Packing Tasks with Dependencies

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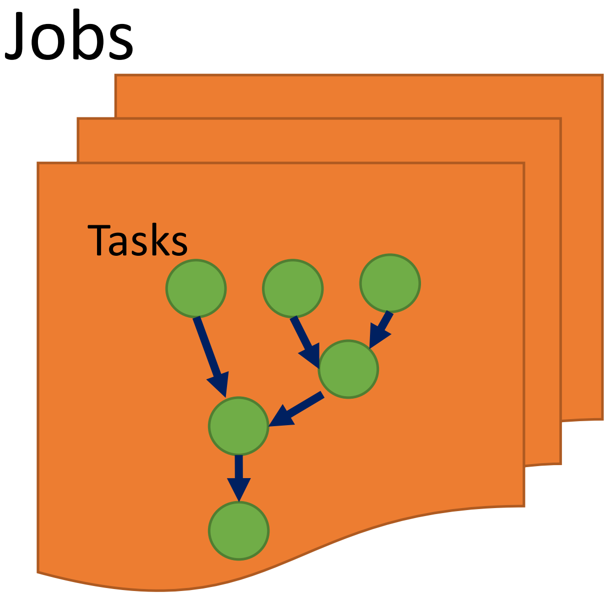
The Cluster Scheduling Problem



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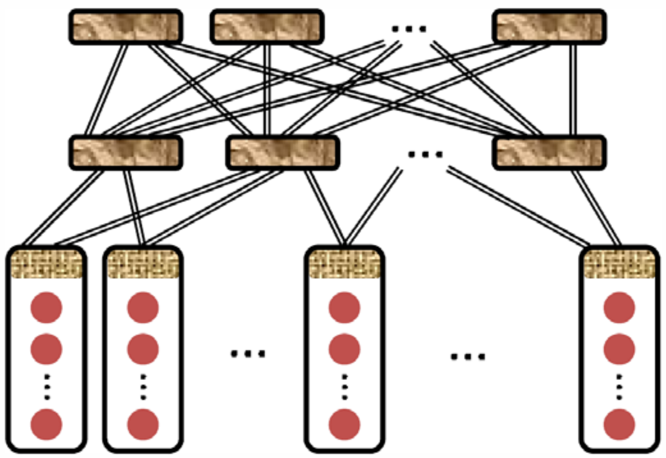

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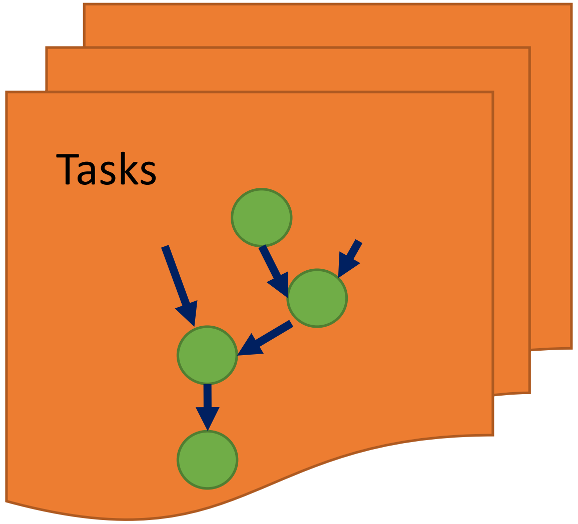

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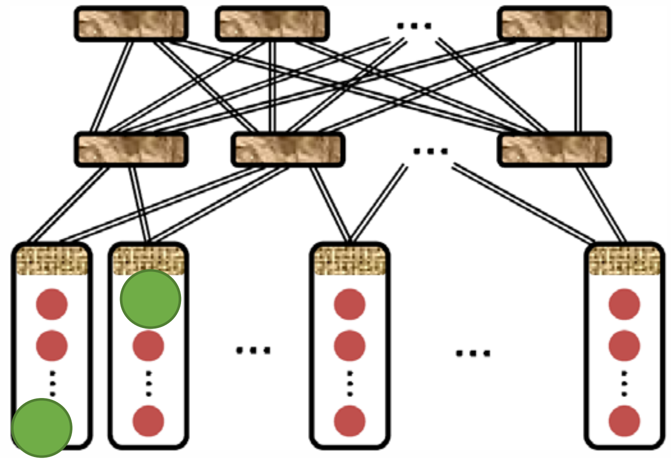

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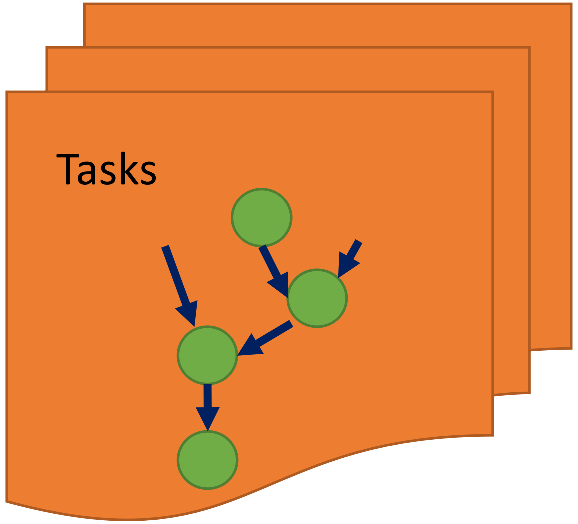

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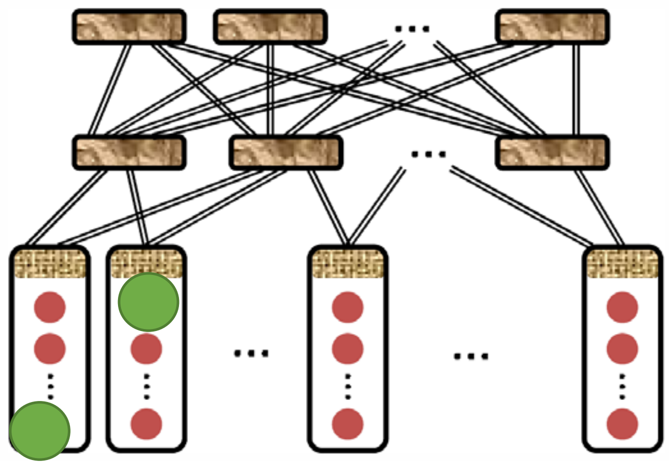
- High cluster utilization
- Fast job completion
- Guarantees (deadlines, fair shares)



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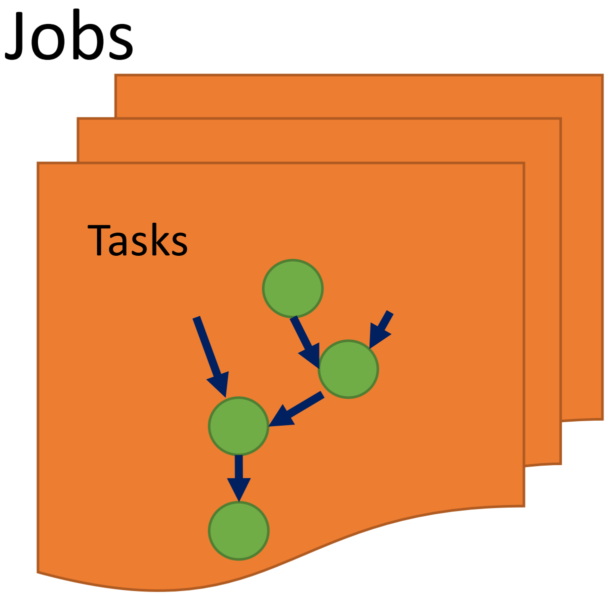

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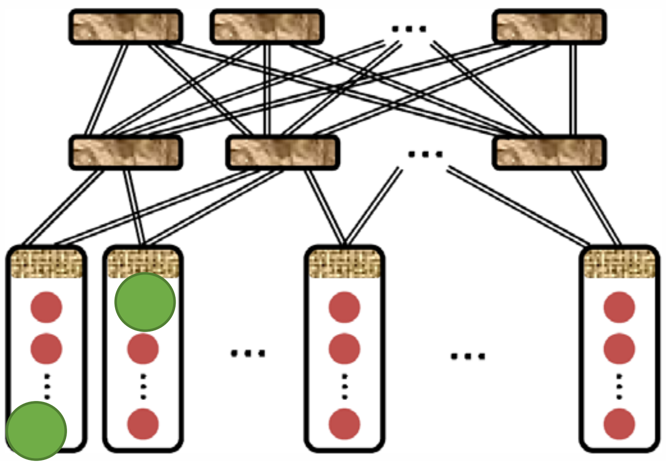
- Scale $\Rightarrow$ fast twitch



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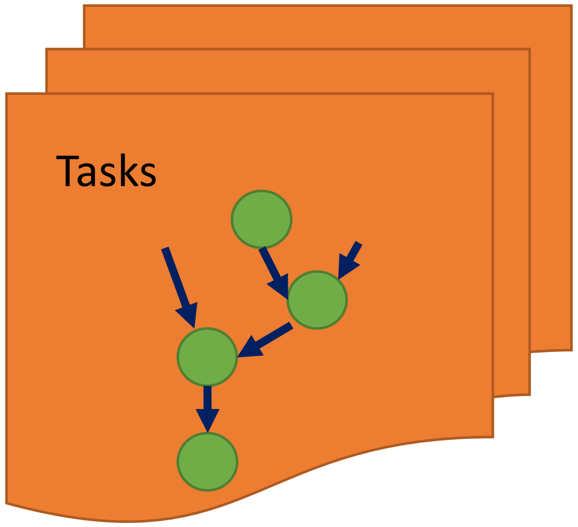

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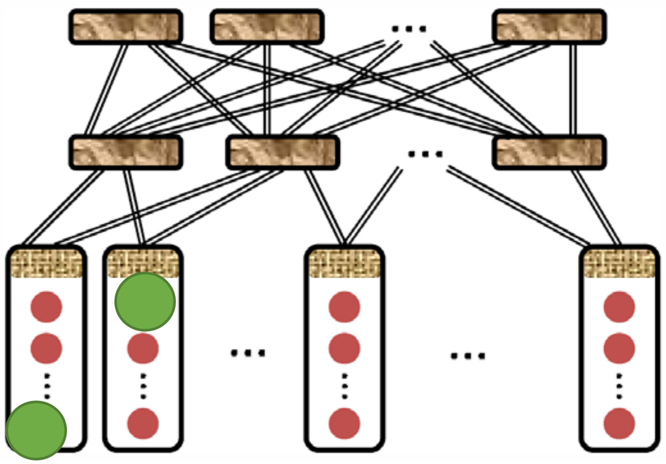

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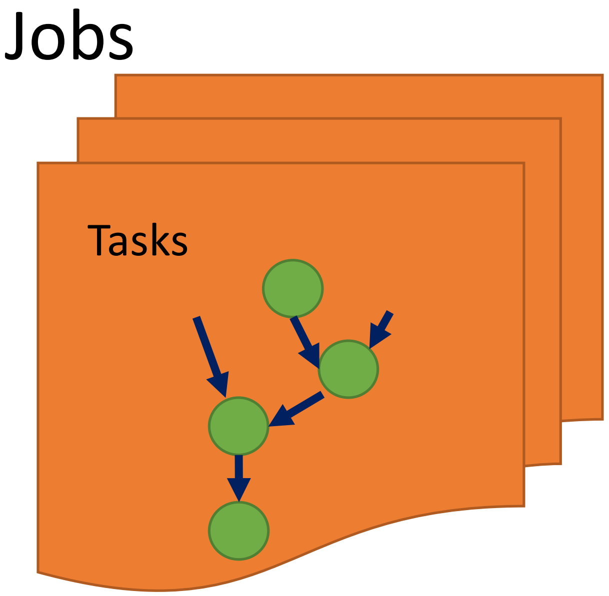

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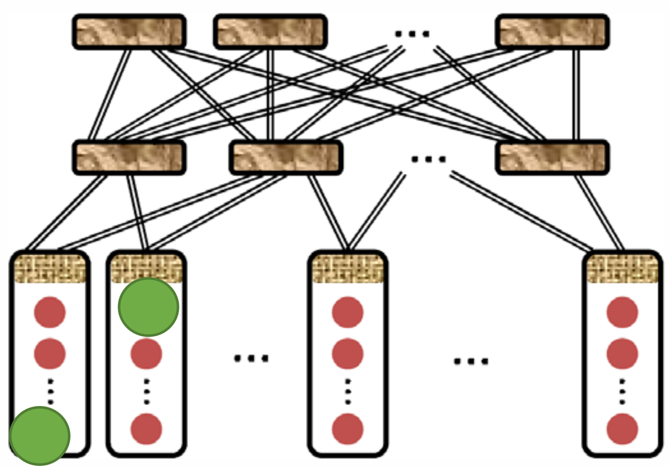

- Large and high-value deployments
  - E.g., Spark, Yarn*, Mesos*, Cosmos
- Today, schedulers are simple and (as we show) performance can improve a lot

Jobs have heterogeneous **DAGs**

User queries $\rightarrow$ Query optimizer $\rightarrow$ Job DAG

(Dryad, Spark-SQL, Hive,…)

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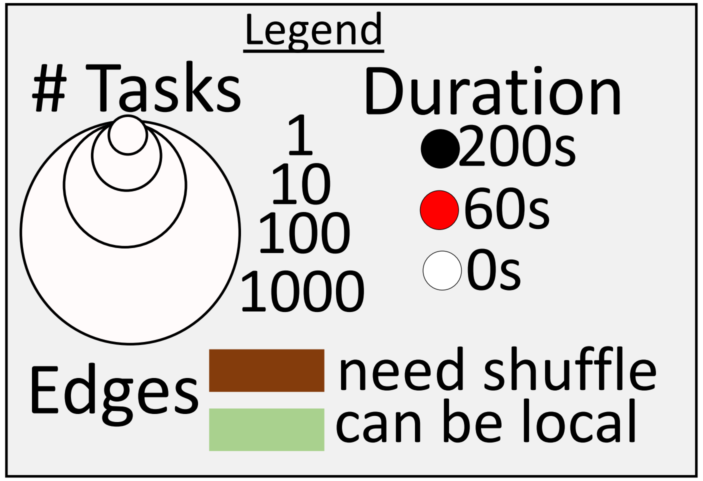
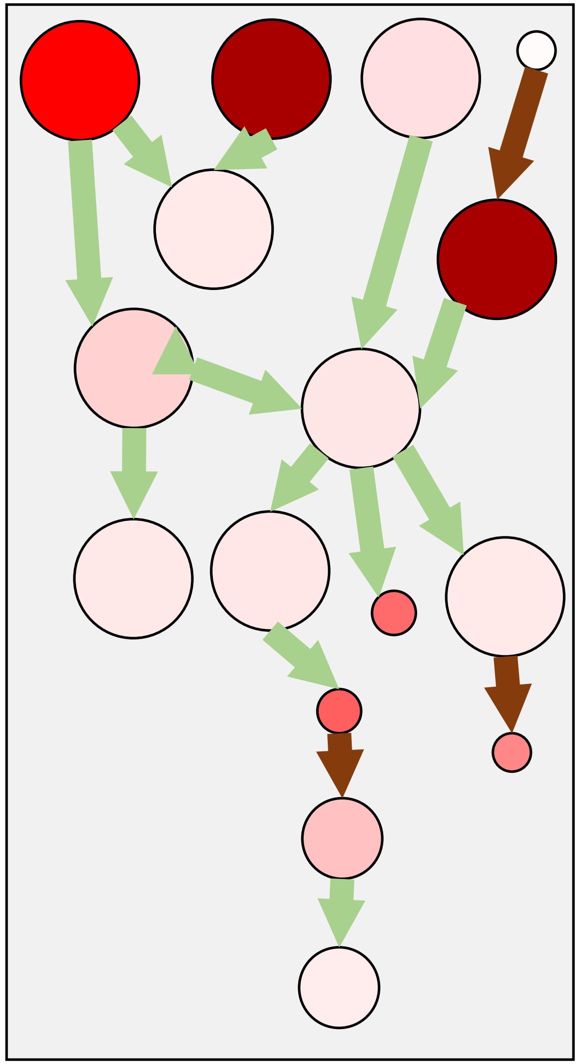


Example DAG



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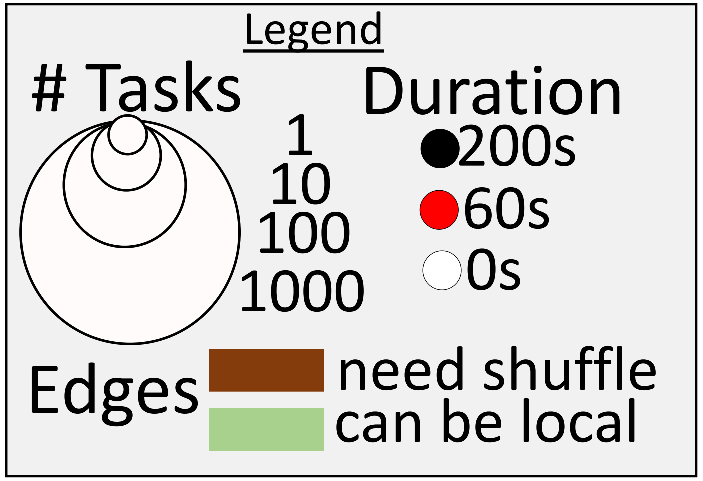

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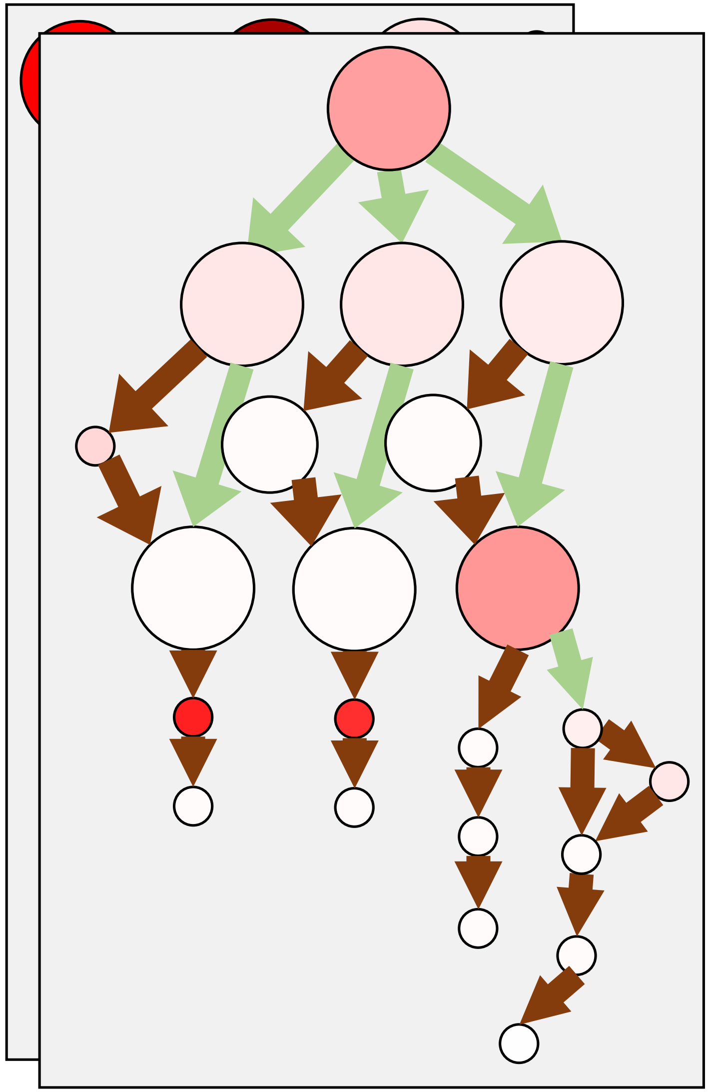
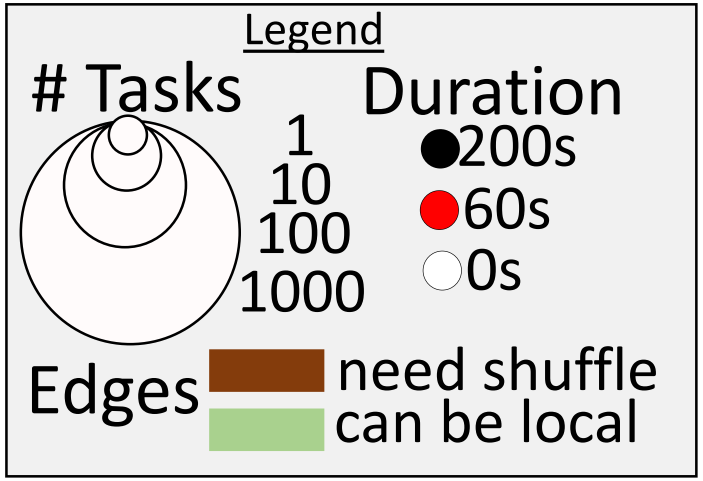


