

IEEE MASS 2020

2020 IEEE 17th International Conference on Mobile Ad Hoc and Sensor Systems (MASS)



# Reducing Makespans of DAG Scheduling through Interleaving Overlapping Resource Utilization



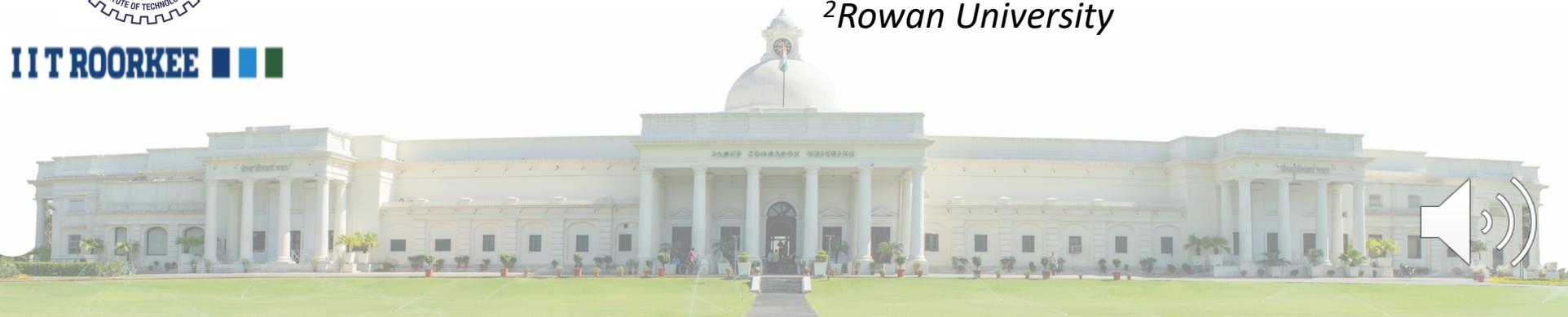
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# Outline

- 1. Introduction
- 2. Problem Formulation
- 3. Scheduling for Perfectly Parallel Stages
- 4. Scheduling for General Stages
- 5. Experiment
- 6. Conclusion



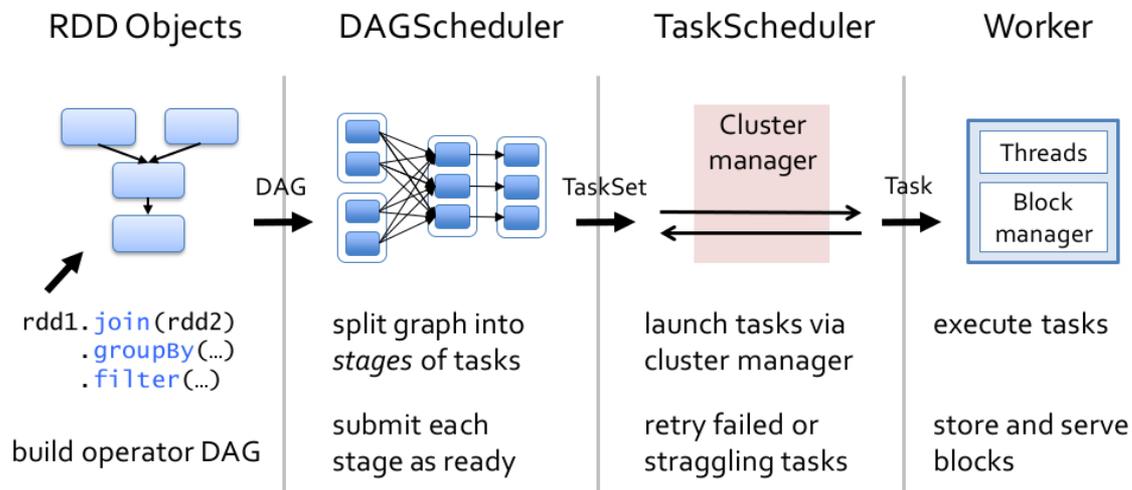
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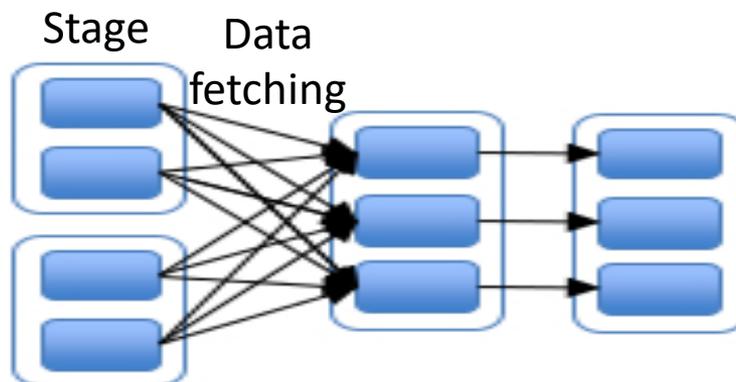
# 1. Introduction

