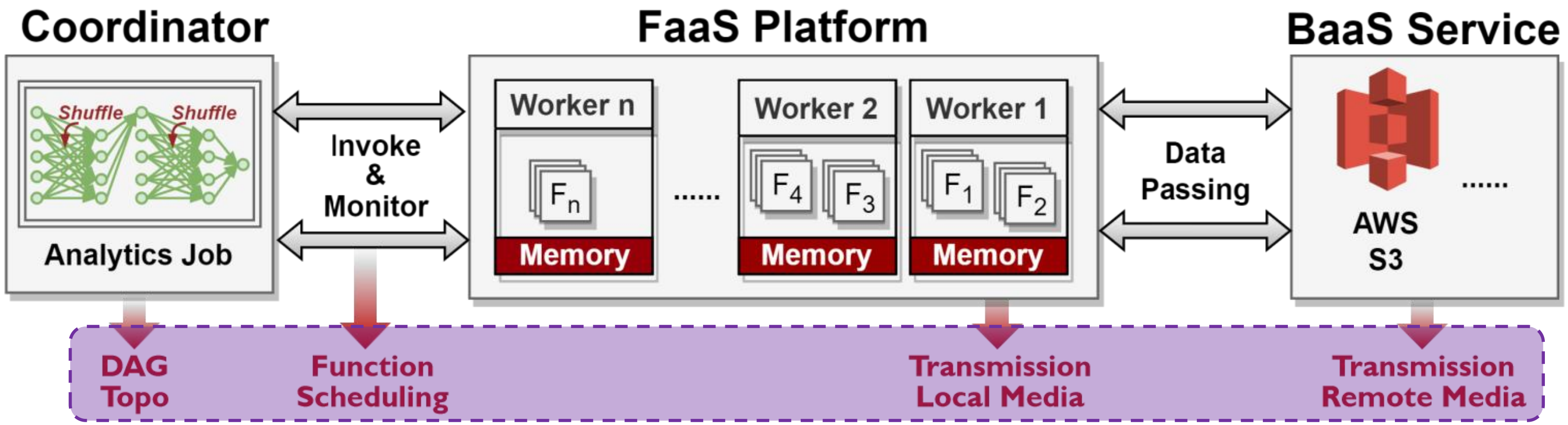
Two-level Shuffle

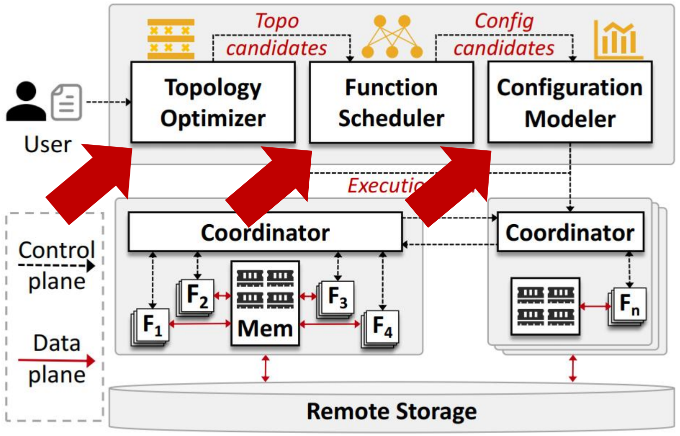
Intra-worker memory Shuffle

Private storage Shuffle

Motivation and Main Idea

Optimize DAG topo, function scheduling, transmission media in a unified way





Unified optimization

❶ Construct multi-level shuffle topology candidates

Decrease requests **Facilitate scheduling**

❷ Generate scheduling plan and optimize transmission media for each candidate topology and output config candidates

Maximize traffic localization **Balance load**

Avoid stragglers

❸ Model configs to select the optimal one form config candidates

Optimal configuration

Topology Optimizer

➢ How to construct the complete multi-level network topo space?

Progressively converging multi-level shuffle

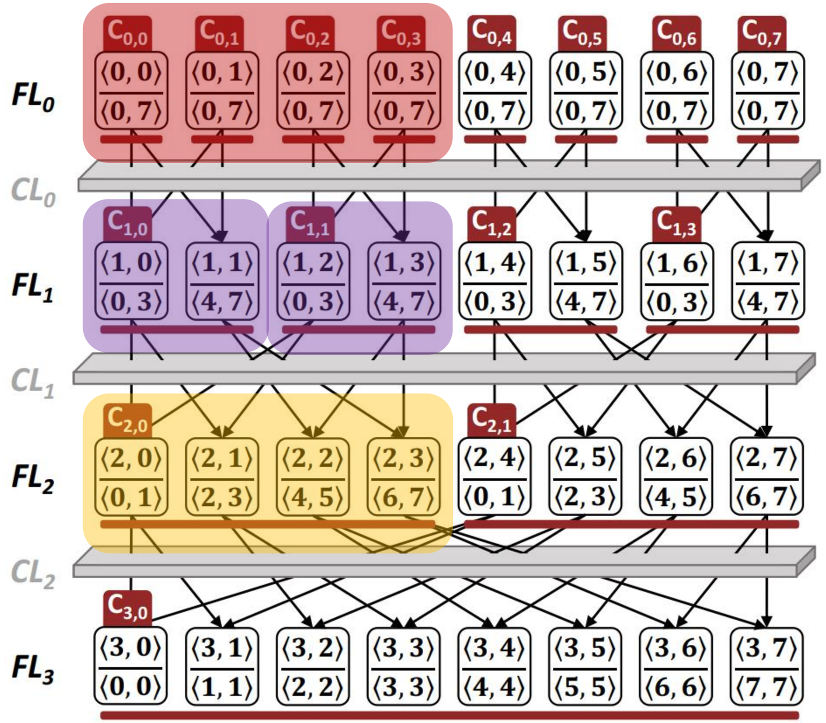
Step1. Divide functions in the $flevel\ i$ into g_i groups