Jobs have heterogeneous DAGs

User queries → Query optimizer → Job DAG
(Dryad, Spark-SQL, Hive,…)

- DAGs have deep and complex structures
- Task durations range from <1s to >100s
- Tasks use different amounts of resources



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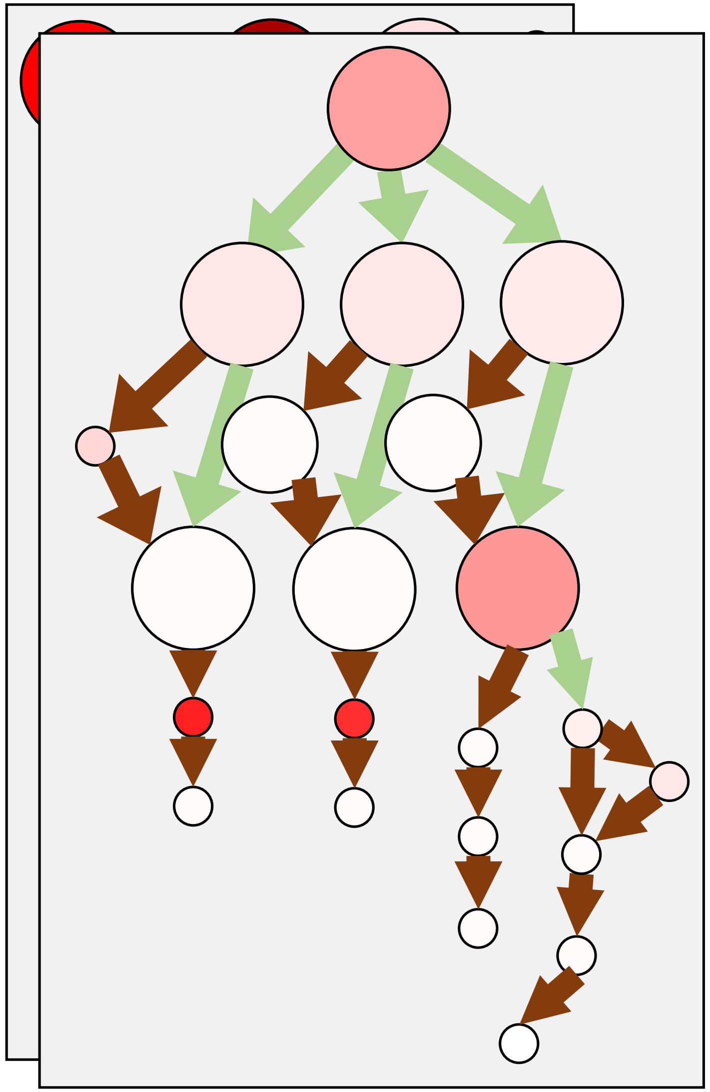
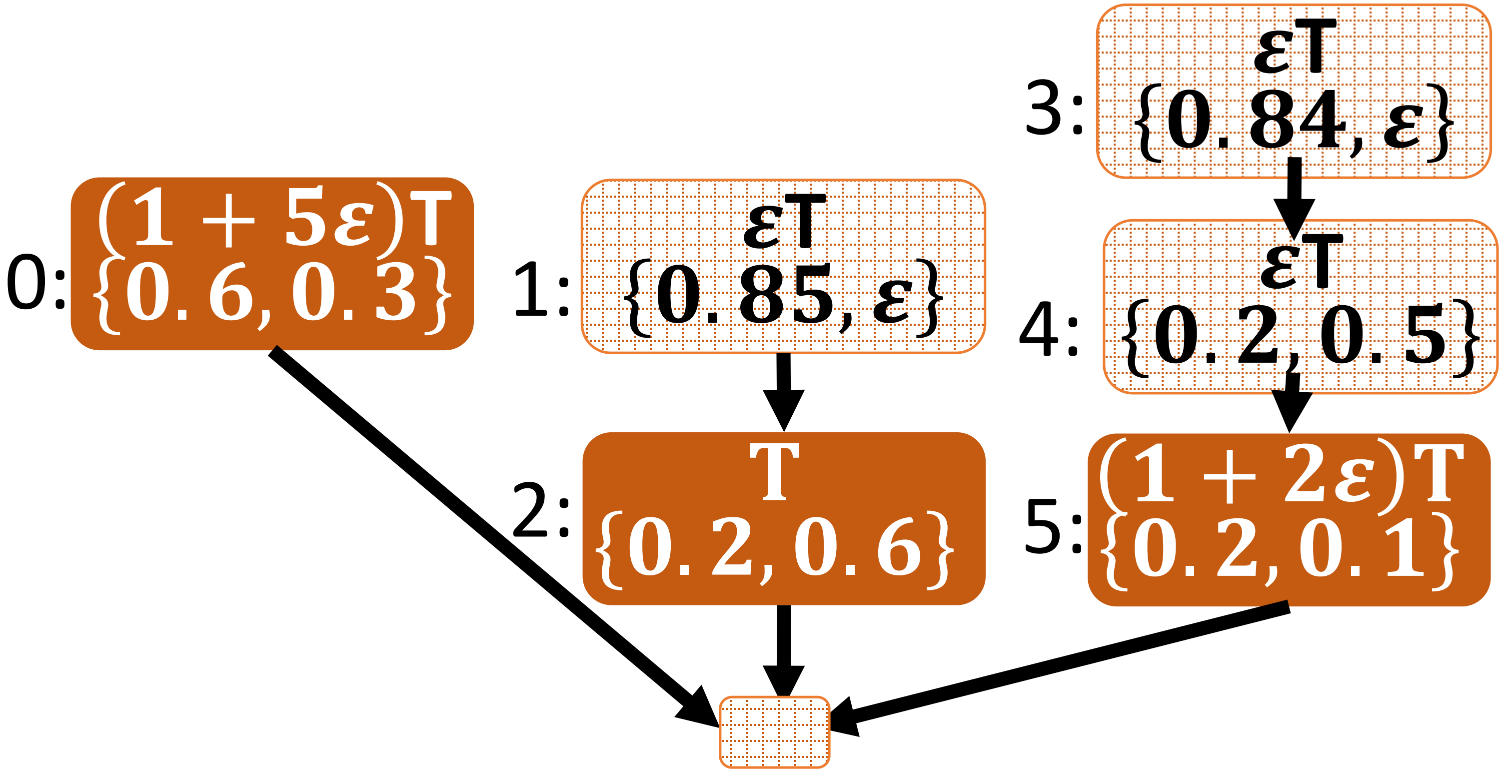


Challenges in scheduling heterogeneous DAGs



Challenges in scheduling heterogeneous DAGs

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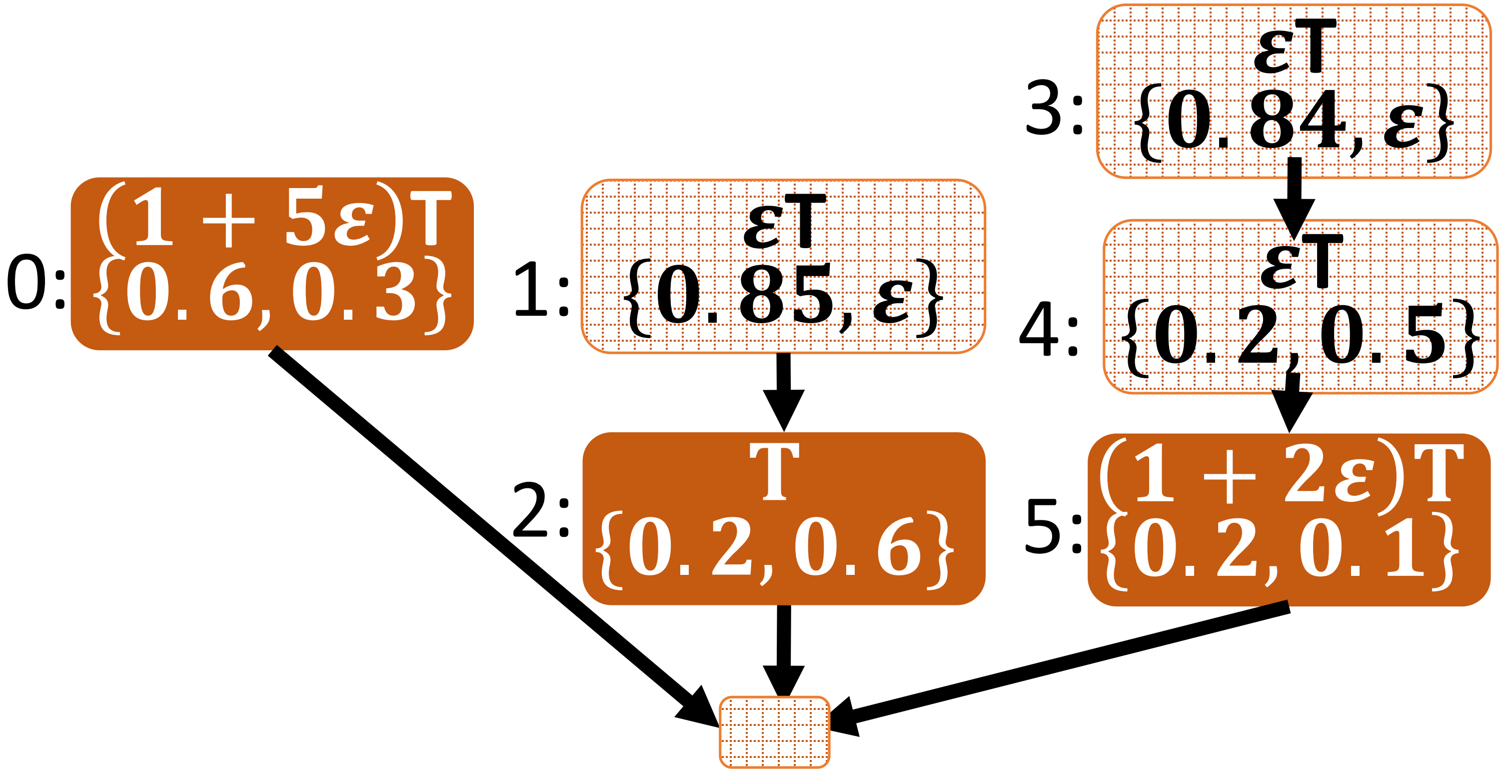

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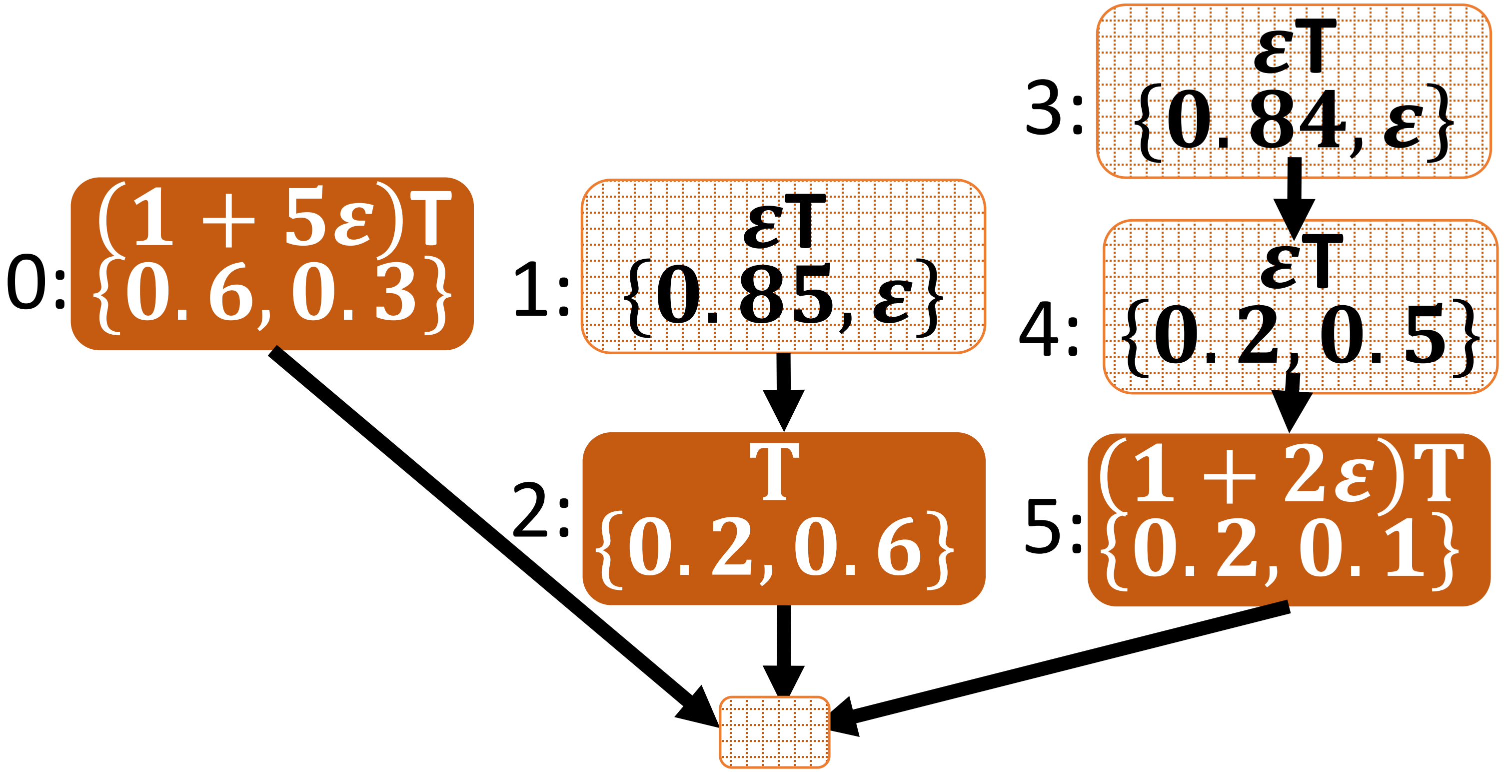

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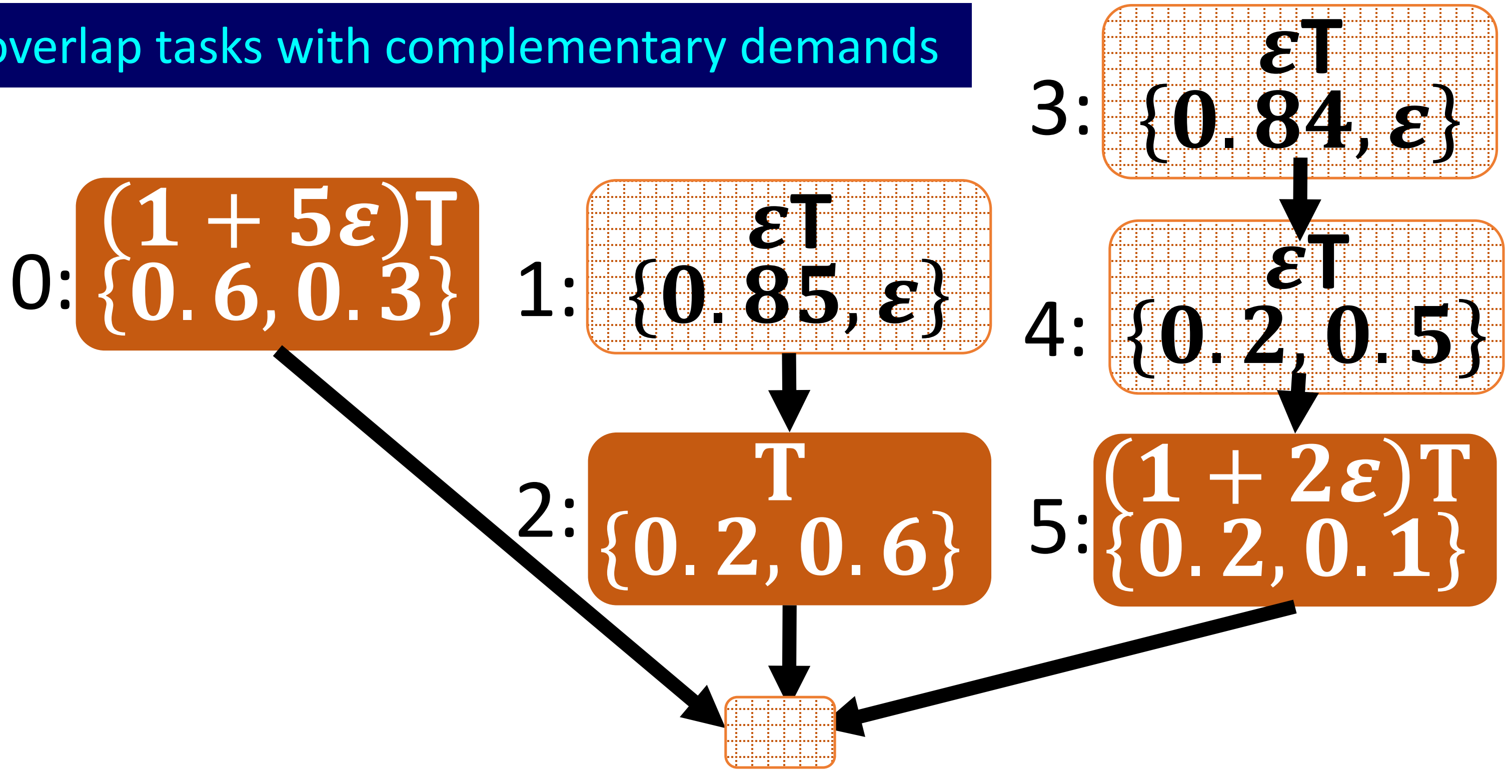