- Apache Spark 
  - A general-purpose distributed computing engine for data processing
  - Large Data: stored as Resilient Distributed Dataset (RDD) objects
  - Data processing flow: RDD transformations with DAG structure



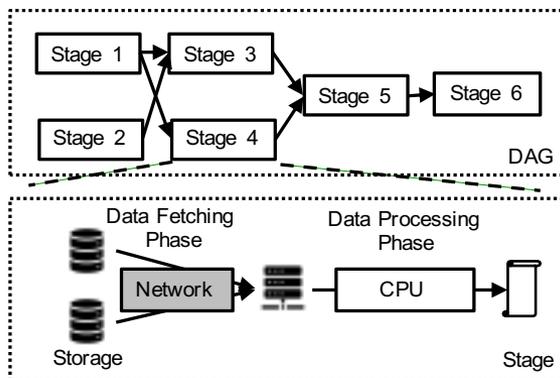
# DAG Scheduler

- Stages in Spark
  - Within each stage: computation tasks that can run in parallel
  - stage execution: data fetching phase and data processing phase
- DAG Scheduler in Spark
  - Parallelism level of each stage
  - Processing sequence of stages

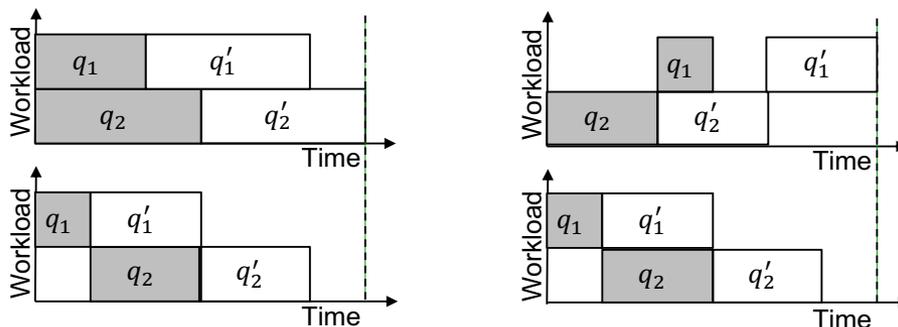


# Motivation

- Observations
  - Data fetching and processing use different resources
  - They can run in pipeline

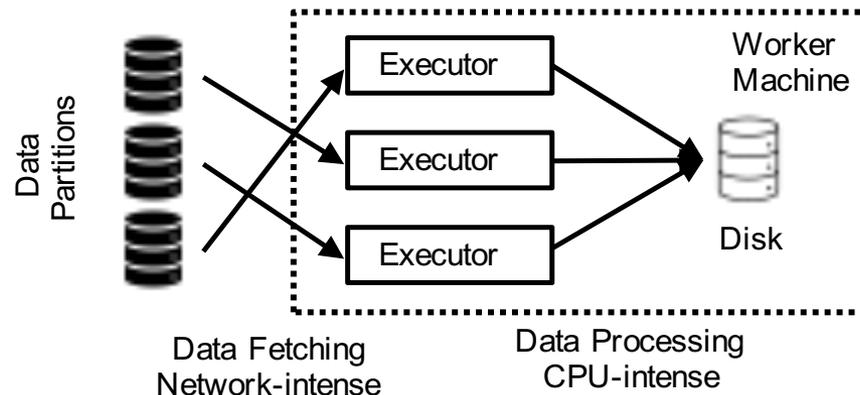


- Contention of either resource would enlarge makespan



# Objective

- Minimize job makespan by reducing resource contentions
  - Focus on optimizing the DAG scheduler of Spark
- Key assumptions:
  - Non-preemptive
  - Equally allocated resources