$$g_0 = N, g_L = 1, g_i = d_i \times g_{i+1} \text{ where } d_i \in N^+/\{1\}$$

Step2. Progressively converge groups

❶ Function linking:

keep all-to-all connection



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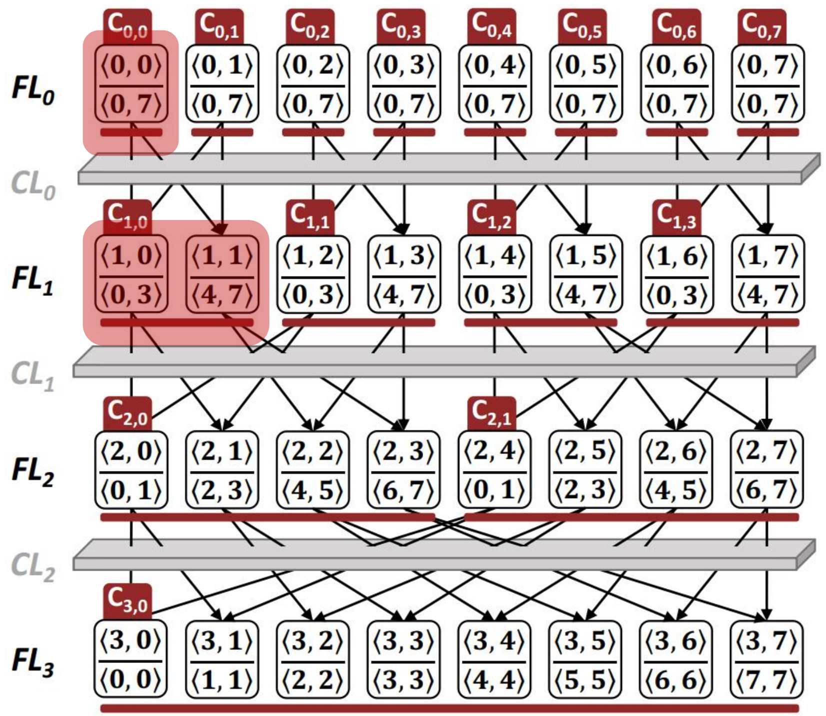
❷ Data passing:

shard data into continuous and equal-sized parts



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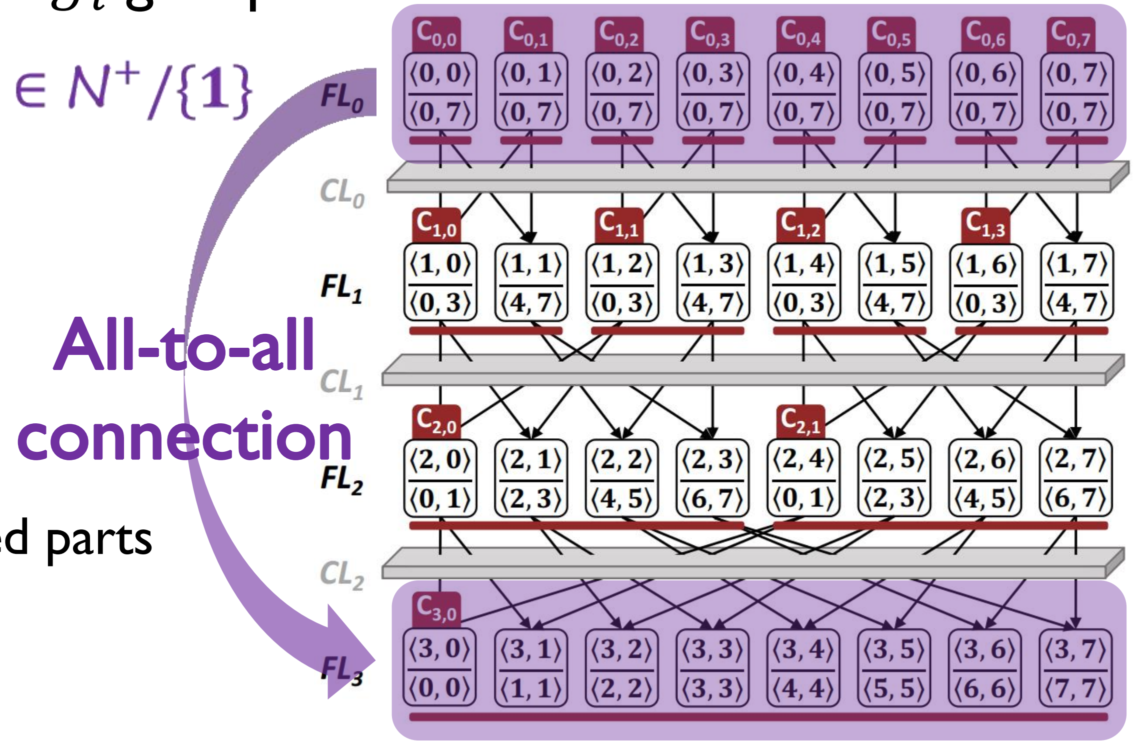


Topology Optimizer

- How to select candidates among massive topologies?