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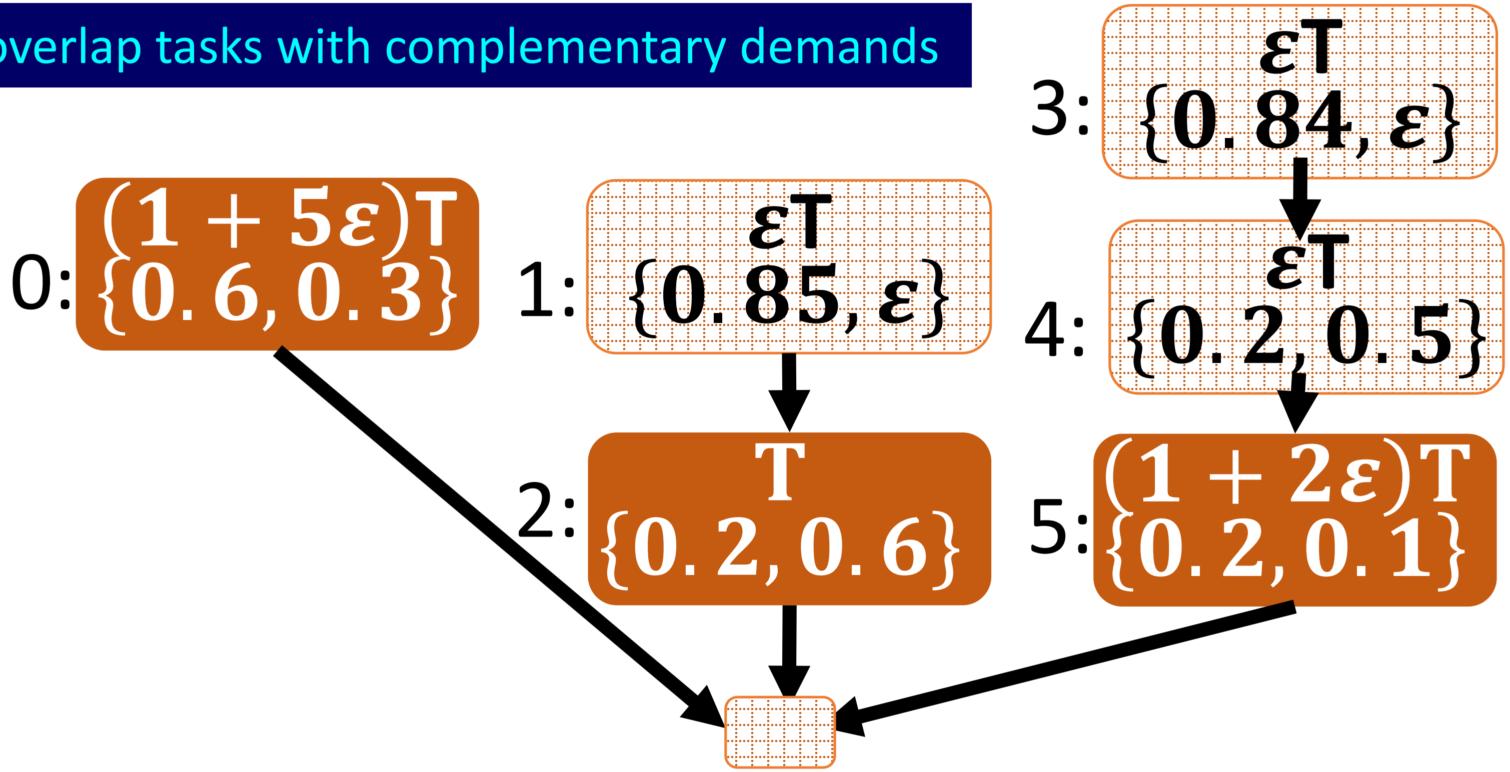

[1] Tetris: Multi-resource Packing for Cluster Schedulers, SIGCOMM'14

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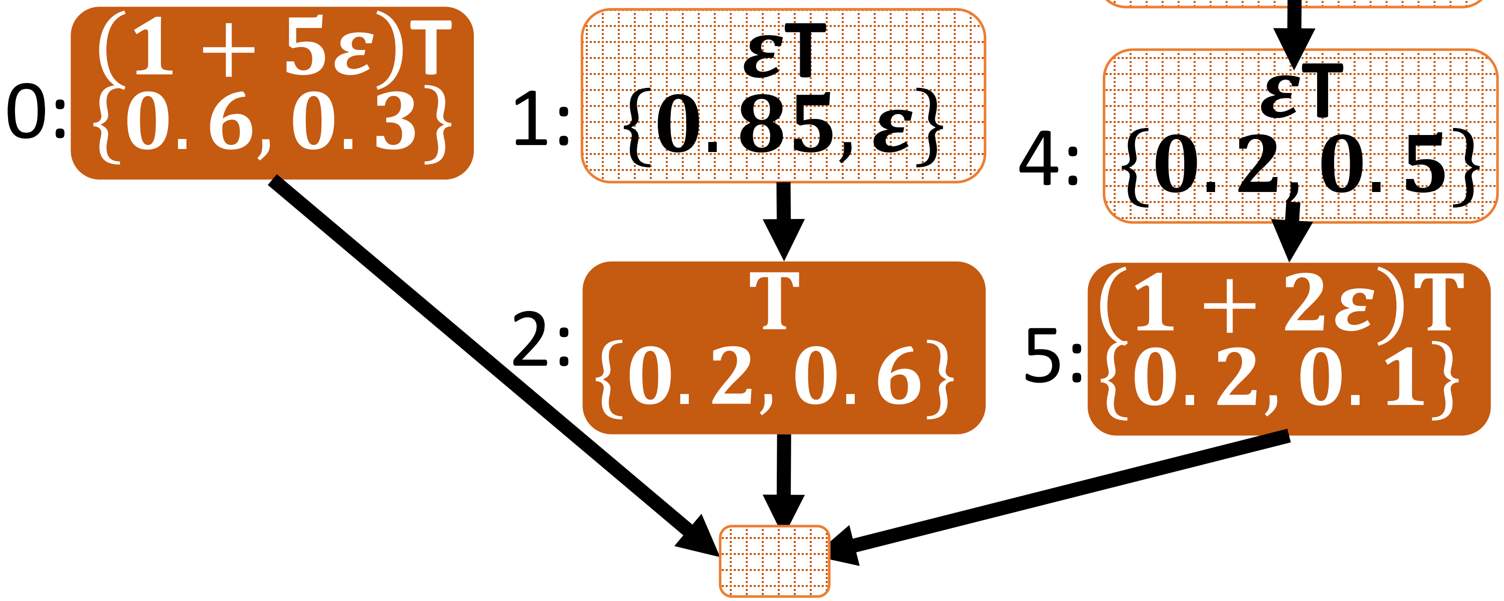

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Technique	Execution Order	Time	Worst-case
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CPSched	$t_0 \to t_3 \to t_4 \to t_5 \to t_1 \to t_2$	$3T$	$O(n) \times$ OPT n tasks
Packers[1]	$t_0 \to t_1 \to t_3 \to t_2 \to t_4 \to t_5$	$3T$	$O(d) \times$ OPT d resources

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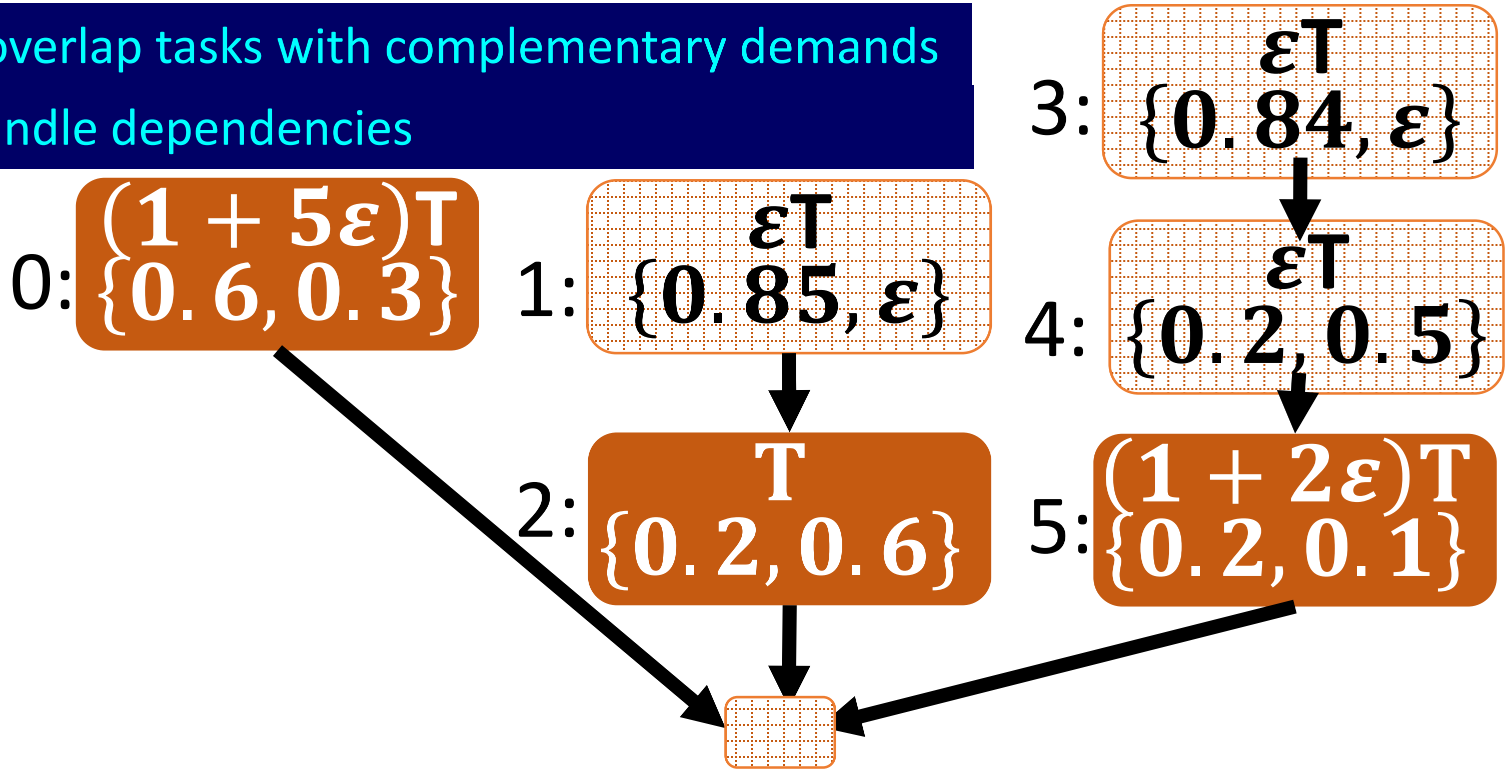

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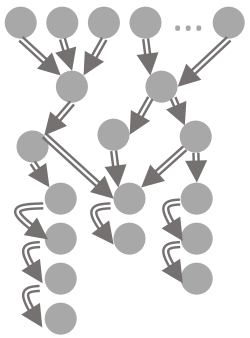
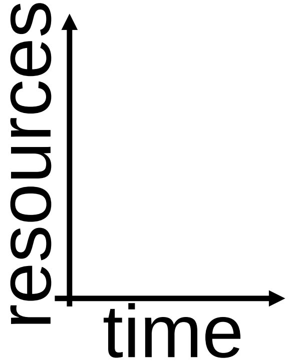
2. Production DAGs are roughly 50% slower than lower bounds
3. Simple variants of “Packing dependent tasks” are NP-hard problems
4. Prior analytical solutions miss some practical concerns
    - Multiple resources
    - Complex dependencies
    - Machine-level fragmentation
    - Scale; Online; …

Given an annotated DAG
and available resources,
compute a good schedule

+ practical model

Main ideas for one DAG





Existing schedulers:

A task is schedulable *after* all its parents have *finished*

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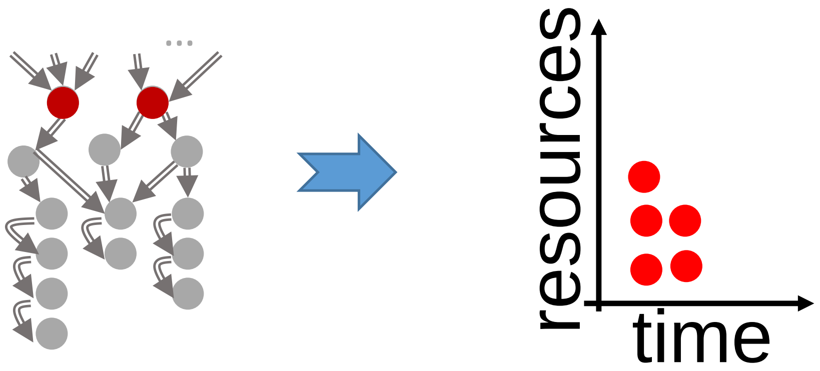

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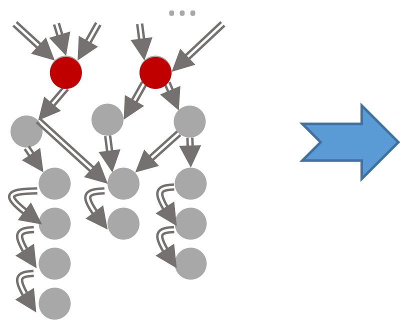

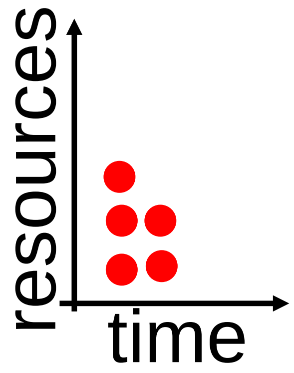

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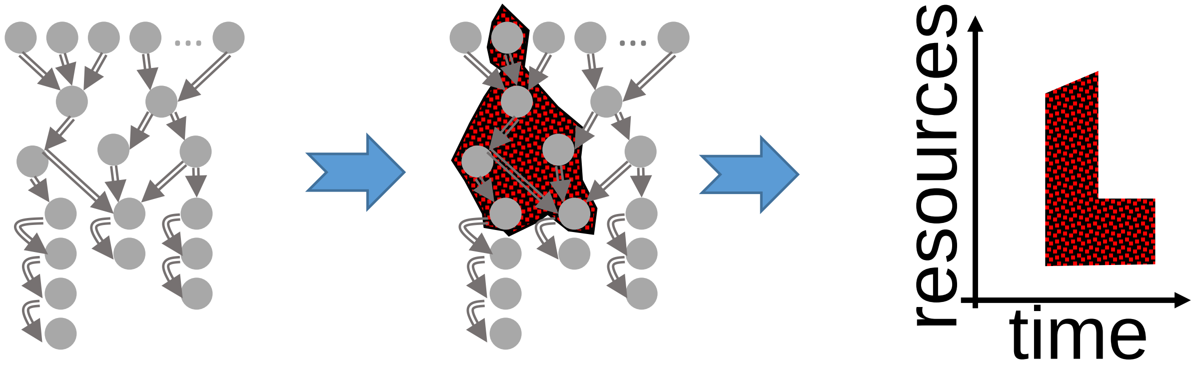

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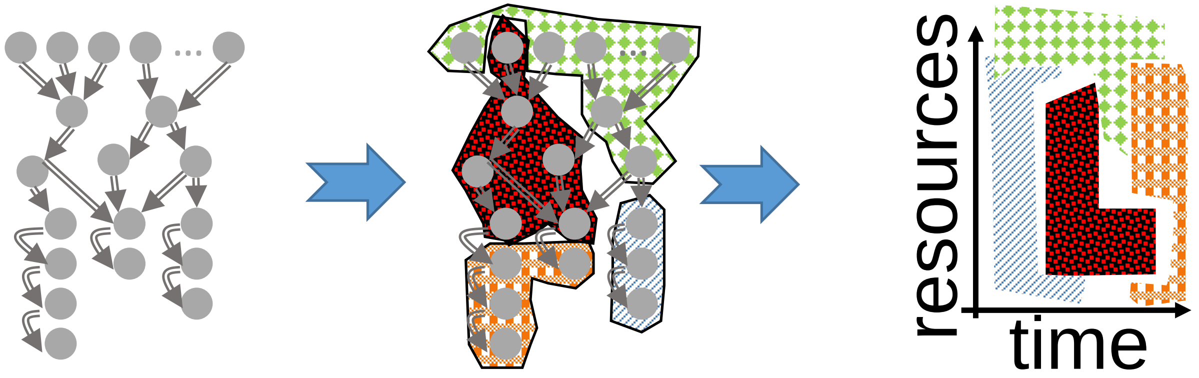

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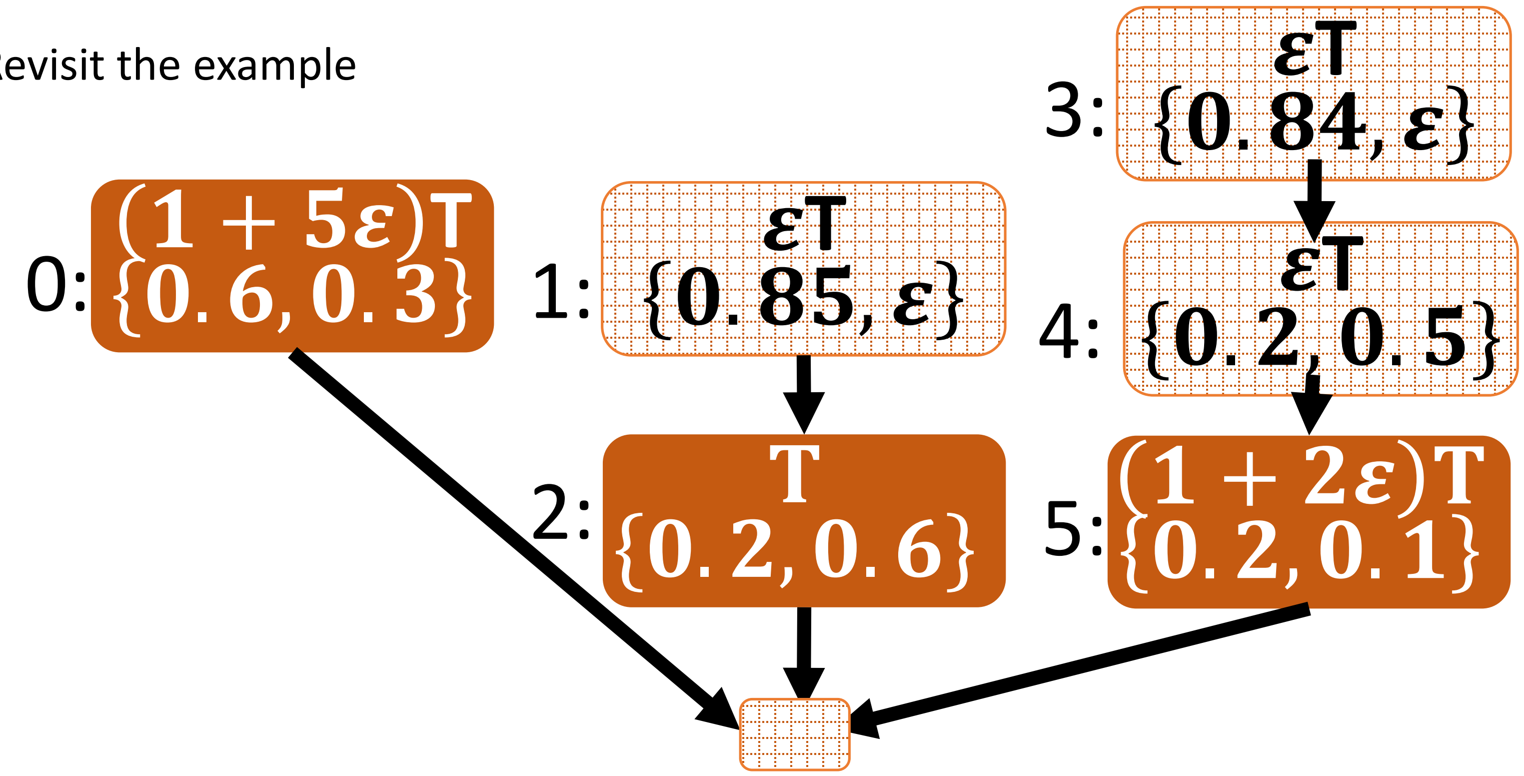
Identifies *troublesome tasks* and places them *first*

Place other tasks around trouble

Does placing troublesome tasks first help?