## 2. Problem Formulation

- DAG shop scheduling problem

min  $\tau$ ,

s.t.  $t'_i \leq t_j, \forall (s_i, s_j) \in E$ ,

Precedence constraint

$$\sum_{s_i \in O(t)} p_i \leq P, \forall t > 0,$$

Computation resource constraint

$$\sum_{s_i \in O(t)} b_i \leq B, \forall t > 0,$$

Bandwidth constraint

$$t_i \geq 0, \forall s_i \in S.$$

Schedule constraint

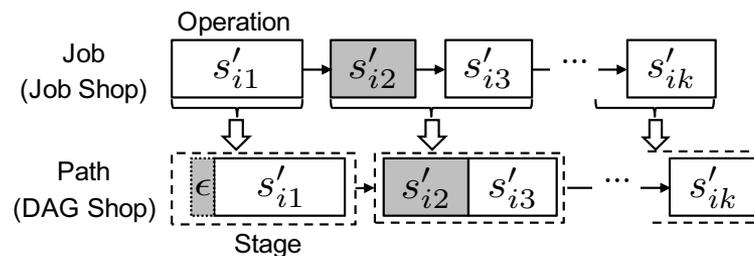
- Decision variables

- Stage processing sequence or starting time  $t_i$
- Number of machines assigned to a stage:  $p_i$
- Bandwidth allocated to a stage:  $b_i$



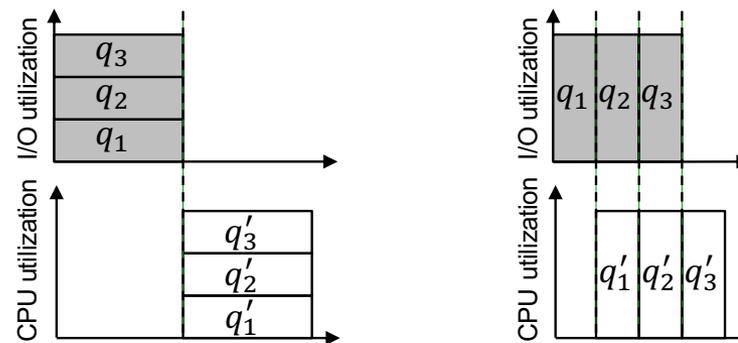
# NP-hardness

- NP-hard, even assuming the speedup is linear (ideal case)
  - Ideal speedup: 2 workers brings 2x speedup
- Proof:
  - Job shop problem (JSP) is NP-hard
  - Instances of JSP can be converted to our problem in polynomial time



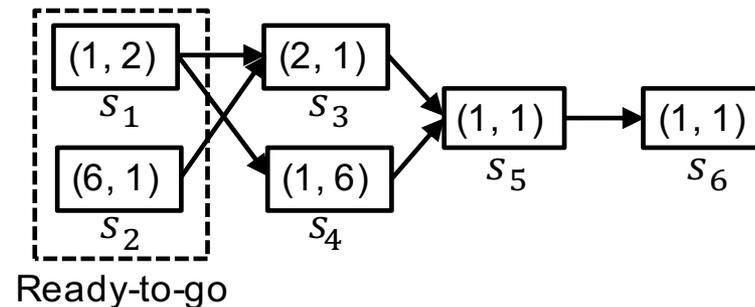
# 3. Scheduling for Perfectly Parallel Stages

- Additional assumption
  - Speedup of any stage  $s_i$  in DAG is linear to  $p_i$
- Contention-free scheduler
  - Contention brings no benefits
  - Should assign all resources to a stage
  - Problem reduced: only need to determine a processing sequence



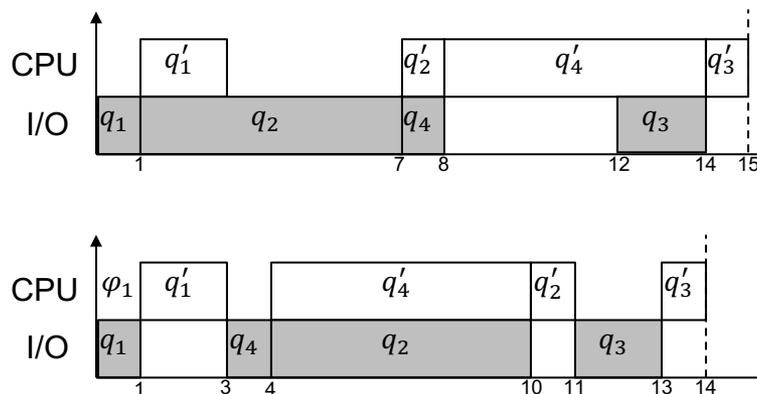
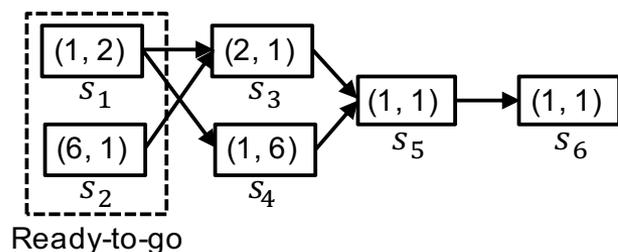
# Contention-free Scheduler