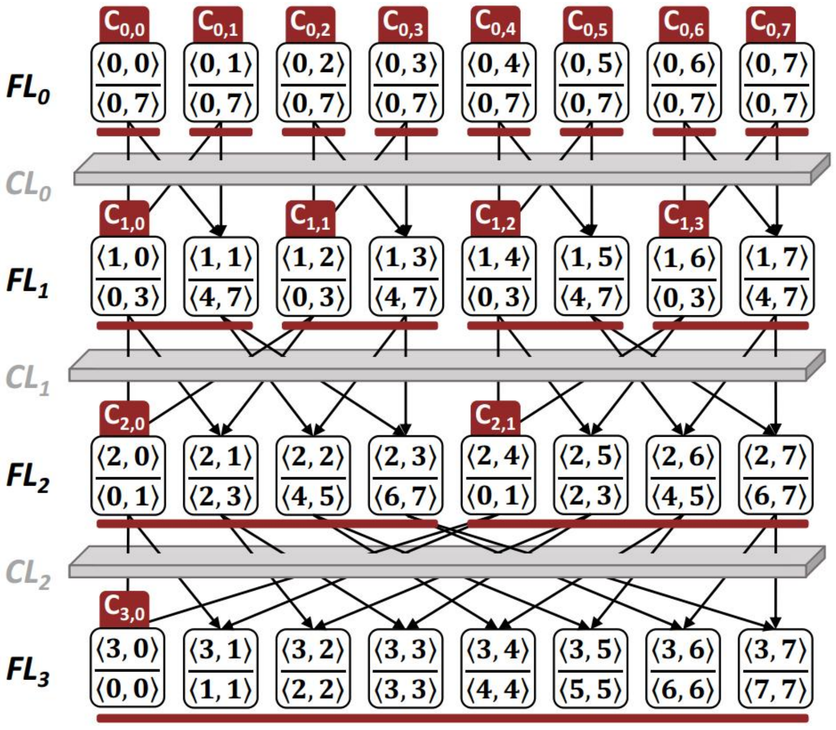
Lightweight candidates selection by dynamic programming

- Find networks with the fewest edges under each possible number of levels L

Step1. A series of optimization problems

$$\text{For } L \in [1, p], \begin{cases} \textbf{minimize } N \times \sum_{i=0}^{L-1} d_i \\ \textbf{subject to } \prod_{i=0}^{L-1} d_i = N \end{cases}$$

Edges



Step2. Bottom-up dynamic programming

- Solve all problems at once with low overhead

$$MinSum(i,j) = \begin{cases} min_{n|i}\,(n + MinSum(i/n, j-1)) & j > 1 \\ i & j = 1 \end{cases}$$

Topology Optimizer

Conclusions:

I. Topology Optimizer outputs topology condidates, each has the fewest edges under their corresponding number of levels L