Revisit the example



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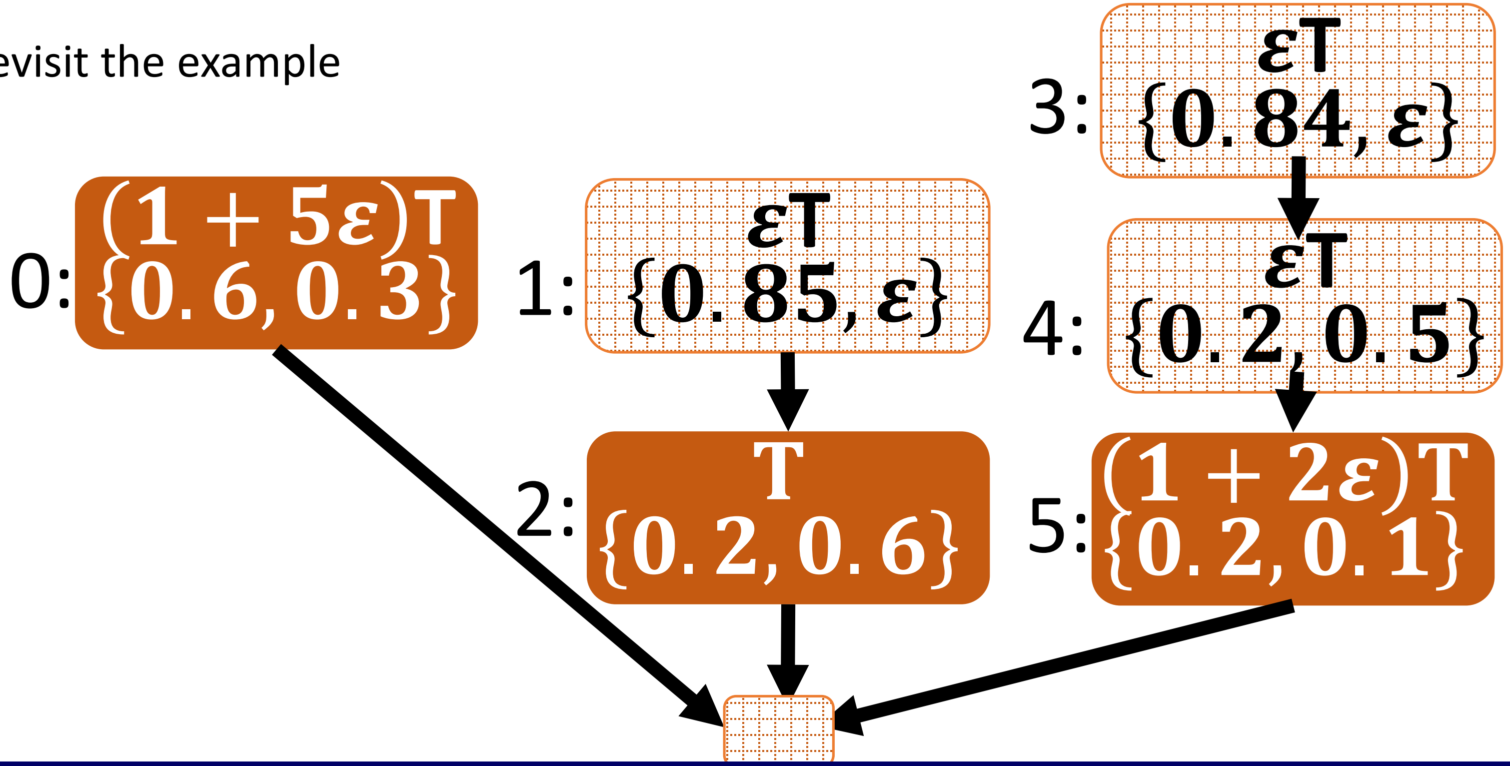

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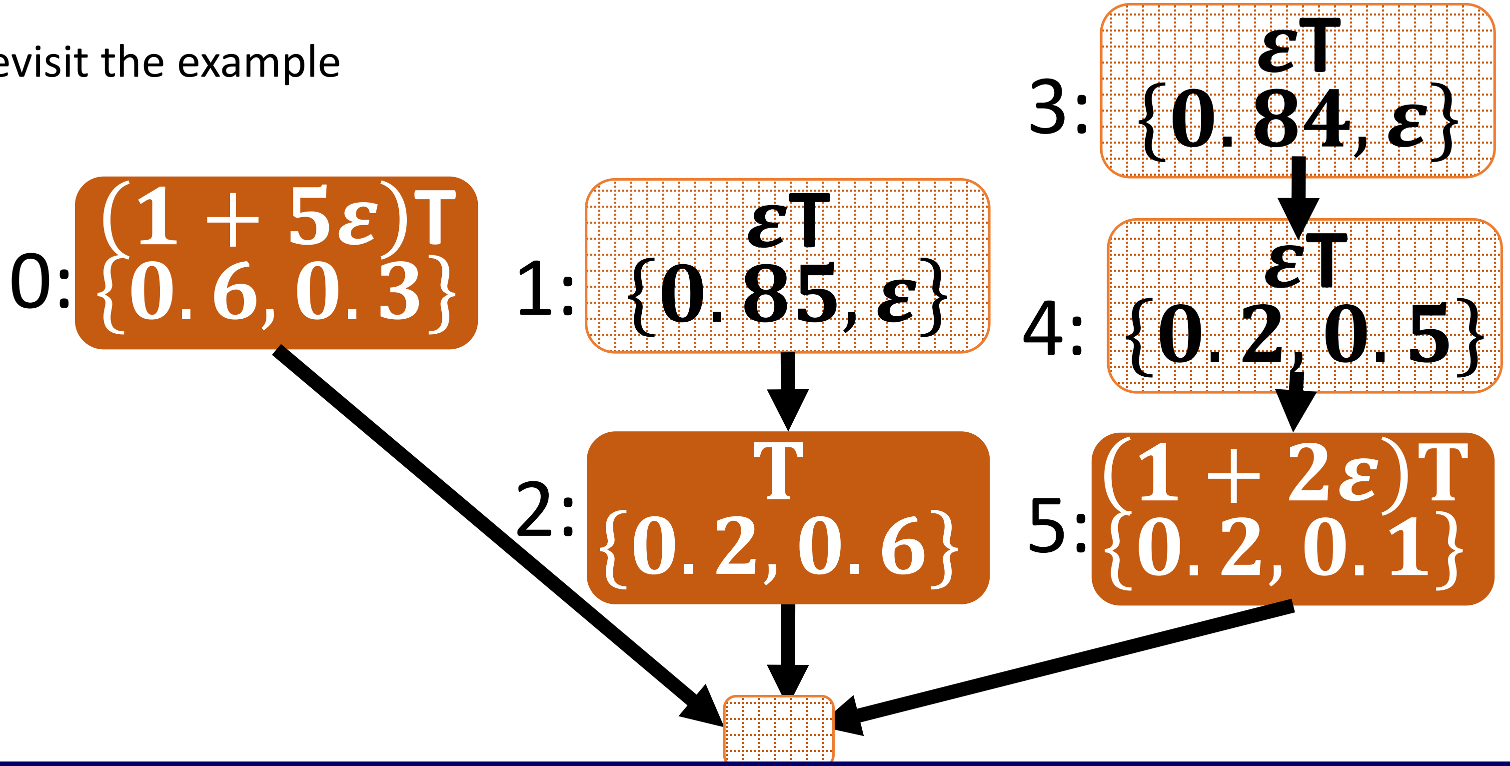

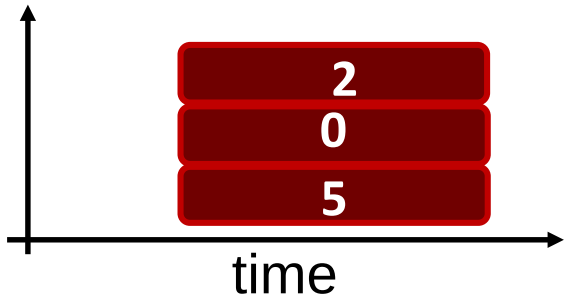

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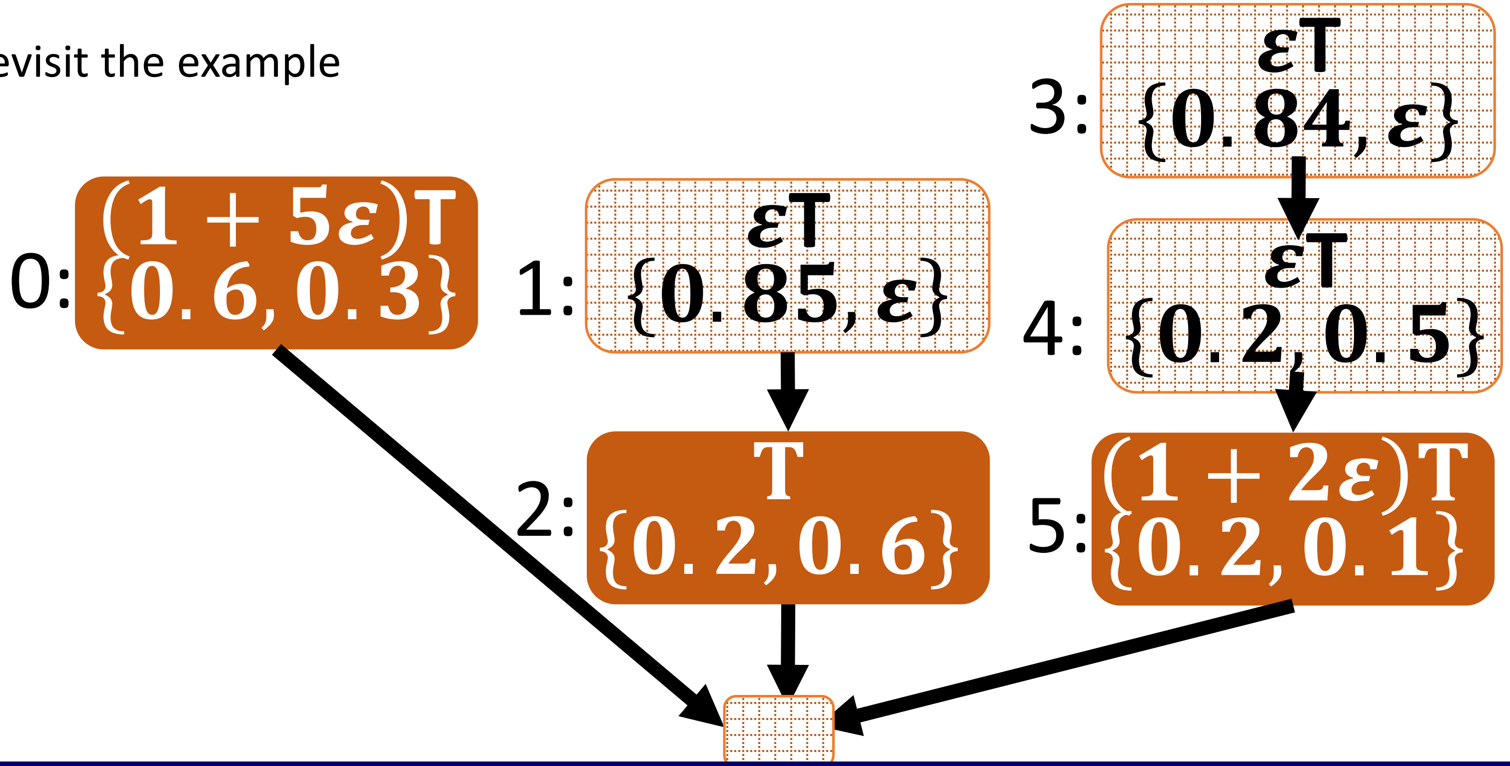

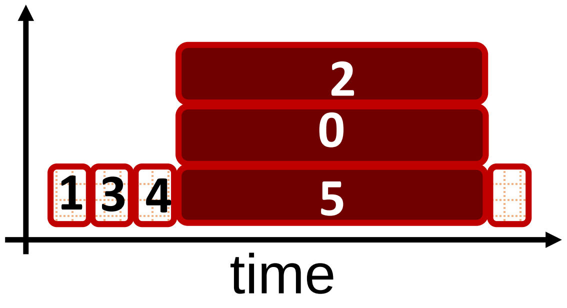

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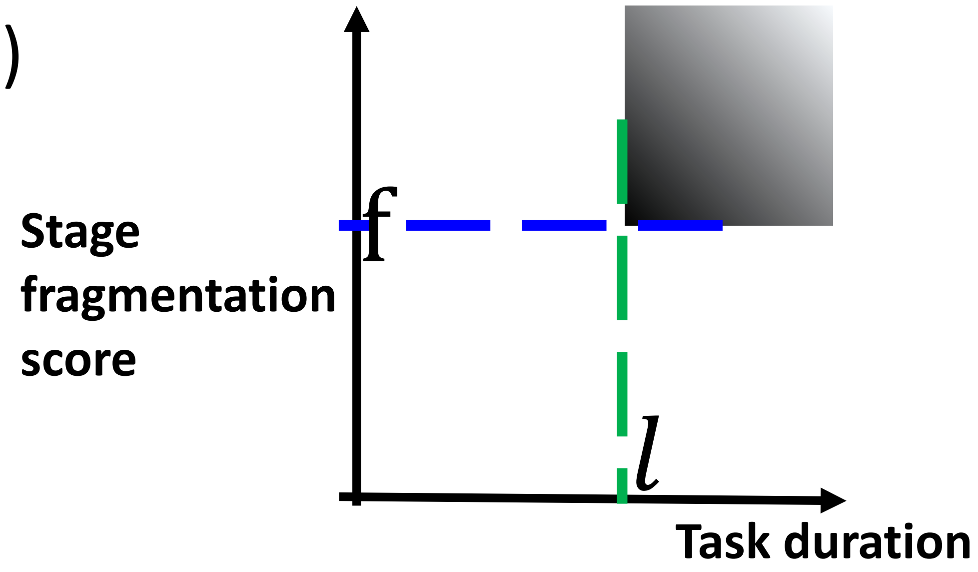

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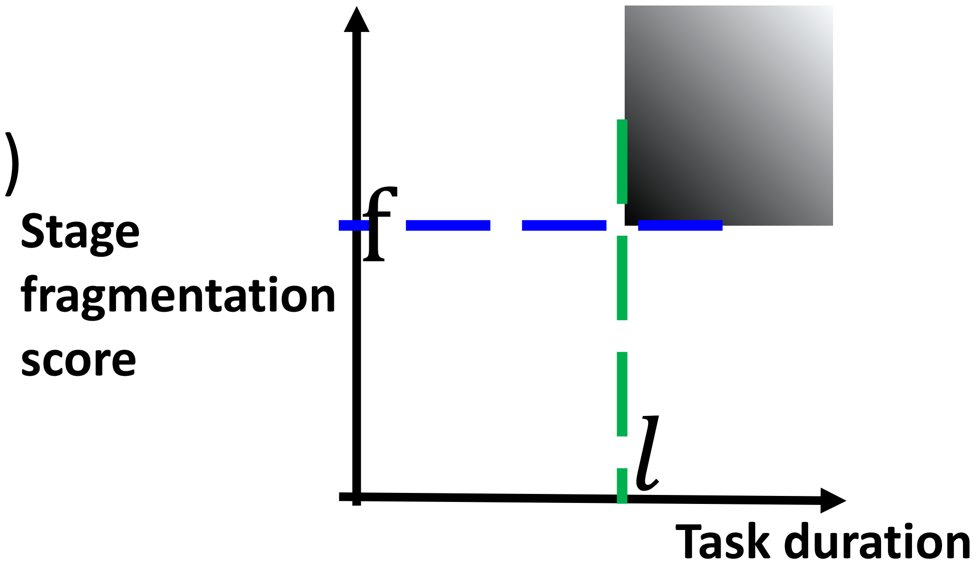
Graphene:

`BuildSchedule(T)` $\left\{ \begin{matrix} \text{and} \\ \text{or} \end{matrix} \right\}$



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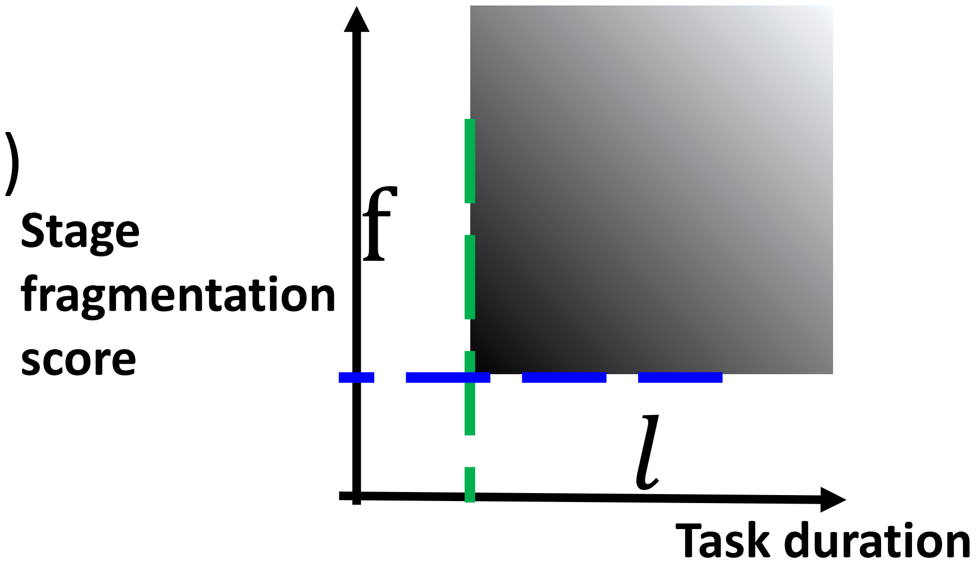

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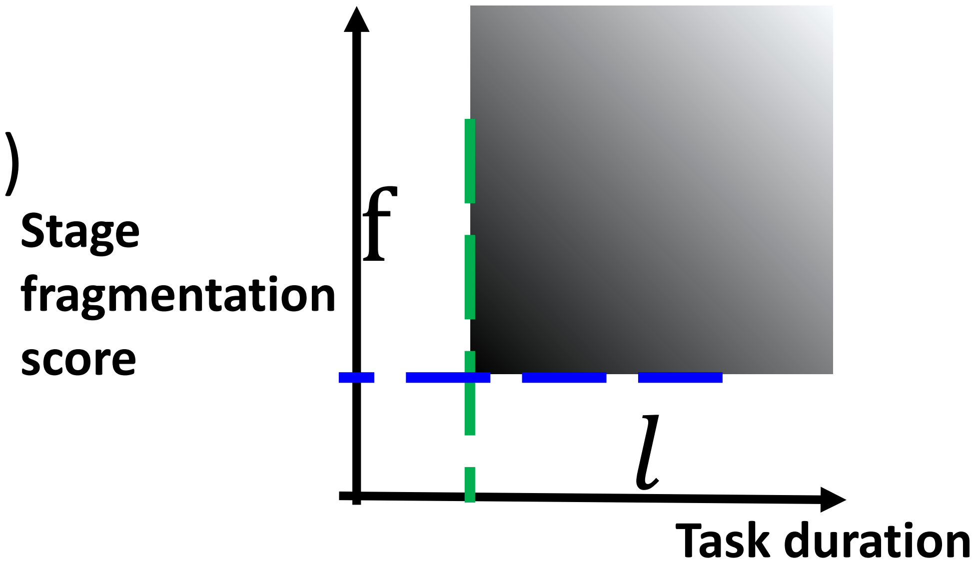
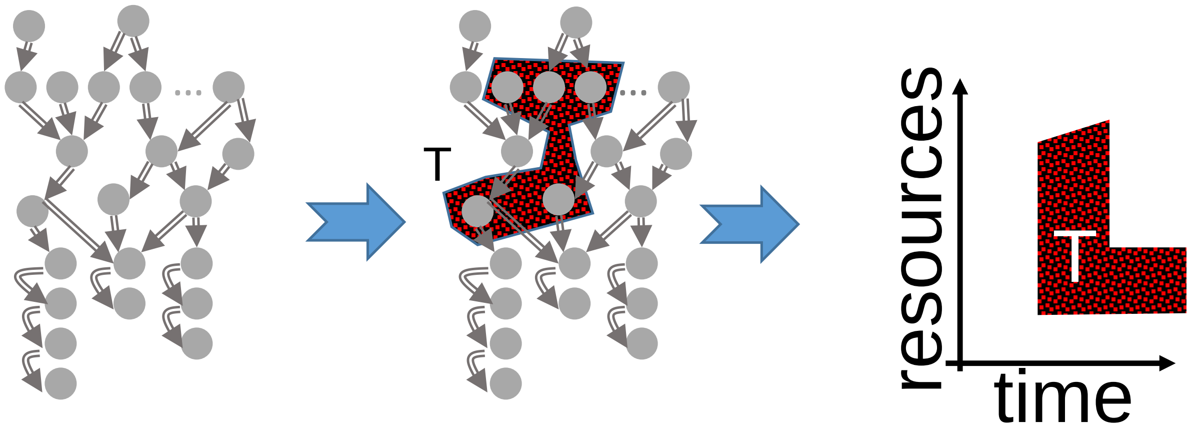