- Apply Johnson's rule on ready-to-go stages
  - Divide stages into comm.-heavy and comp.-heavy groups
  - Sort comp.-heavy group by comm. time in ascending order
  - Sort comm.-heavy group by comp. time in descending order
- Example
  - (a, b): tuple represents the length of comm. and comp., respectively



# Properties

- Our scheduler brings additional precedence constraints

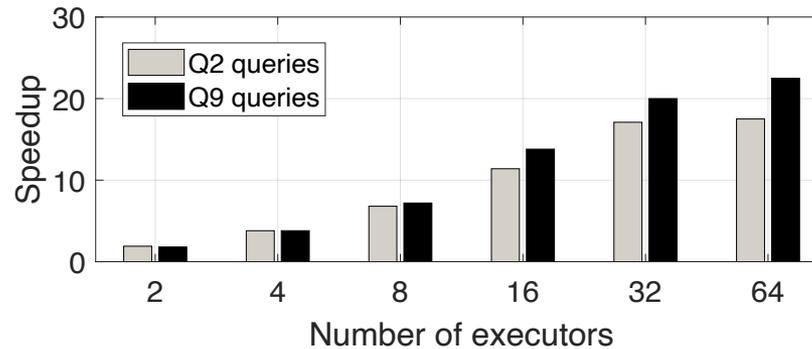


- Our contention-free scheduler is  $3/2$ -approximate if comp. and comm. of each stage have unit lengths.
  - The lost is bounded: our scheduler will not leave both resources idle



# 4. Scheduling for General Stages

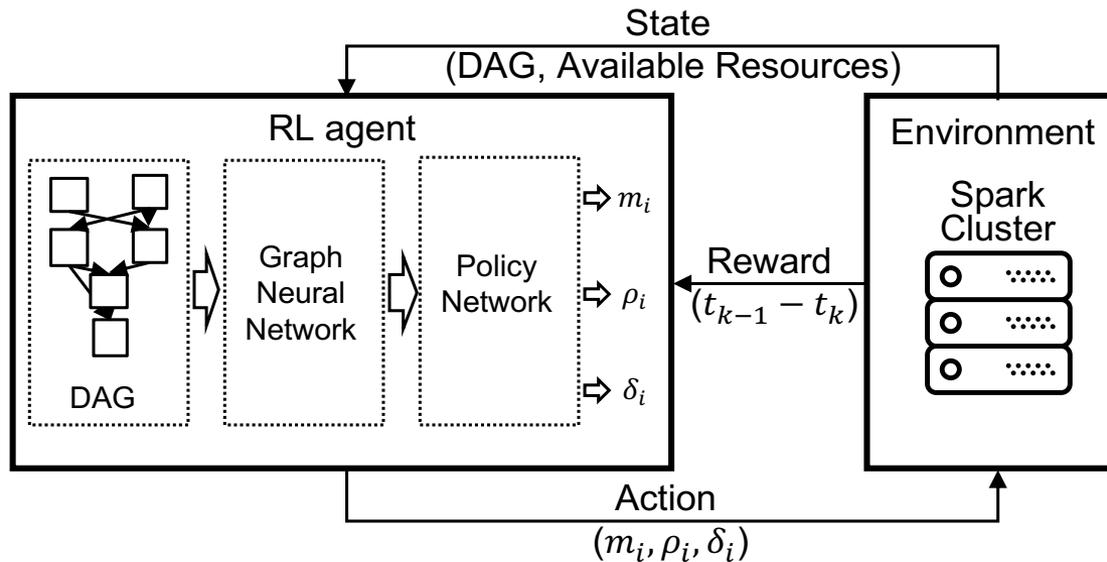
- General cases: speedup of  $s_i$  is not linear to  $p_i$



- Should have limitations on number of workers
  - Assigning too many workers to a stage is a waste
  - Set parallelism level limitations for comp. resources  $p_i$