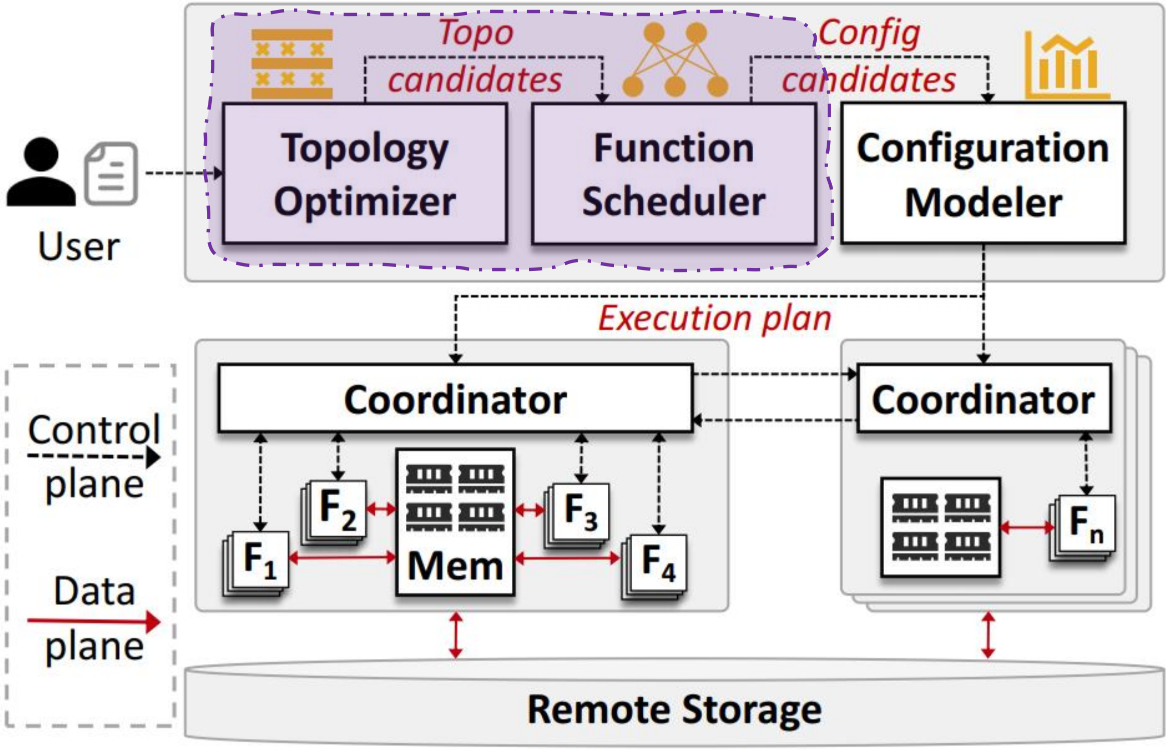
Step1. A series

For L ∈ [1,

Step2. Bottom-

- Solve all prob

$MinSum(i, j) =$

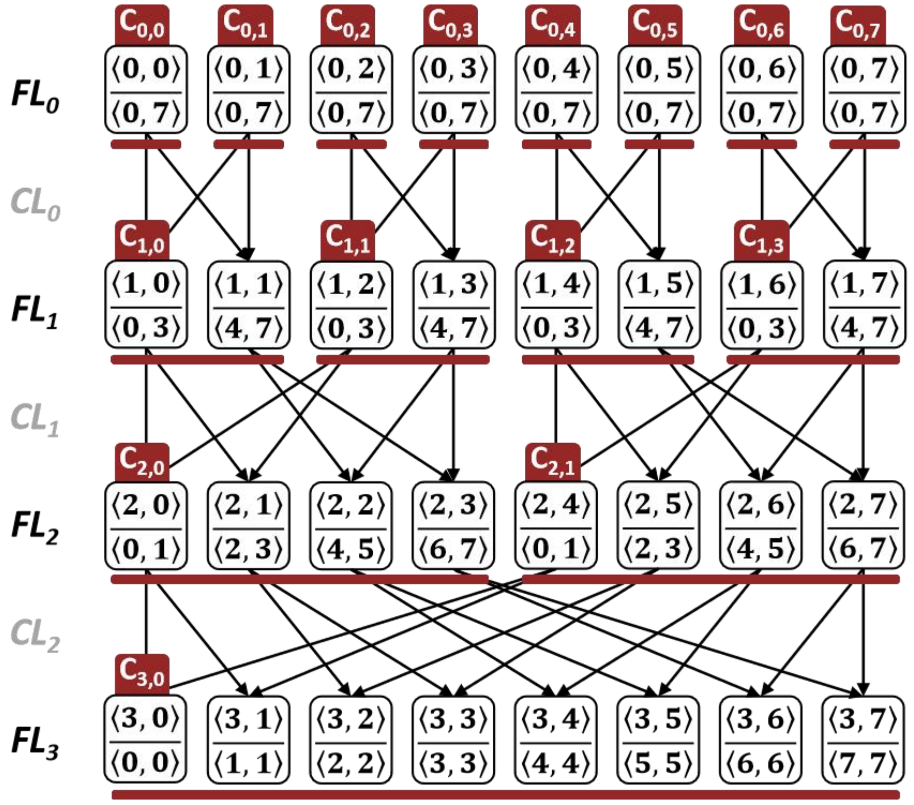


Function Scheduler

- How to meet all the scheduling requirements?

Interleaved complete bipartite graphs partitioning

- Scheduling requirements
  - Maximize traffic localization
  - Avoid transmission stragglers
  - Ensure load balancing



Function Scheduler

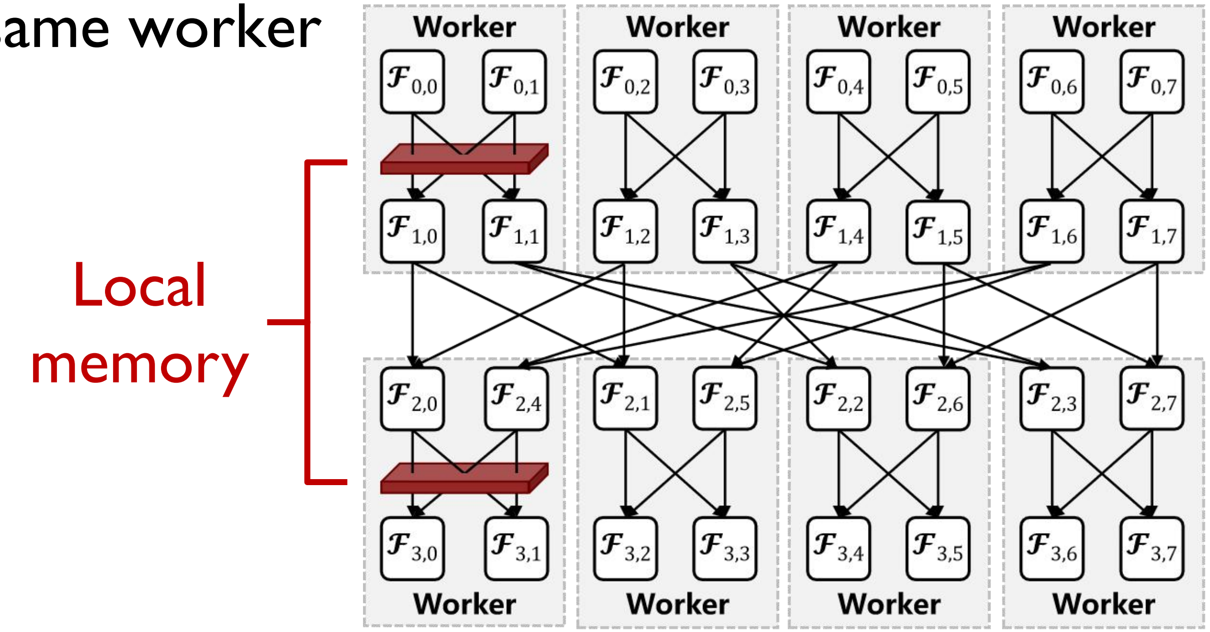
➢ How to meet all the scheduling requirements?

Interleaved complete bipartite graphs partitioning

➢ Adjacent function levels: complete bipartite graphs (CBG)

- Search the CBGs: schedule to the same worker

Maximize traffic localization



Function Scheduler

- How to meet all the scheduling requirements?