Extensions

1) Explore different choices of T in parallel
2) Recurse
3) Memoize …

Schedule dead-ends



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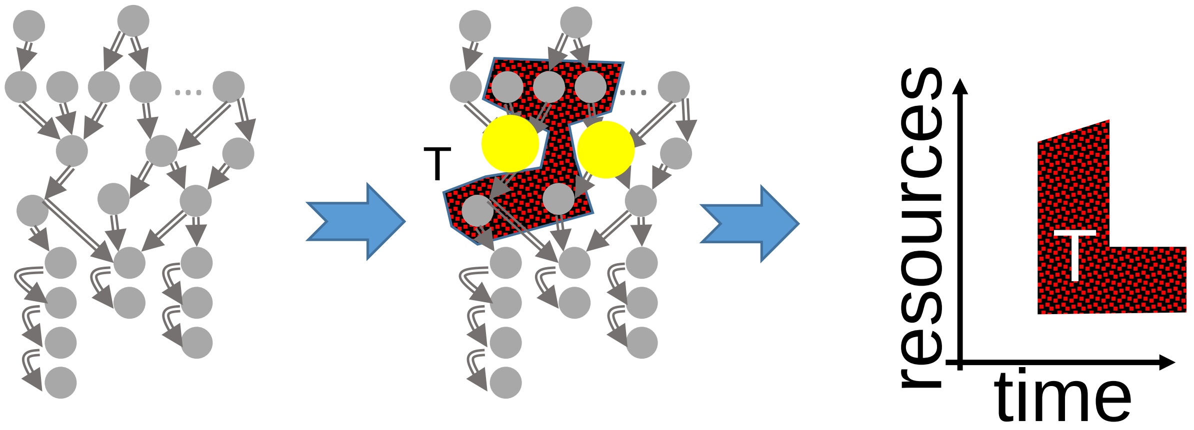

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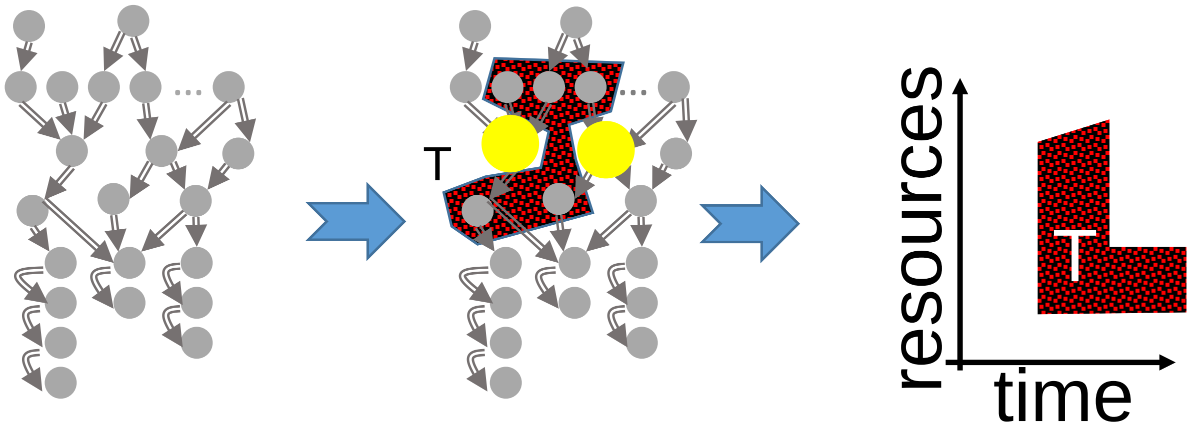

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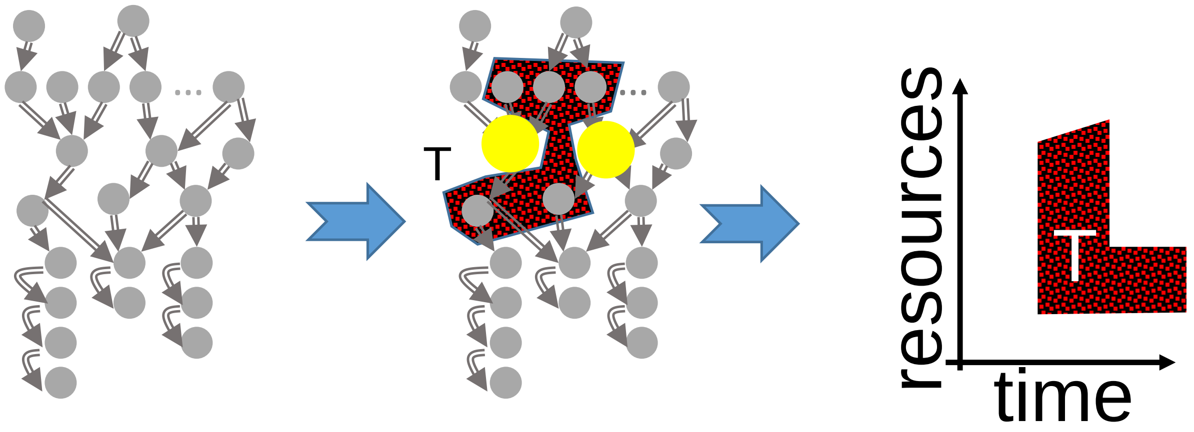

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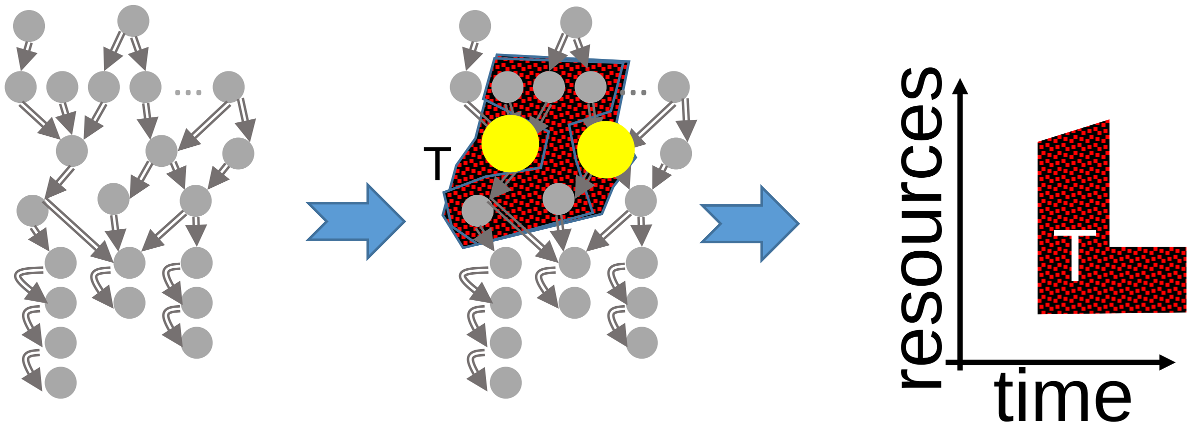

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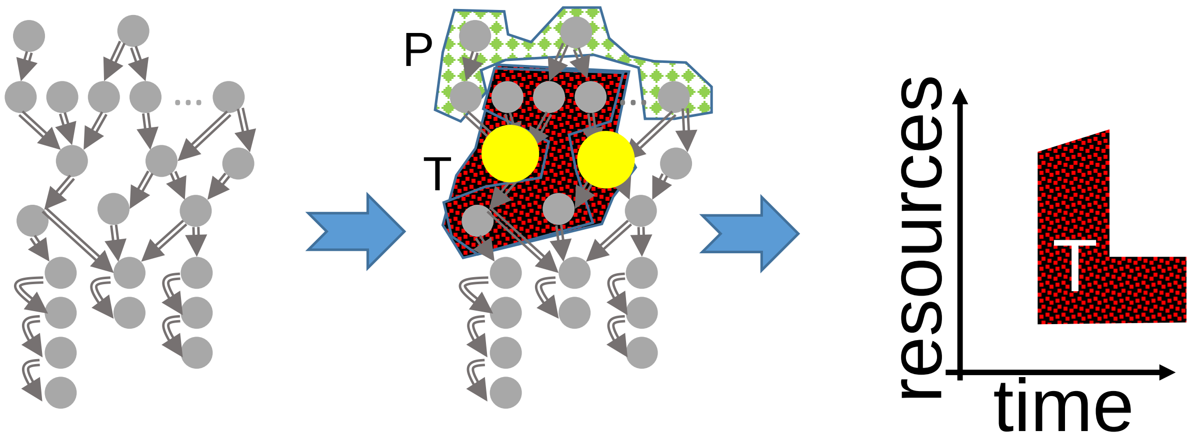

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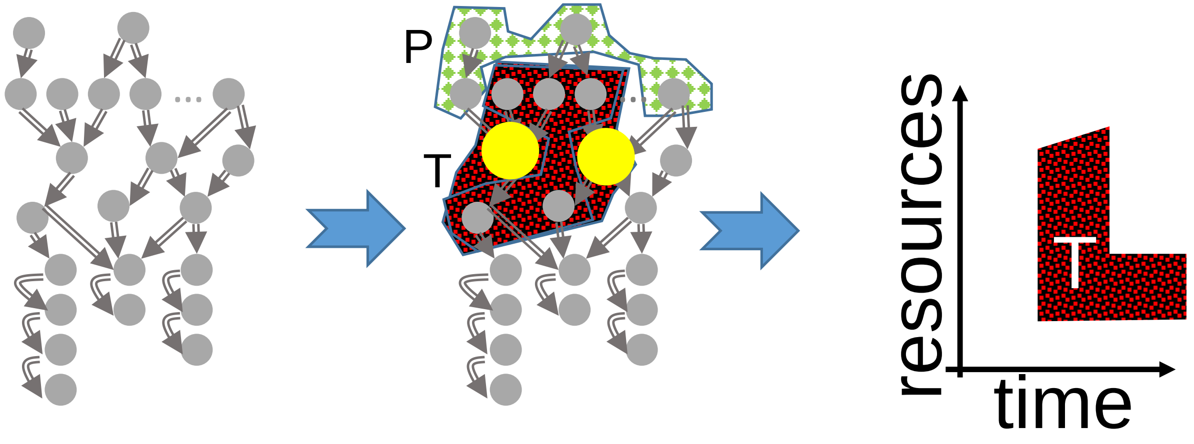

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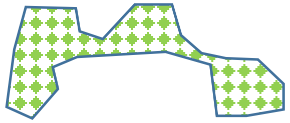
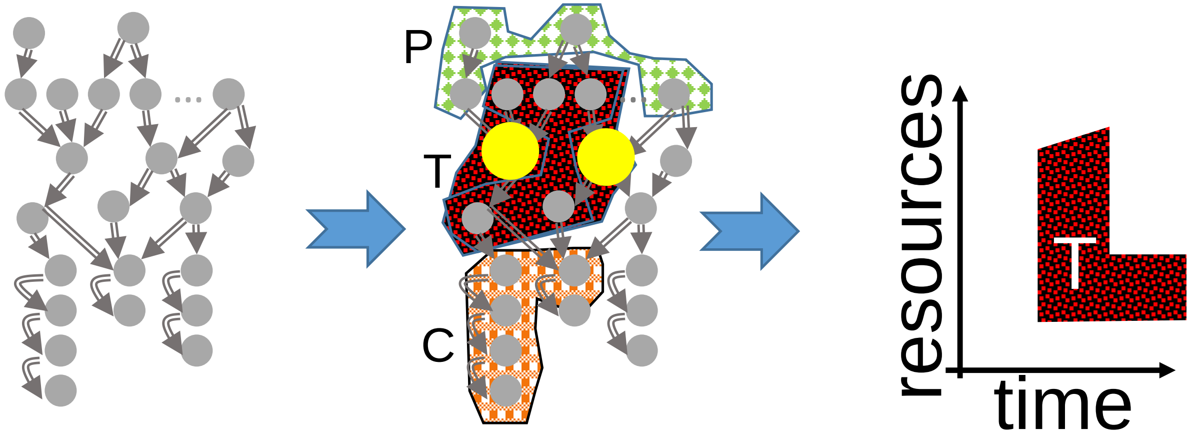
2) When placing tasks in , P, have to go *backwards* (place task after all children are placed)

Schedule dead-ends



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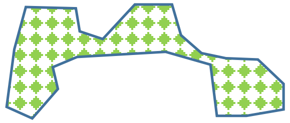
2) When placing tasks in , P, have to go *backwards* (place task after all children are placed)

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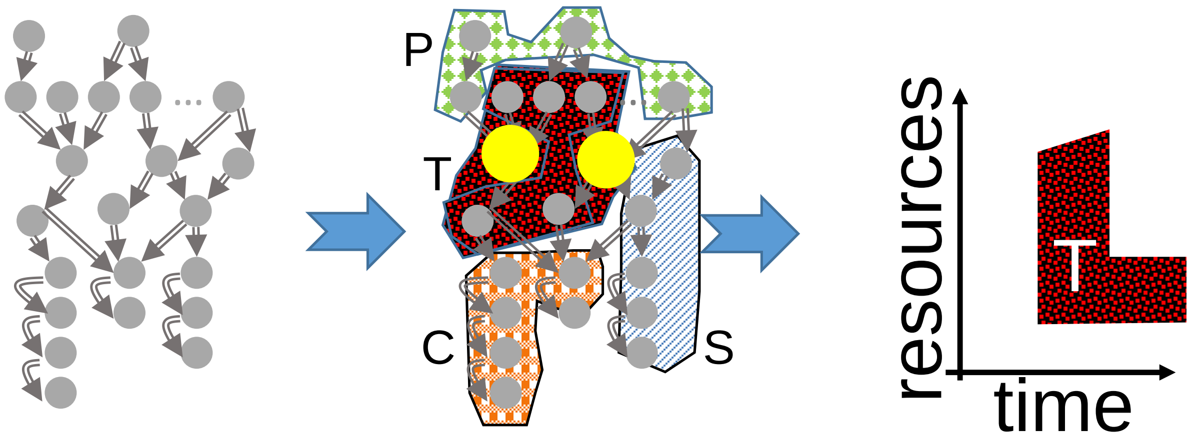

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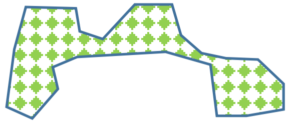
2) When placing tasks in , P, have to go *backwards* (place task after all children are placed)

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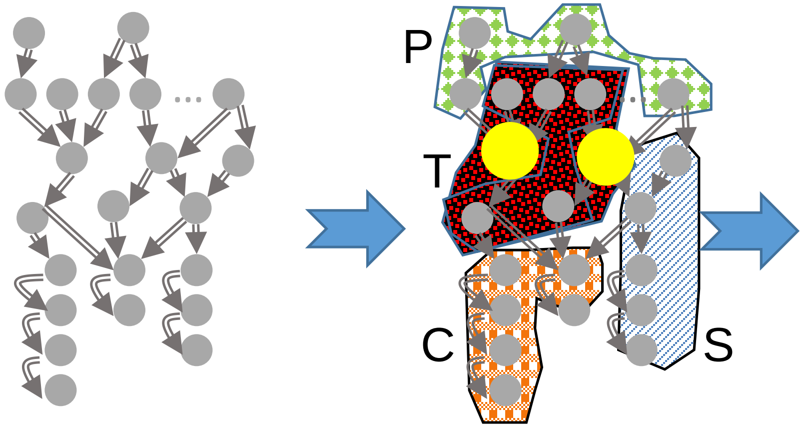
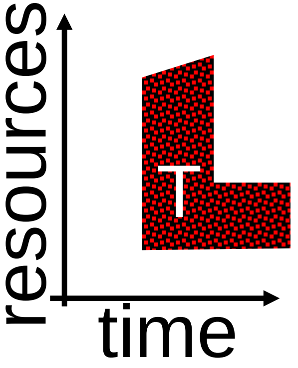
Which of these orders are legit?

$T_{fb}P_bS_fC_f$

$T_{fb}P_bC_fS_f$

$T_{fb}S_{fb}P_bC_f$





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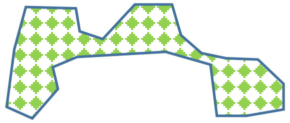
2) When placing tasks in , P, have to go *backwards* (place task after all children are placed)

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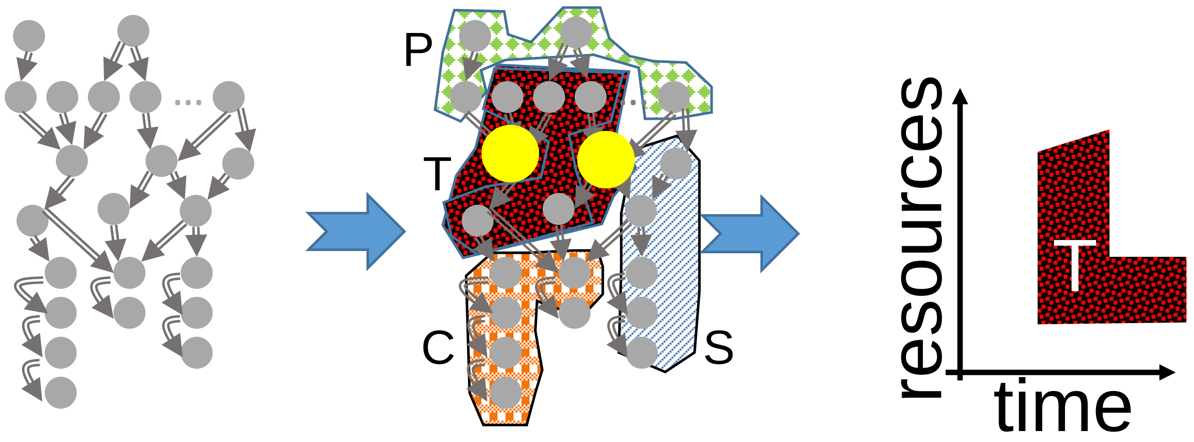

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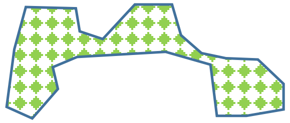
2) When placing tasks in  , P, have to go *backwards* (place task after all children are placed)

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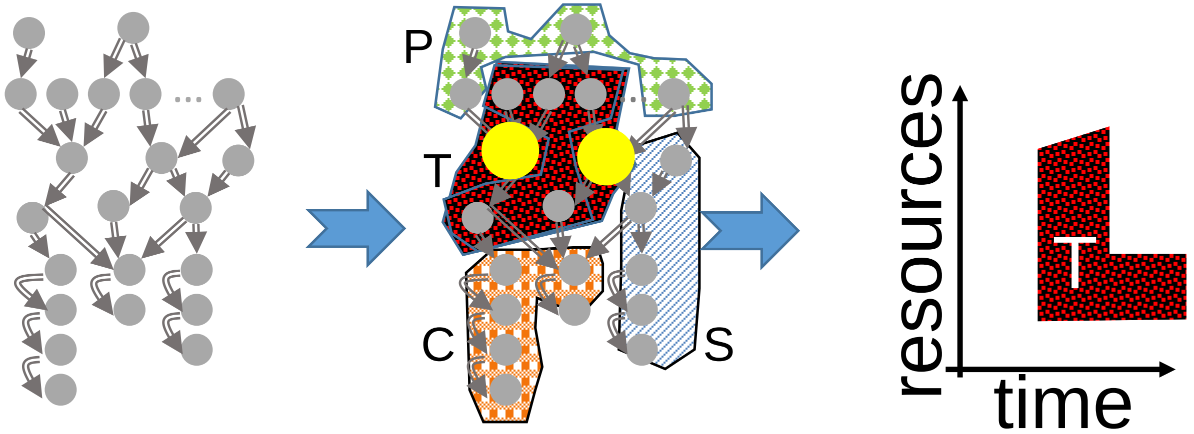