# Reinforcement Learning based Scheduler

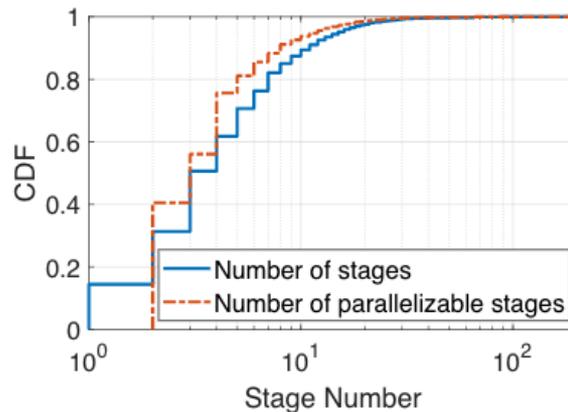


- RL framework:
  - State: use graph neural network to encode a DAG
  - Action: parallelism limitations, priority level and delay of each stage
  - Reward: expected time consumption for executing remaining stages

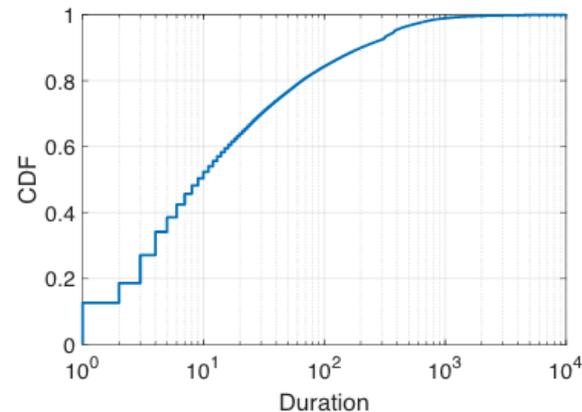


# 5. Experiment

- Experiment setting:
  - Alibaba trace data v2018: contains 2,775,025 jobs
  - Use m4.xlarge instance of AWS EC2 to build spark clusters



(a) The stage number distribution

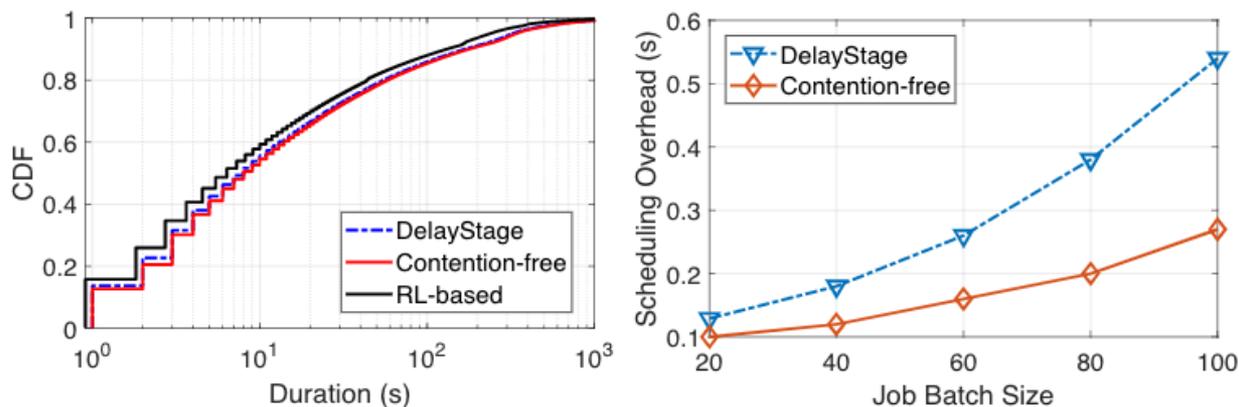


(b) The stage duration distribution



# Experiment Result

- Makespan comparison



- Utilization improvement

THE AVERAGE RESOURCE UTILIZATION

	Default	DelayStage	RL-based
Average CPU utilization	37.9%	46.1%	50.4%
Average Network utilization	43.5%	54.5%	56.4%



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# 6. Conclusion

- Resource contention in DAG scheduling increase makespan
- Contention-free scheduler for ideal stages
  - DAG shop scheduling problem
  - NP-hard
  - A  $3/2$  approximation algorithm based on Johnson's rule
- RL-based scheduler for general stages
  - Apply graph neural network to encode stages
  - Adaptively adjust the contention level
- Resource utilization improve by about 30%



# Thanks

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For any questions, don't hesitate to email me at  
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