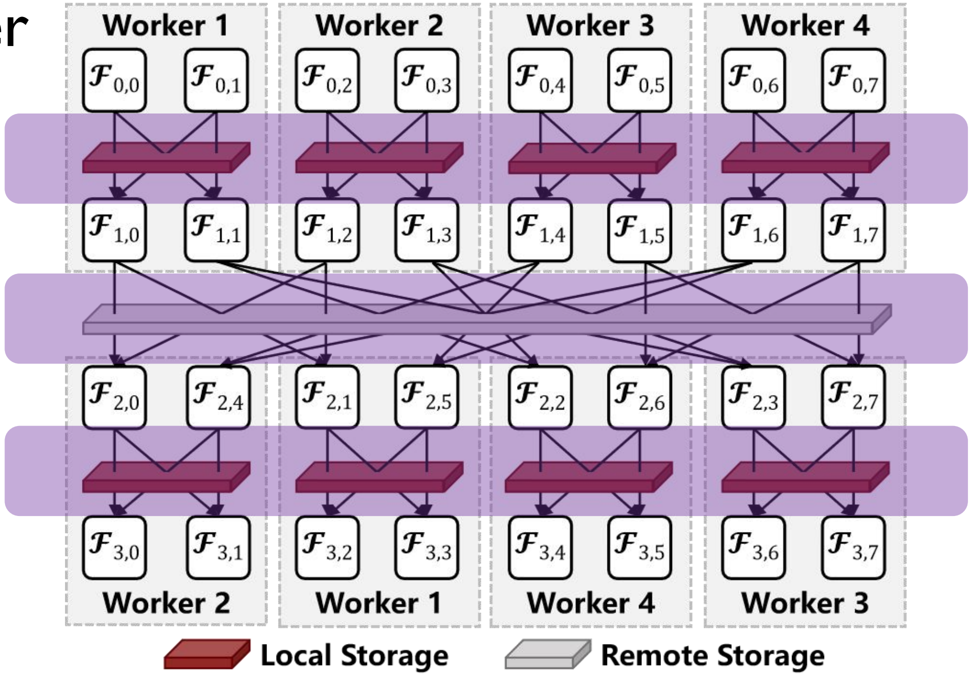
Interleaved complete bipartite graphs partitioning

- Adjacent function levels: complete bipartite graphs
  - Search the CBGs: schedule to the same worker

    Maximize traffic localization
  - Adopt the same transmission media: within a communication level

    Avoid stragglers
  - Employ interleaved local memory and remote storage: across communication levels

    Balance load



Function Scheduler

Conclusions:

I. Function Scheduler outputs configuration candidates, each has the fewest edges under their corresponding number of levels and meets all scheduling requirements

- Adjacent function levels: complete bipartite graphs
  - Search the CB(
    Maximize traffic
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    communication le
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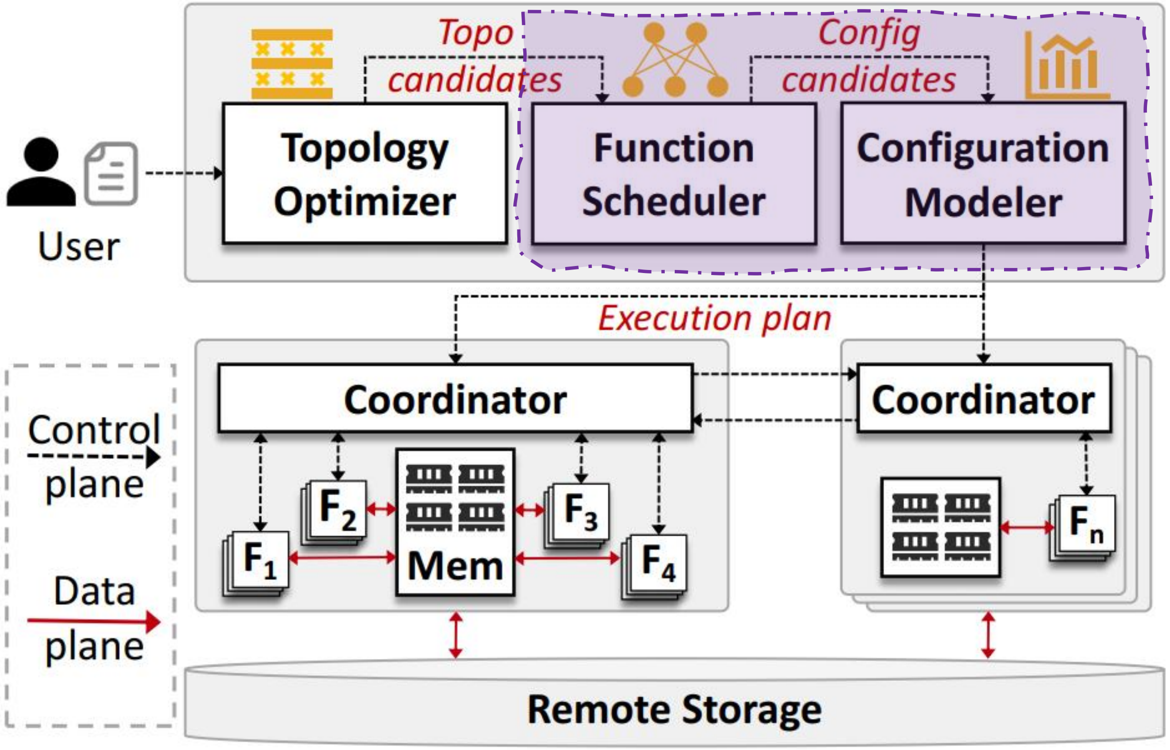
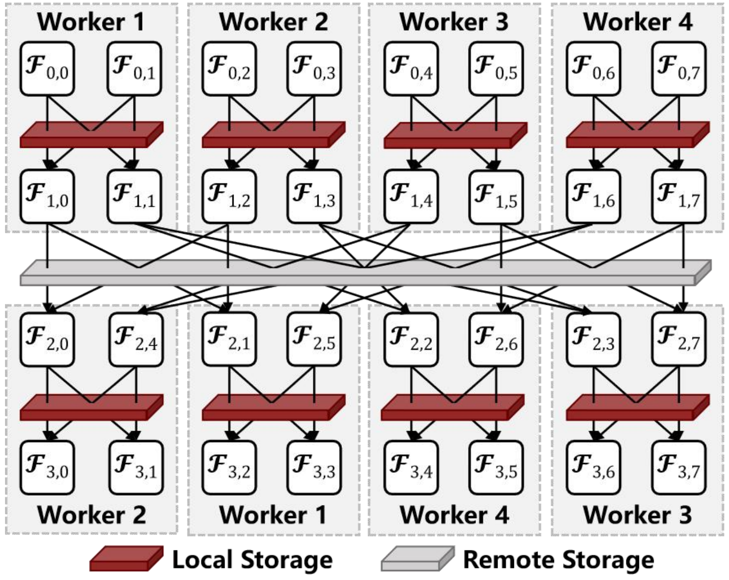