Graphene explores all orders and avoids dead-ends

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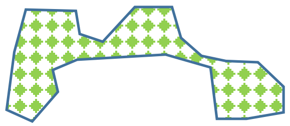
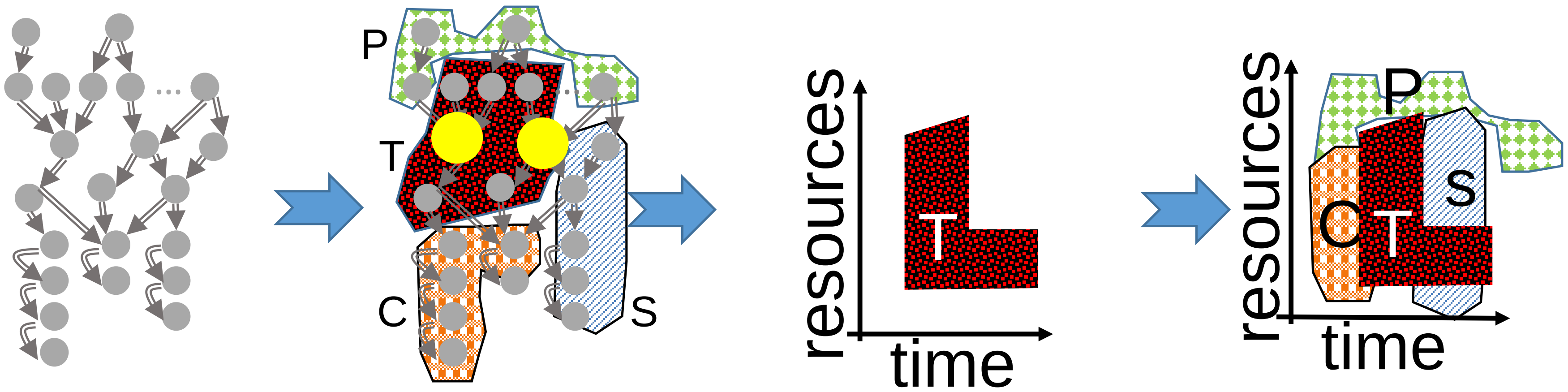
2) When placing tasks in , P, have to go *backwards* (place task after all children are placed)

Main ideas for one DAG



1. Identify *troublesome tasks* and place them *first*
2. Systematically place tasks to avoid dead-ends

Computed offline schedule for

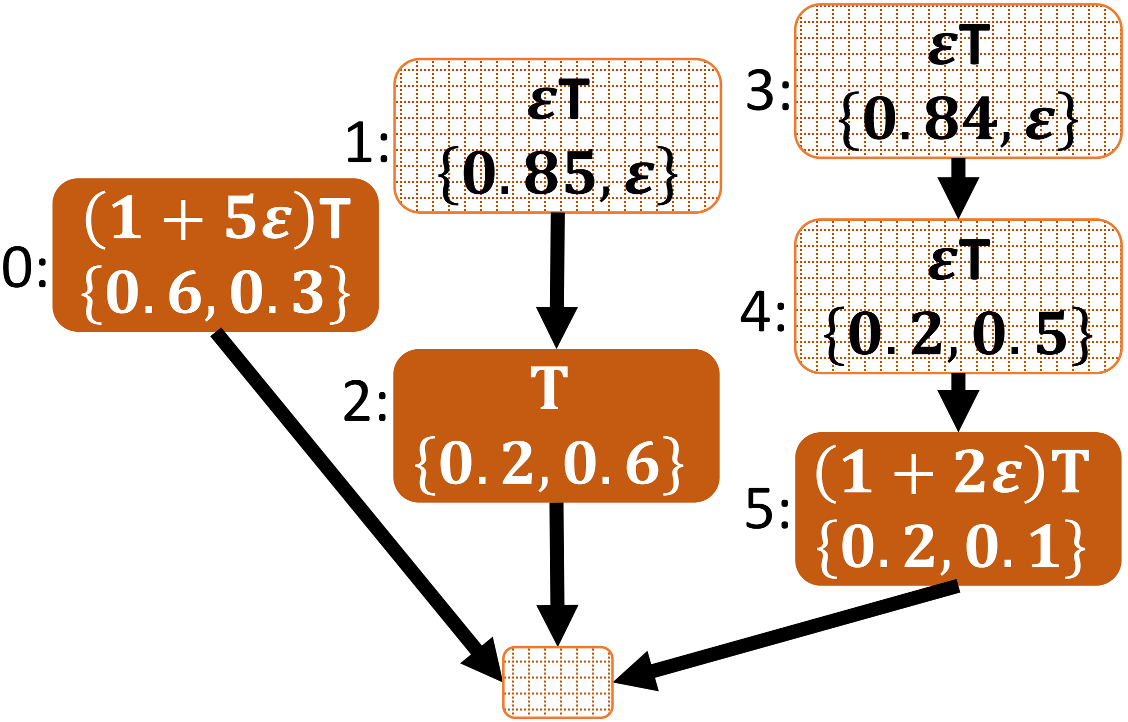
One DAG

Production clusters have

Multiple DAGs

Convert offline schedule to priority order on tasks

Convert offline schedule to priority order on tasks



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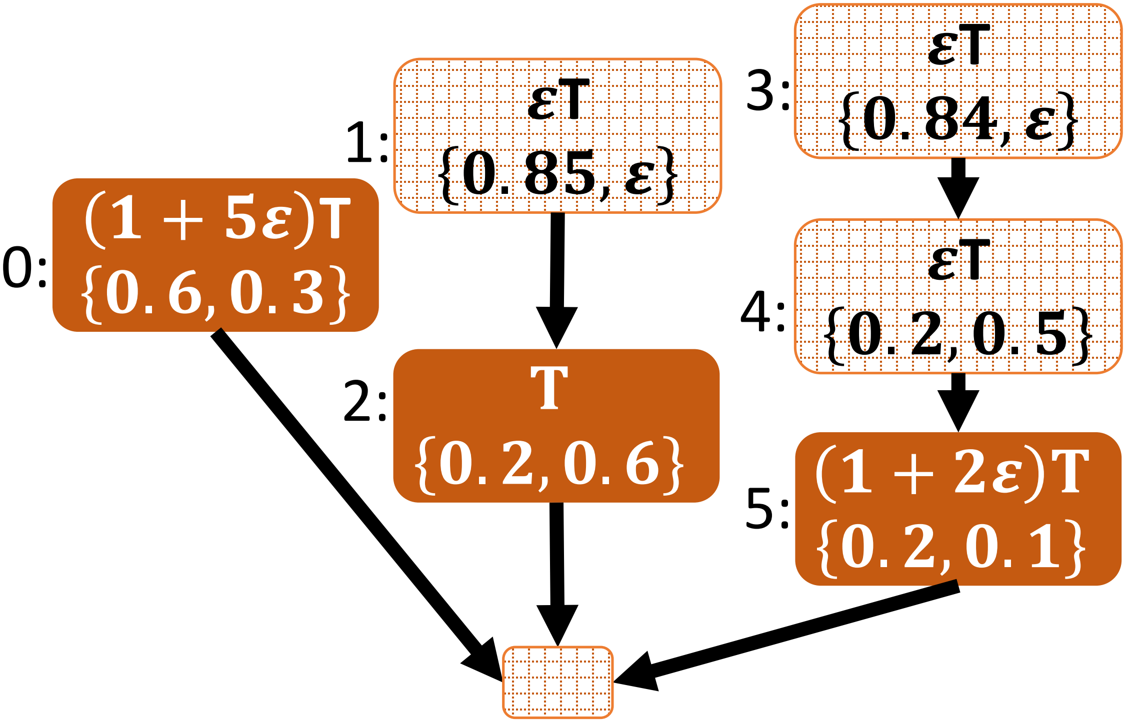

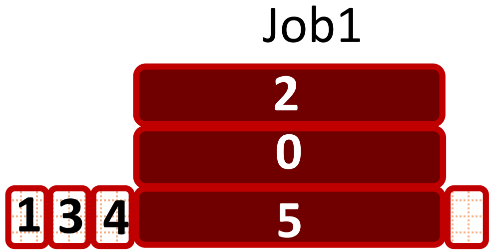

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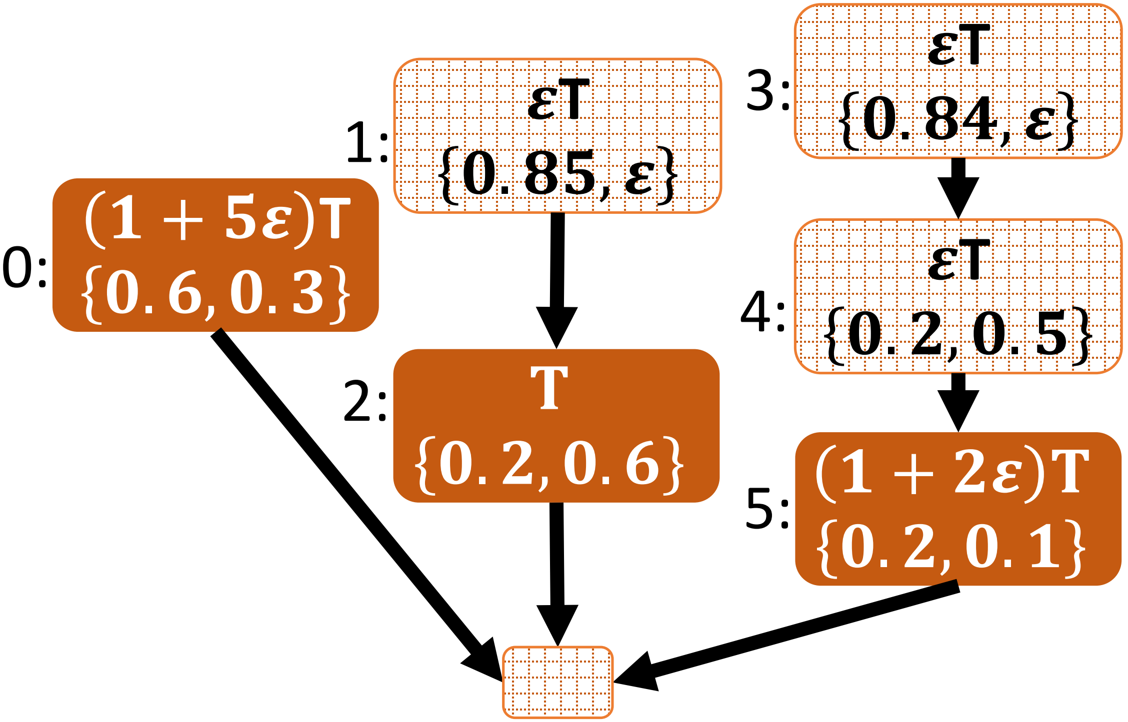

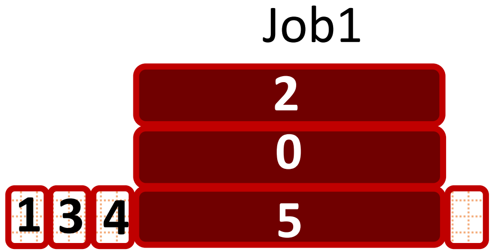

$$t_1 \rightarrow t_3 \rightarrow t_4 \rightarrow \{t_0, t_2, t_5\}$$

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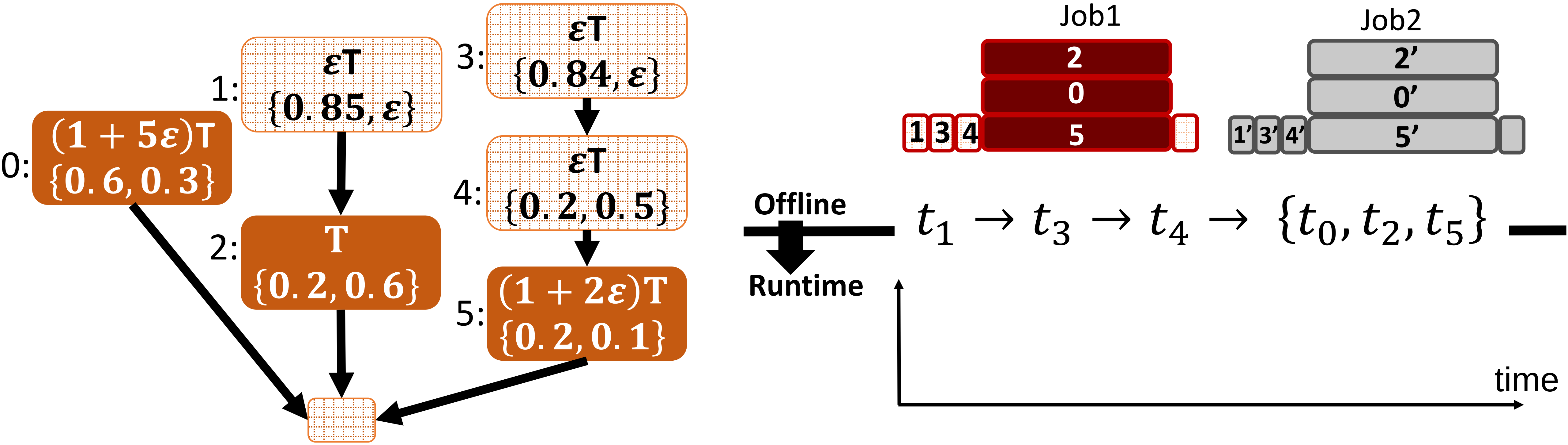

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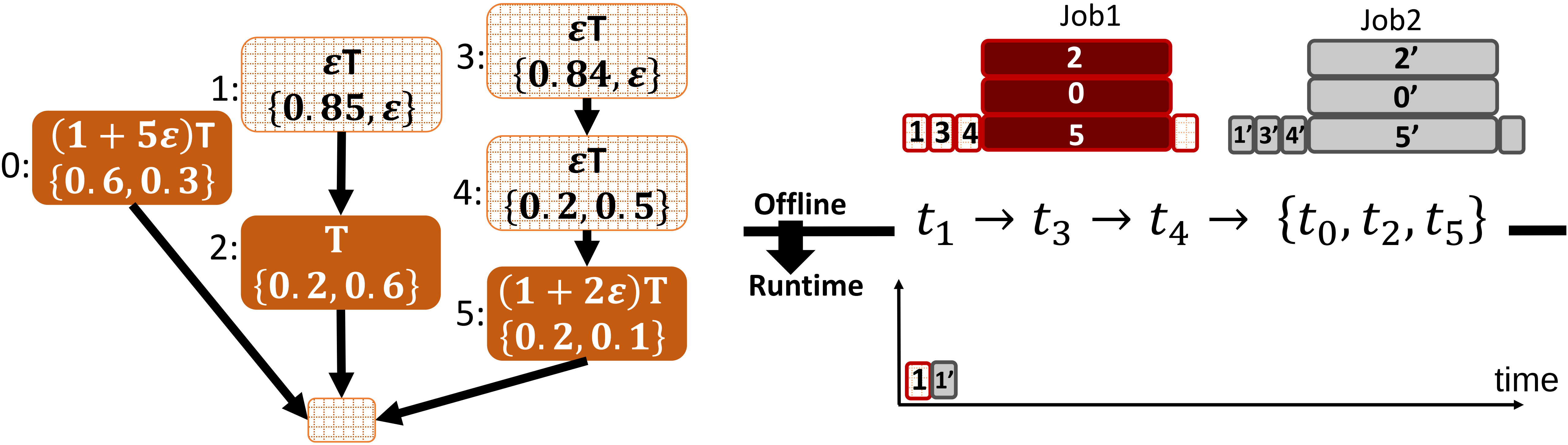

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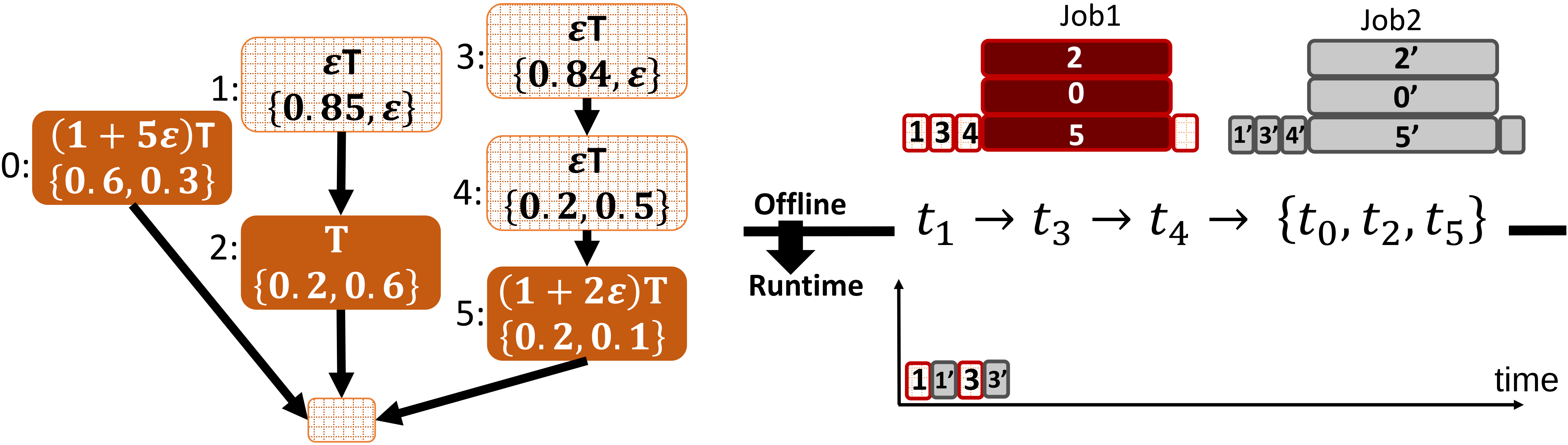

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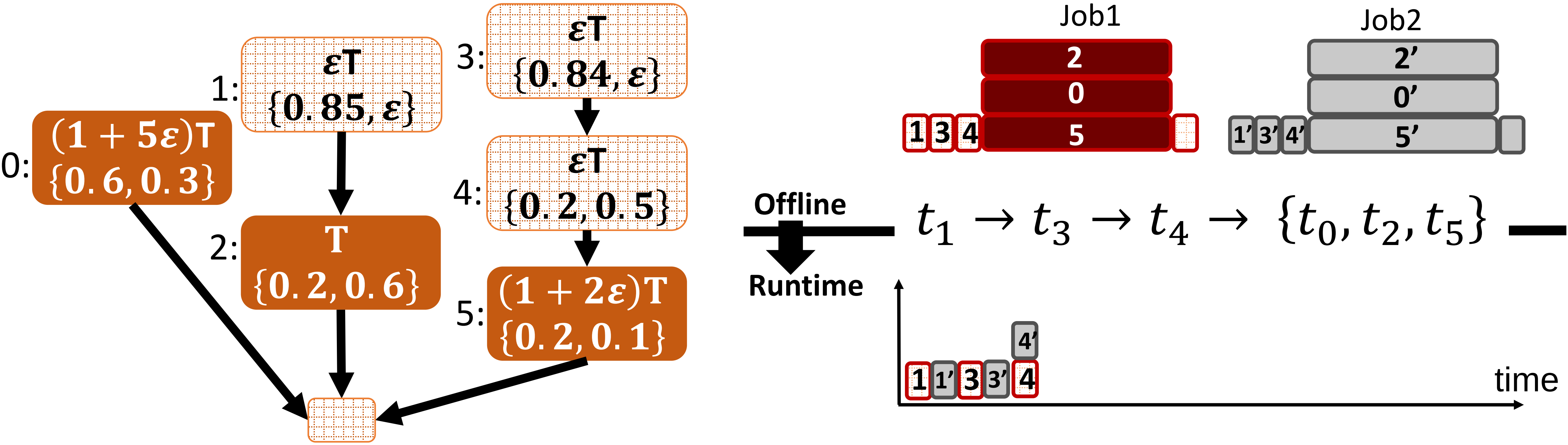