Configuration Modeler

➢ How to select the optimal configuration from config condidates?

Estimate data passing time of candidate configurations

- Model application characteristics and platform features to data passing time
  - Within a level: maximum of function and storage
  - Across levels: S3-based and memory-based



function-side storage-side

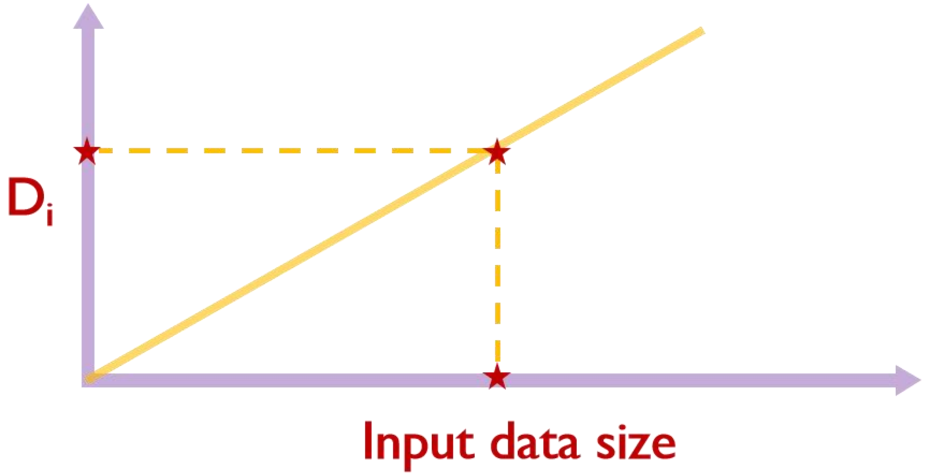
$$T = 2 * \sum_{i=0}^{L-1} \begin{cases} \max\left(\frac{D_i}{N * b_f}, \frac{R_i}{q_s}\right), \textit{S3 levels.} \\ \max\left(\frac{D_i}{M * b_t}, \frac{R_i}{M * q_t}\right), \textit{memory levels.} \end{cases}$$

Configuration Modeler

➢ How to select the optimal configuration from L config condidates?

Estimate candidate configuration's data passing time

- Model data passing time for S3-based and memory-based level
- The volume of intermediate data D_i: available at the runtime
  - Input data size and D_i: linear/non-linear but deterministic
  - Sample and profile

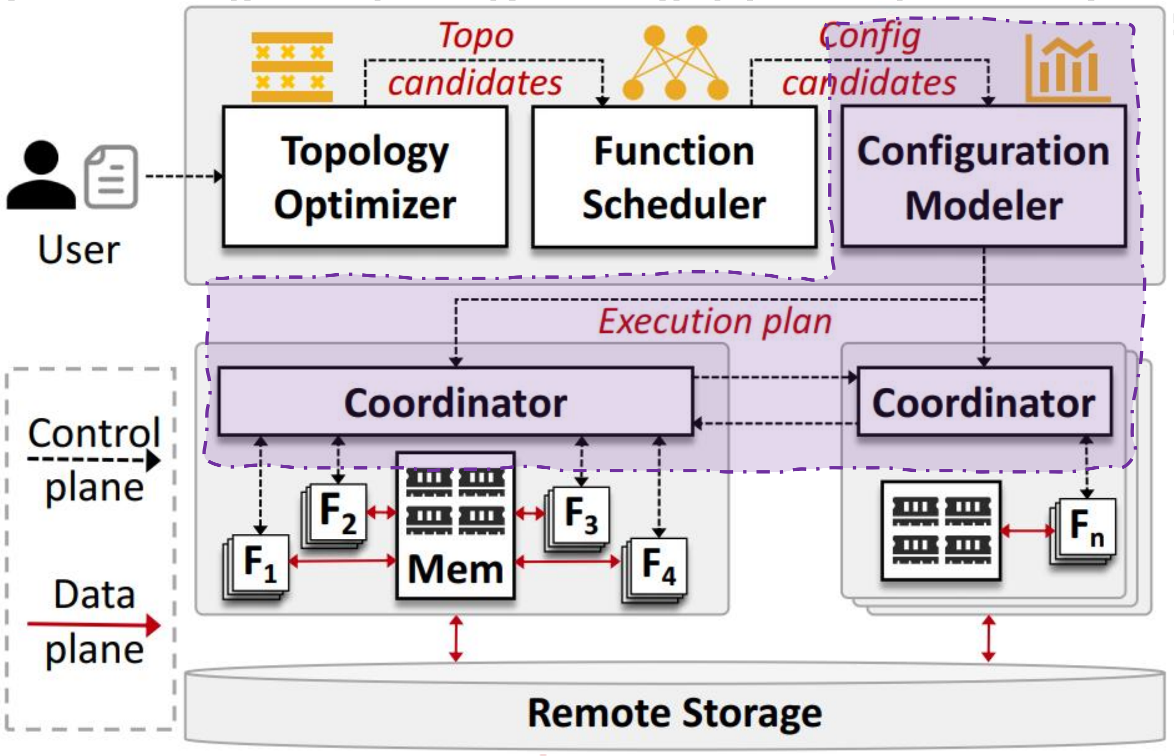


Configuration Modeler

Conclusions:

I. Configuration Modeler outputs the optimal configuration and dispatch it to distributed coordinators

- The volume of
  - Input data s
  - Sample and



Experiments

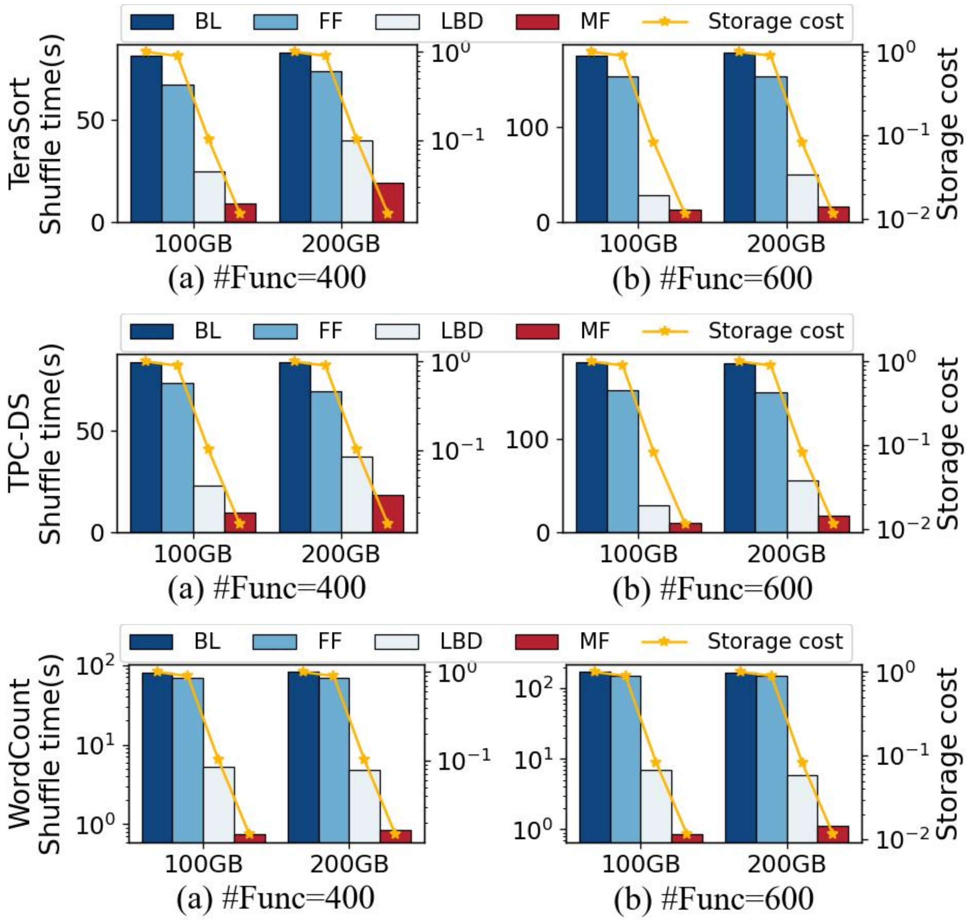
- Testbed:
  - 10 Amazon EC2 m6i.x24large instances

vCPU	Memory/GiB	Network bandwidth/Gib
96	384	37.5

- Workloads
  - TeraSort, TPC-DS, WordCount
- Comparisons:
  - **Baseline:** use single-level shuffle and transfer all data via S3
  - **FaaSFlow:** adopt the intra-worker memory shuffle
  - **Lambada:** employ the mesh-based two-level shuffle

Shuffle Time and Storage Cost

➢ Three workloads: 100GB/200GB input data size, 400/600 functions



Conclusions:

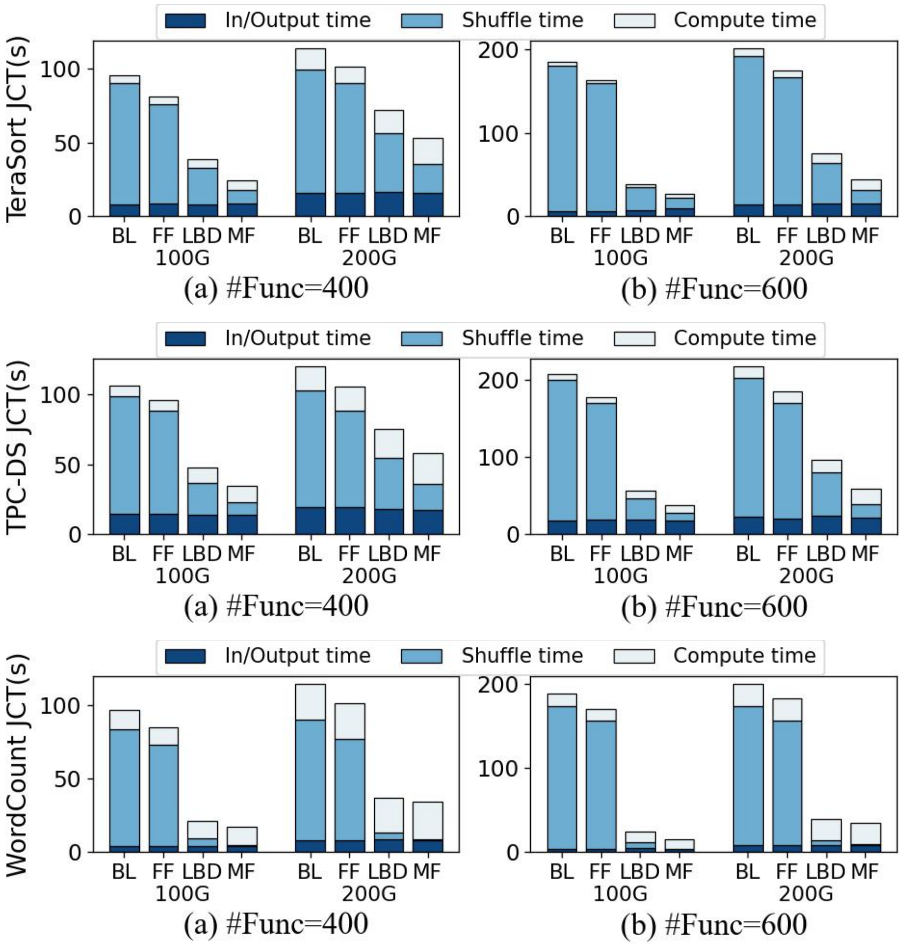
Under Terasort workload, compared to Baseline, FaaSFlow, and Lambada