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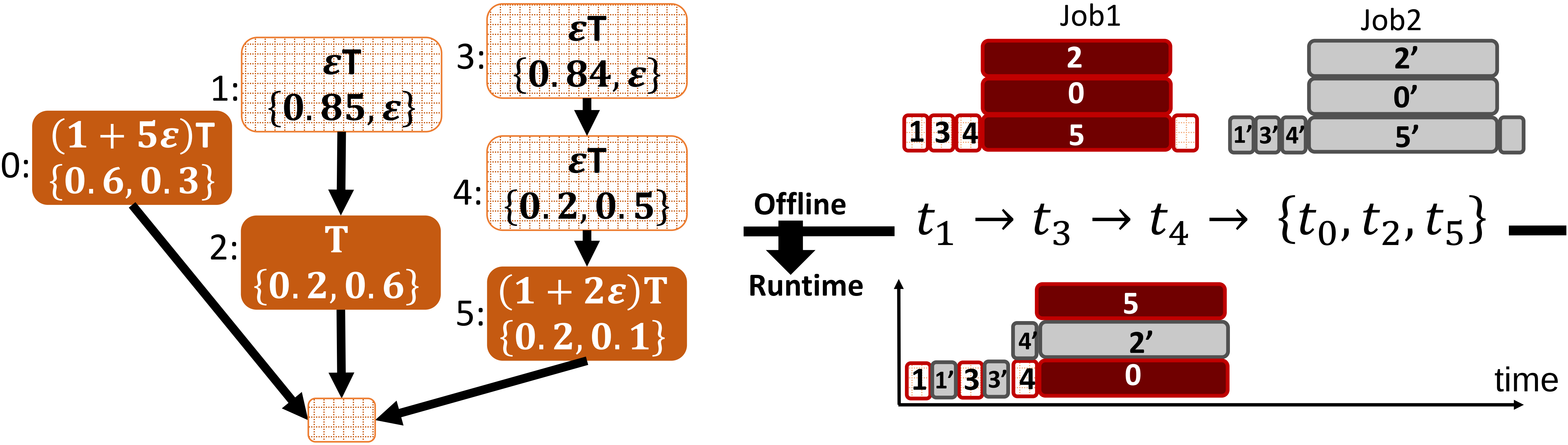

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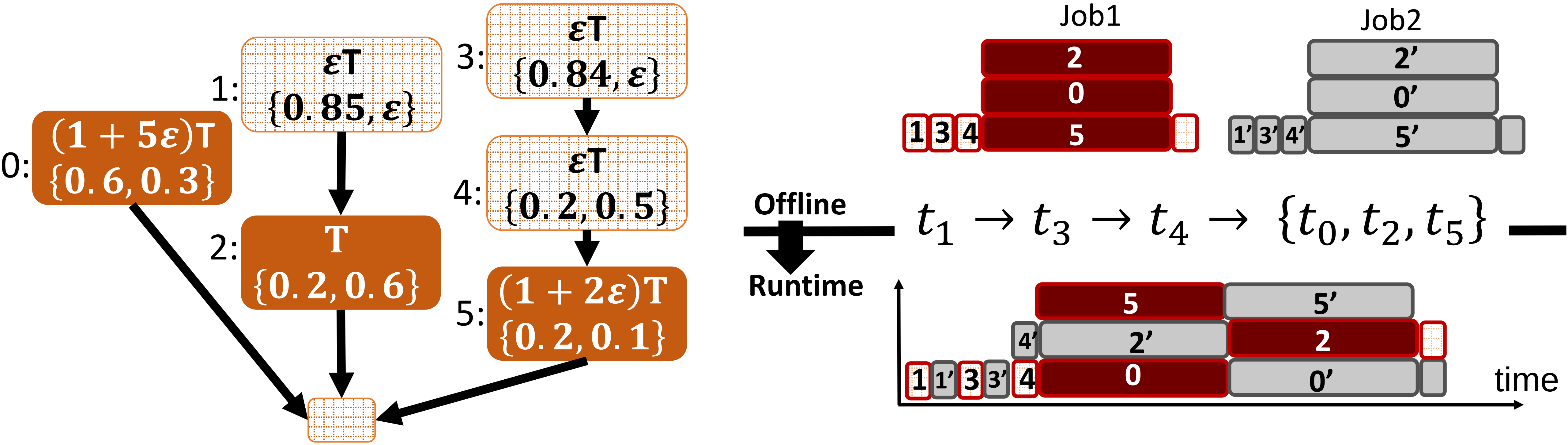

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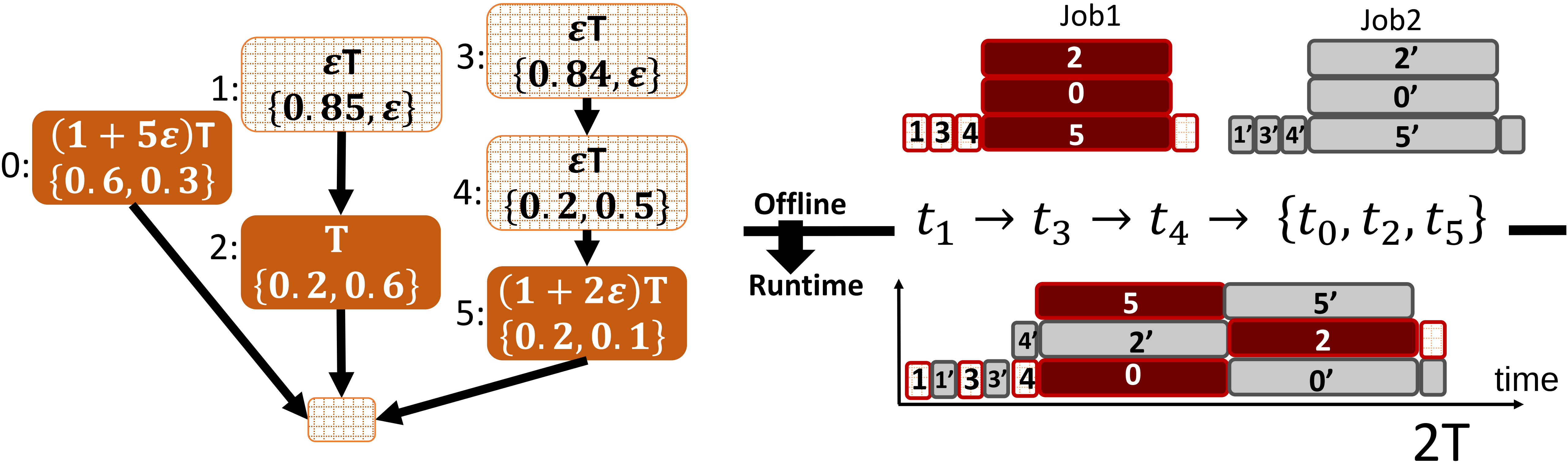

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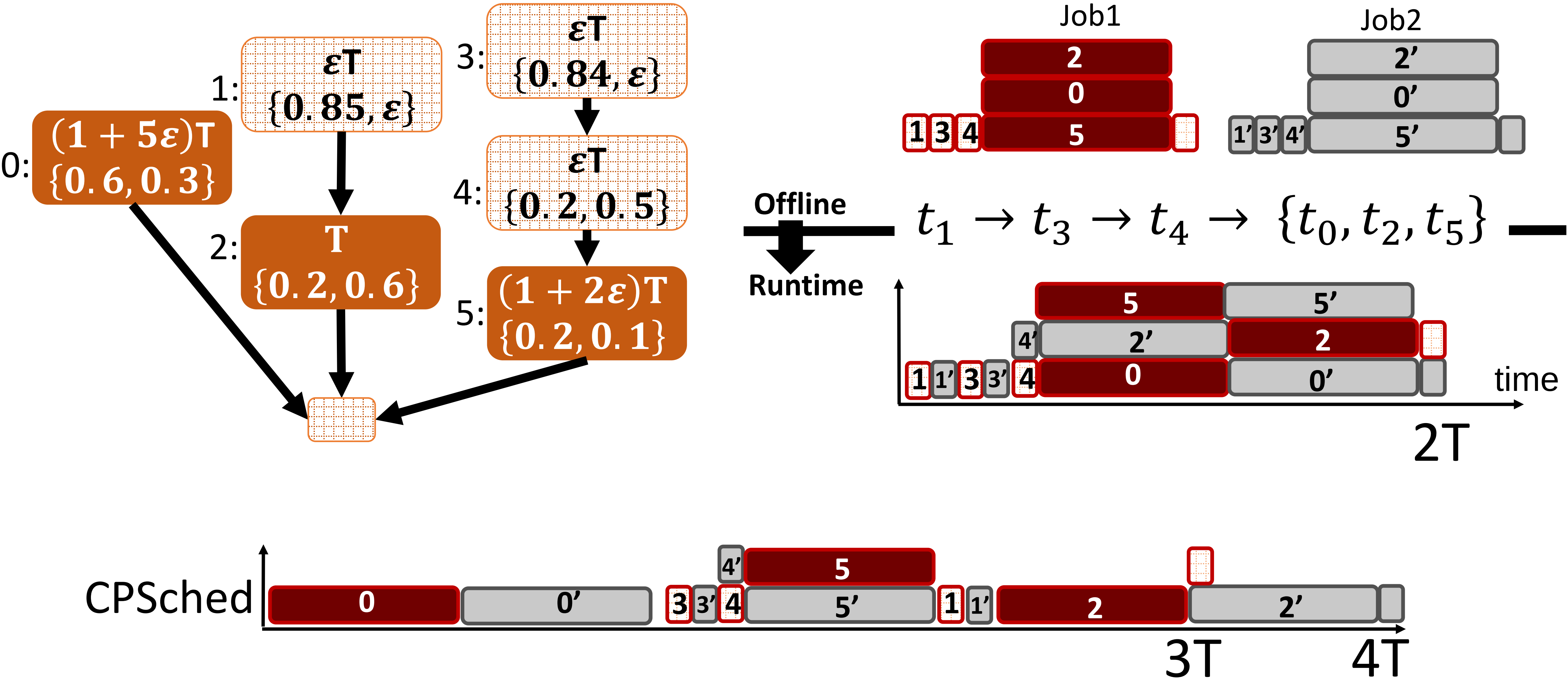

Main ideas for multiple DAGs

1) Convert offline schedule to priority order on tasks

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1) Convert offline schedule to priority order on tasks
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   (a) Multi-resource packing
   (b) “SRPT” to lower average job completion time
   (c) Bounded amount of unfairness
   (d) Overbooking …

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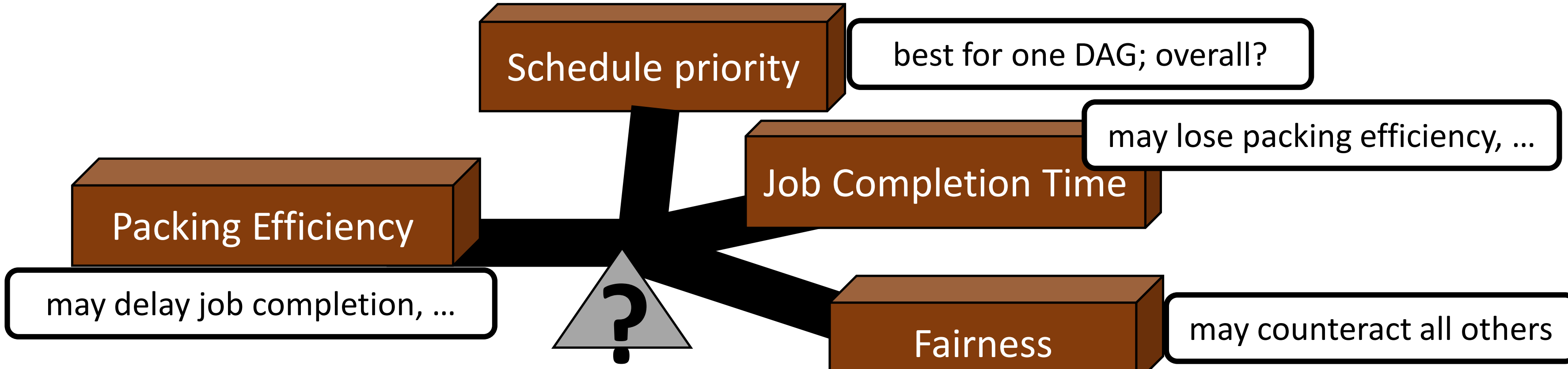
Trade-offs:



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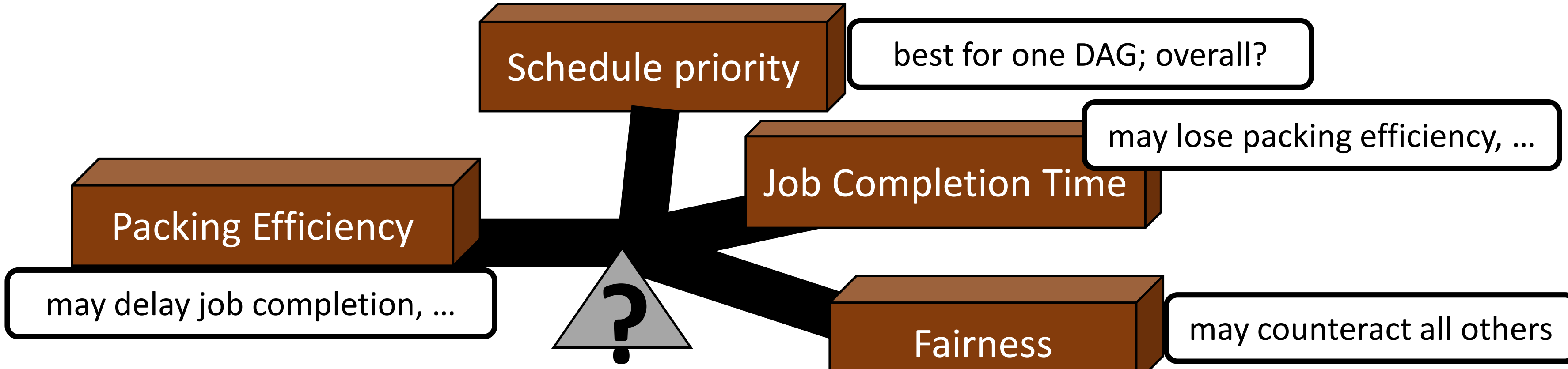

We show that:
{best "perf" |bounded unfairness} ~ best "perf"

Graphene summary & implementation

1) Offline, schedule each DAG by placing troublesome tasks first
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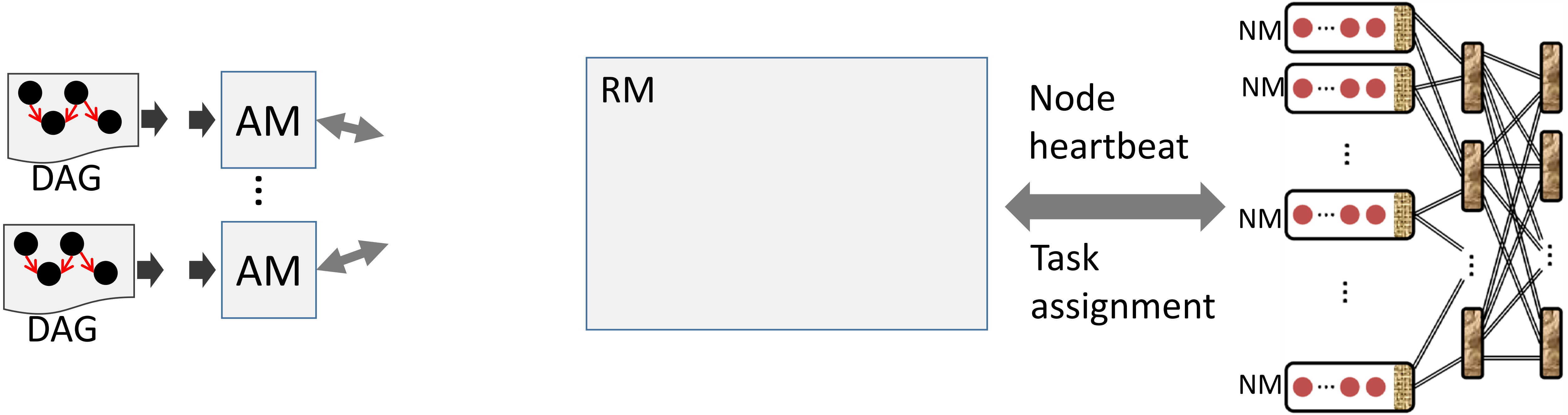

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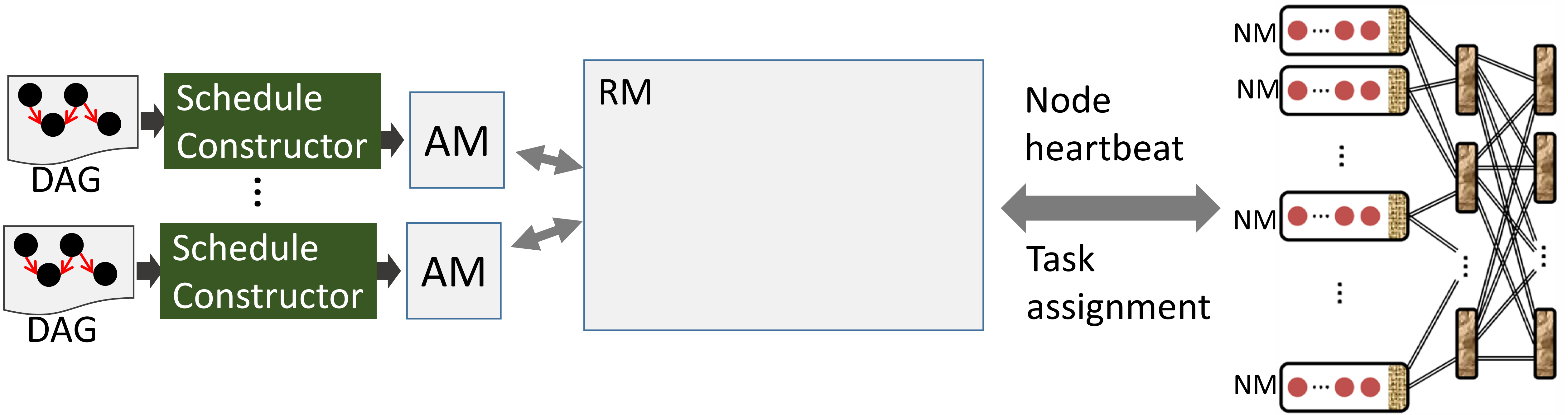

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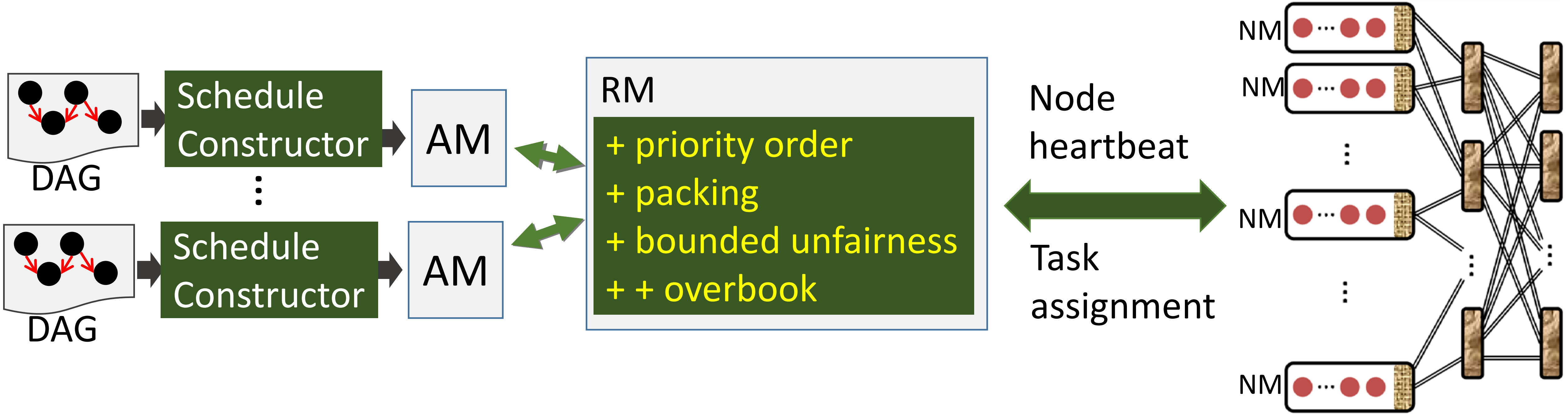