I. **MinFlow** improves the shuffle speed up to 14.1X, 12.4X, and 3X respectively;

II. **MinFlow** reduces the storage cost up to 98.84%, 98.71%, and 86%, respectively

Job Completion Time

➢ Three workloads: 100GB/200GB input data size, 400/600 functions



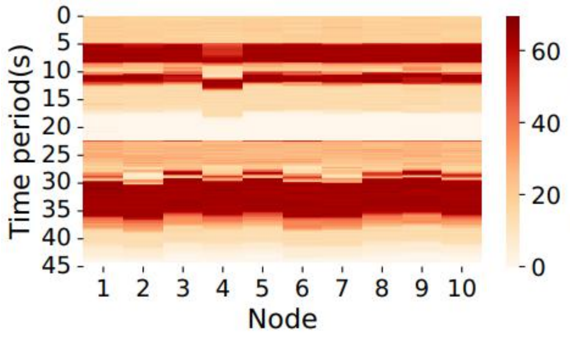
Conclusions:

Under Terasort workload, compared to Baseline, FaaSFlow, and Lambada

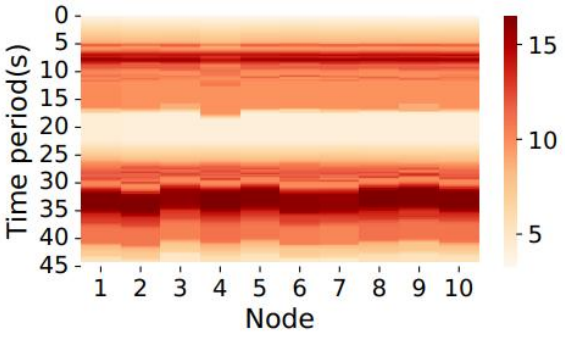
1. **MinFlow** reduces the job completion time up to 85.16%, 83.25%, and 41.35%, respec tively;

Load Balance

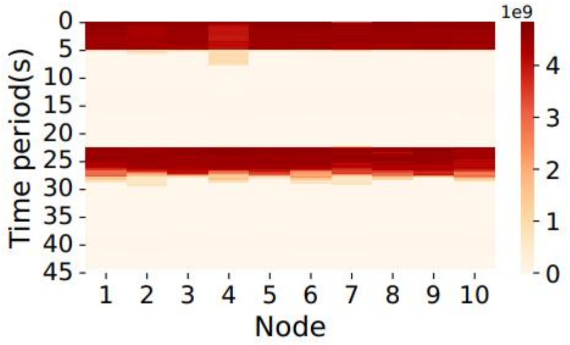
- ➢ Terasort workload: 200GB input data size, 600 functions



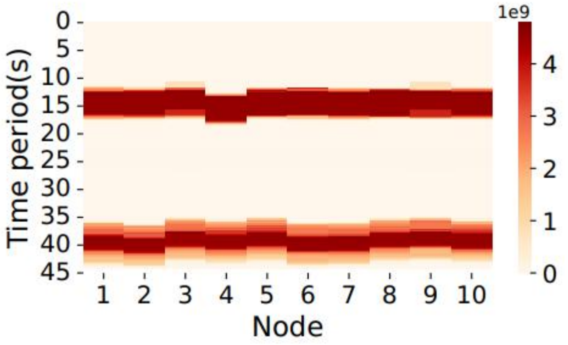
(a) CPU utilization



(b) Memory utilization



(c) Receive throughput (byte/s)



(d) Sent throughput (byte/s)

Conclusions:

1. All types of resource (i.e., CPU utilization, Memory utilization, Receive throughput, and Sent throughput) are load-balanced among workers

Conclusions

- **MinFlow**: High-performance and Cost-efficient Unified Data Passing Framework for I/O-intensive Stateful Serverless Analytics
  - Progressively converging multi-level shuffle: minimize data passing requests
  - Interleaved complete bipartite graph scheduling: maximize traffic localization
  - Estimate data passing time: select the optimal configuration
- More evaluation results and analysis are in the paper
- The source code is at https://github.com/lt2000/MinFlow
  - Reproduce all results with Amazon cloud: tens of hours and thousands of dollars

Thanks for your attention!

Q&A

Contact email:
little314@mail.ustc.edu.cn