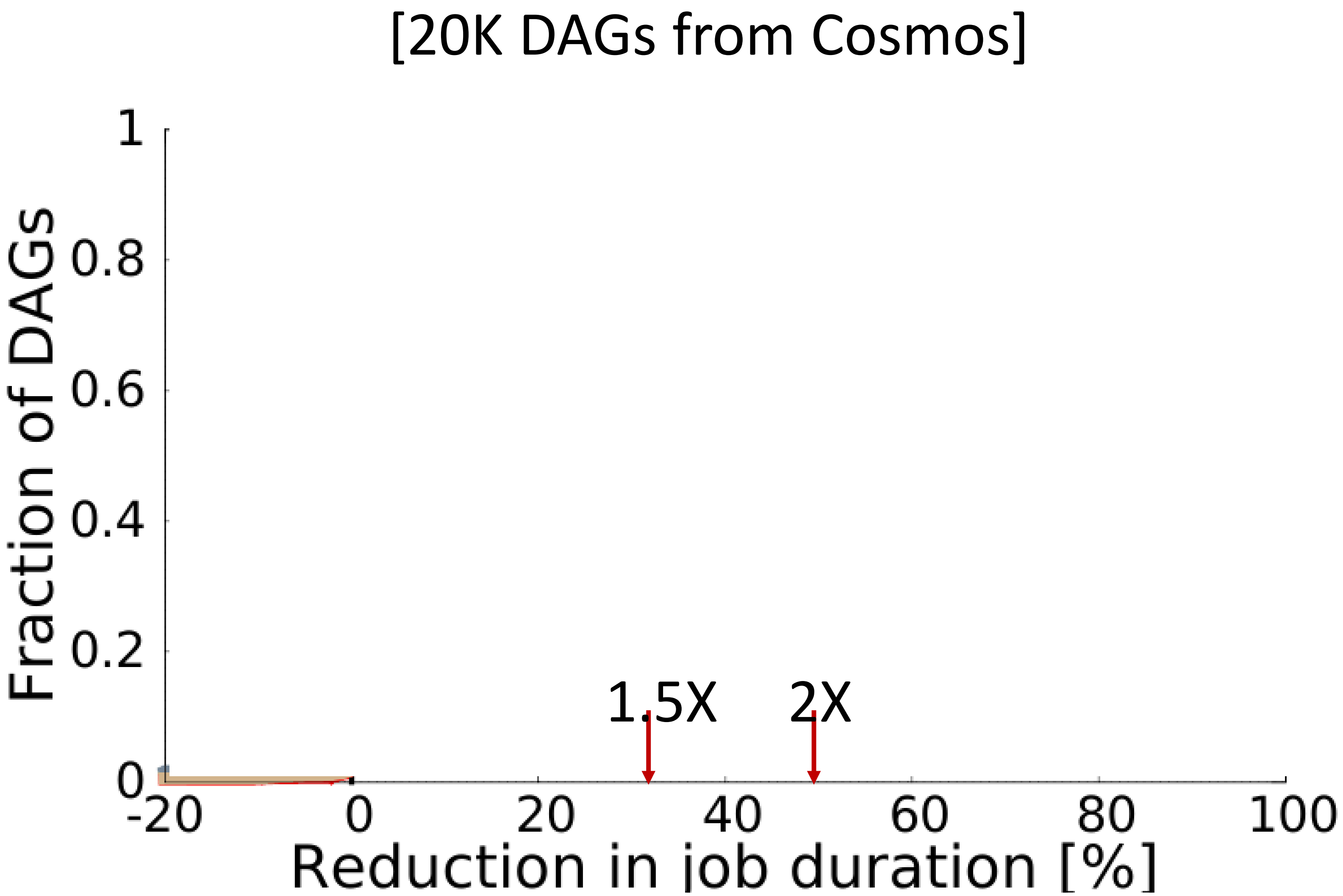
Implementation details

- DAG annotations
- Bundling: improve schedule quality w/o killing scheduling latency
- Co-existence with (many) other scheduler features

Evaluation

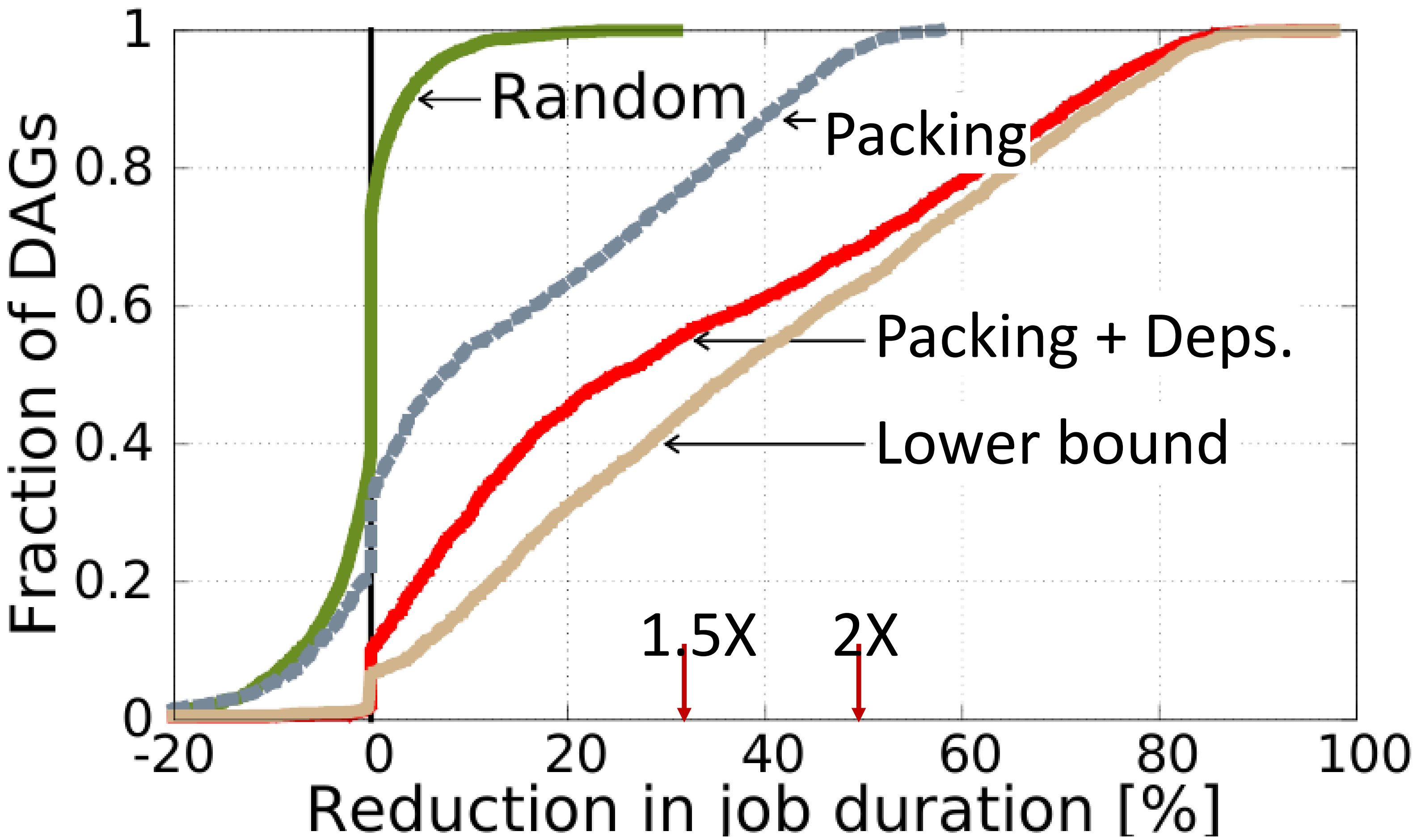
- Prototype
  - 200 server multi-core cluster
  - TPC-DS, TPC-H, …, GridMix to replay traces
  - Jobs arrive online
- Simulations
  - Traces from production Microsoft Cosmos and Yarn clusters
  - Compare with many alternatives

Results - 1


[20K DAGs from Cosmos]
Fraction of DAGs
1
0.8
0.6
0.4
0.2
0
-20
0
20
40
60
80
100
Reduction in job duration [%]
1.5X
2X

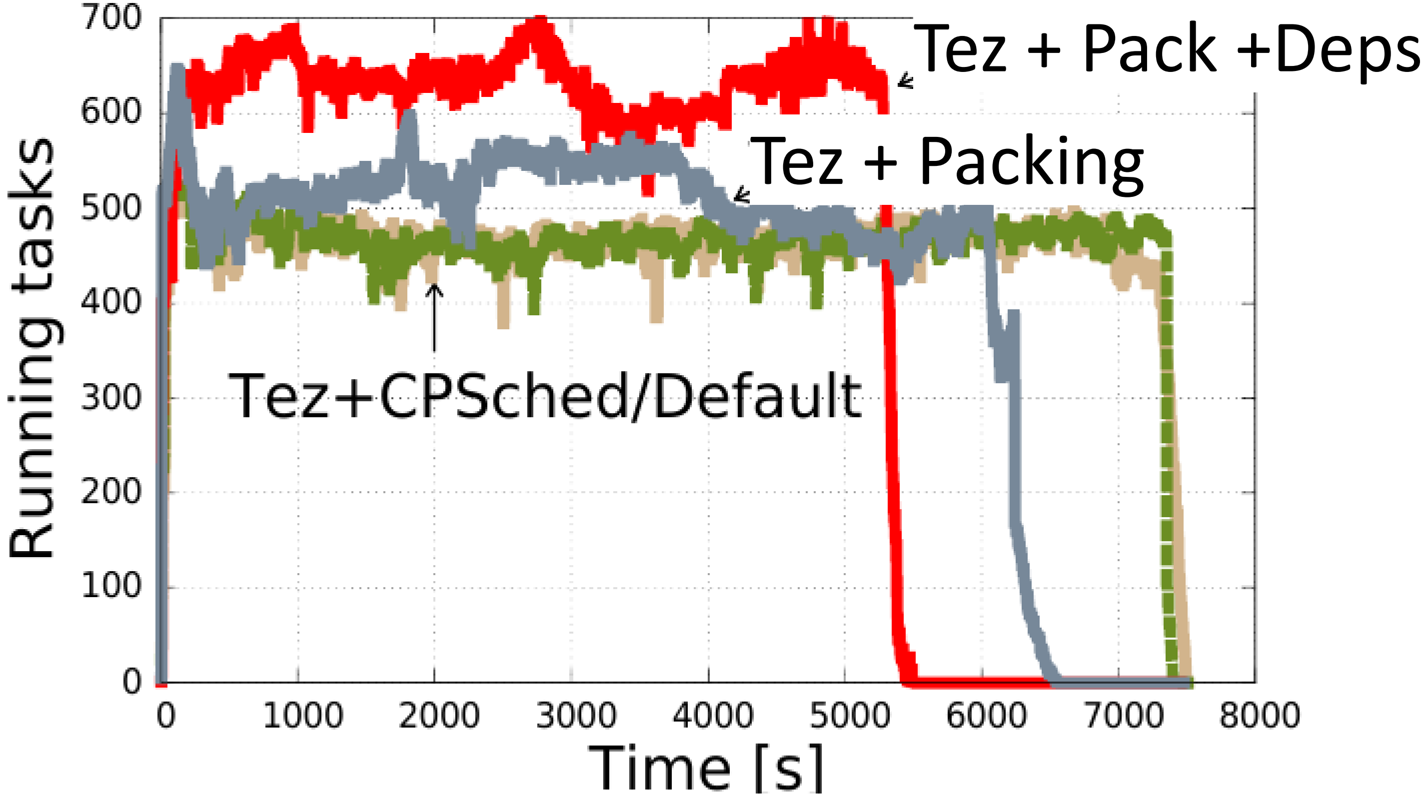
Results - 1

[20K DAGs from Cosmos]



Results - 2

[200 jobs from TPC-DS, 200 server cluster]



Results - 2

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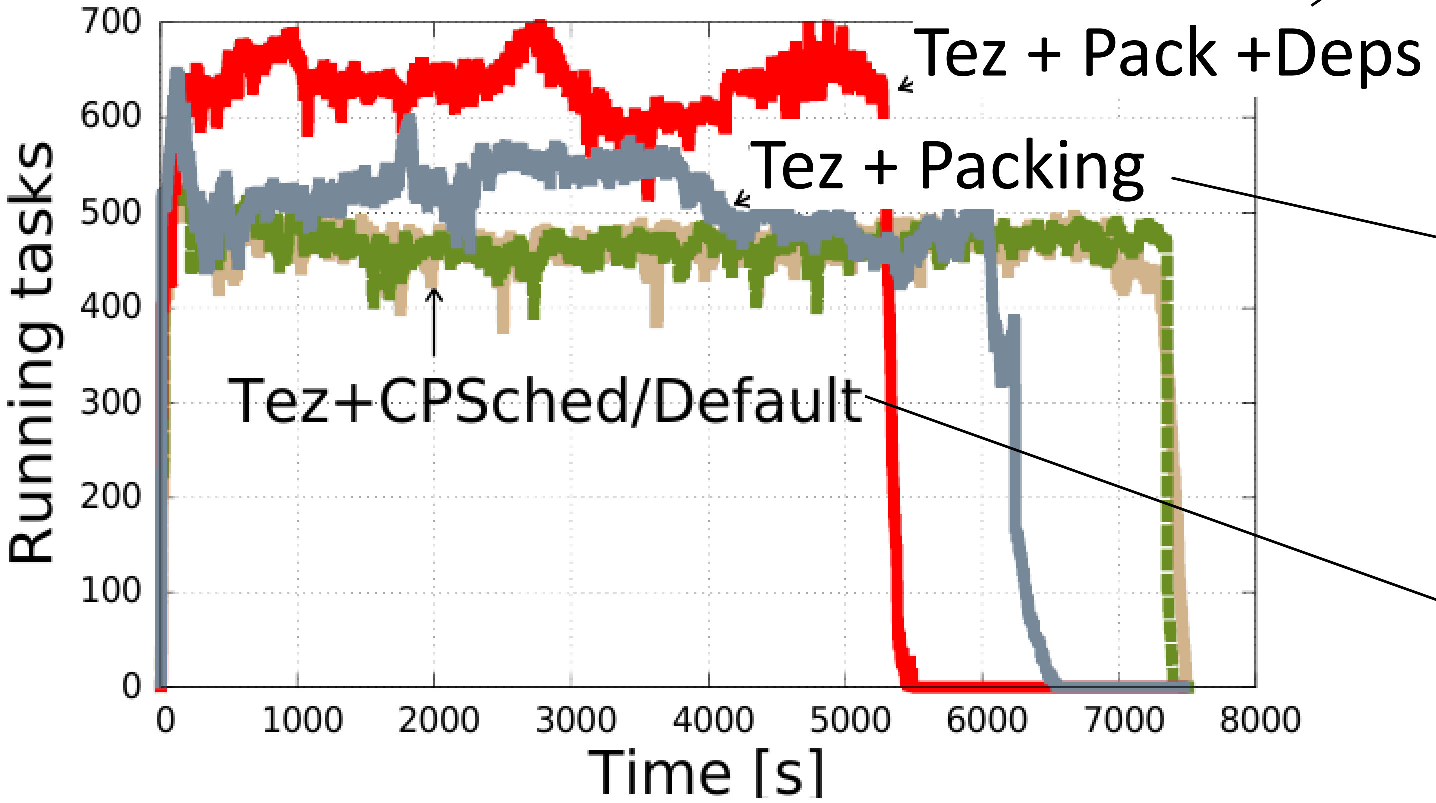

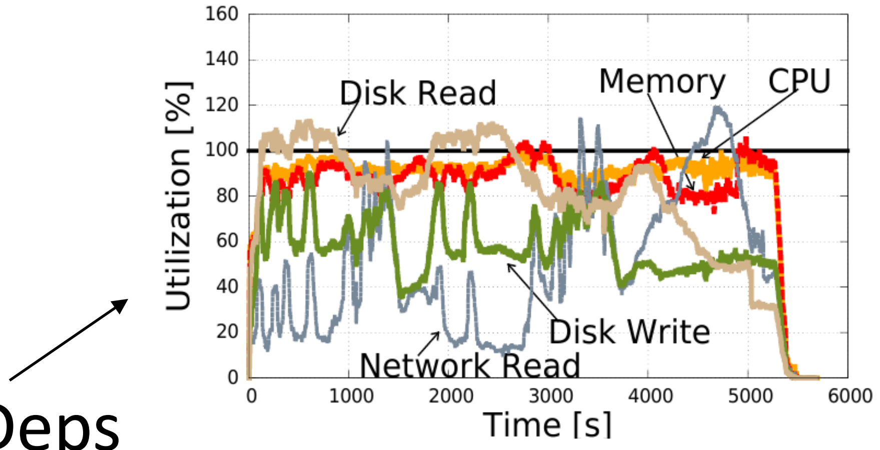

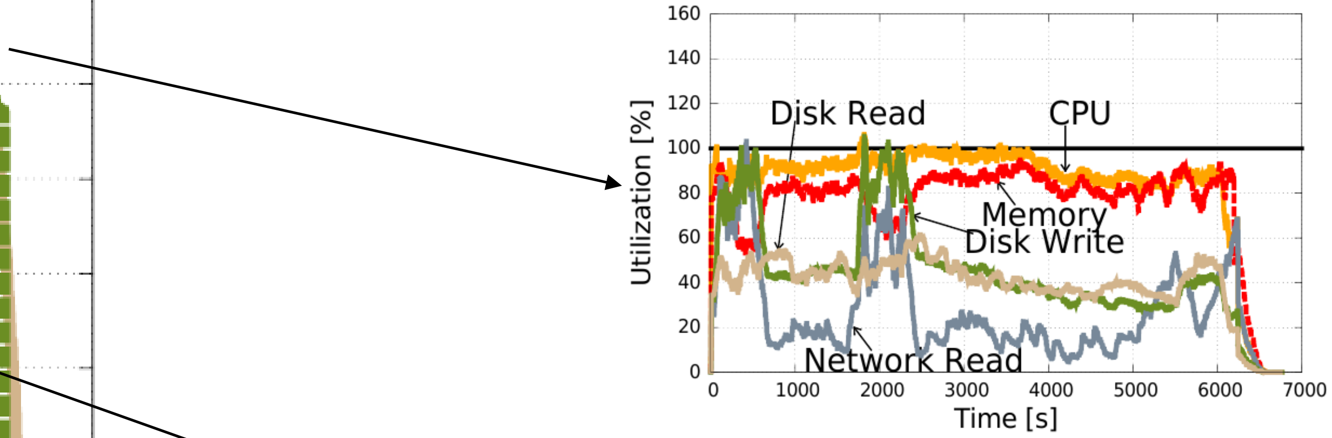

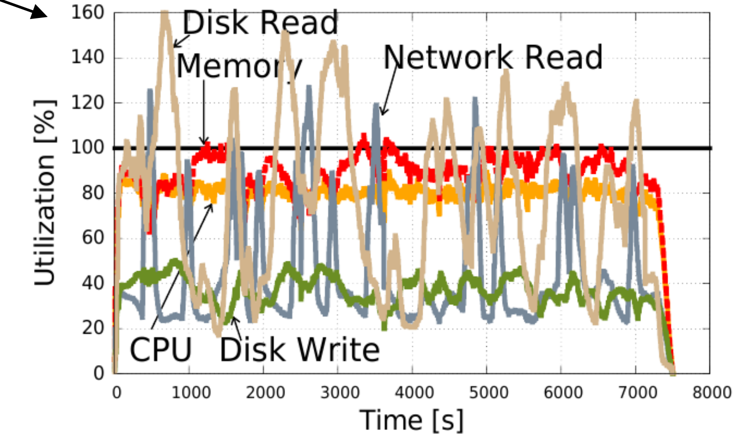

Scheduling heterogeneous DAGs well requires an online solution that handles multiple resources and dependencies

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Graphene

- Offline, construct per-DAG schedule by placing troublesome tasks first
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- New lower bound shows nearly optimal for half of the DAGs

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Experiments show gains in job completion time, makespan, …

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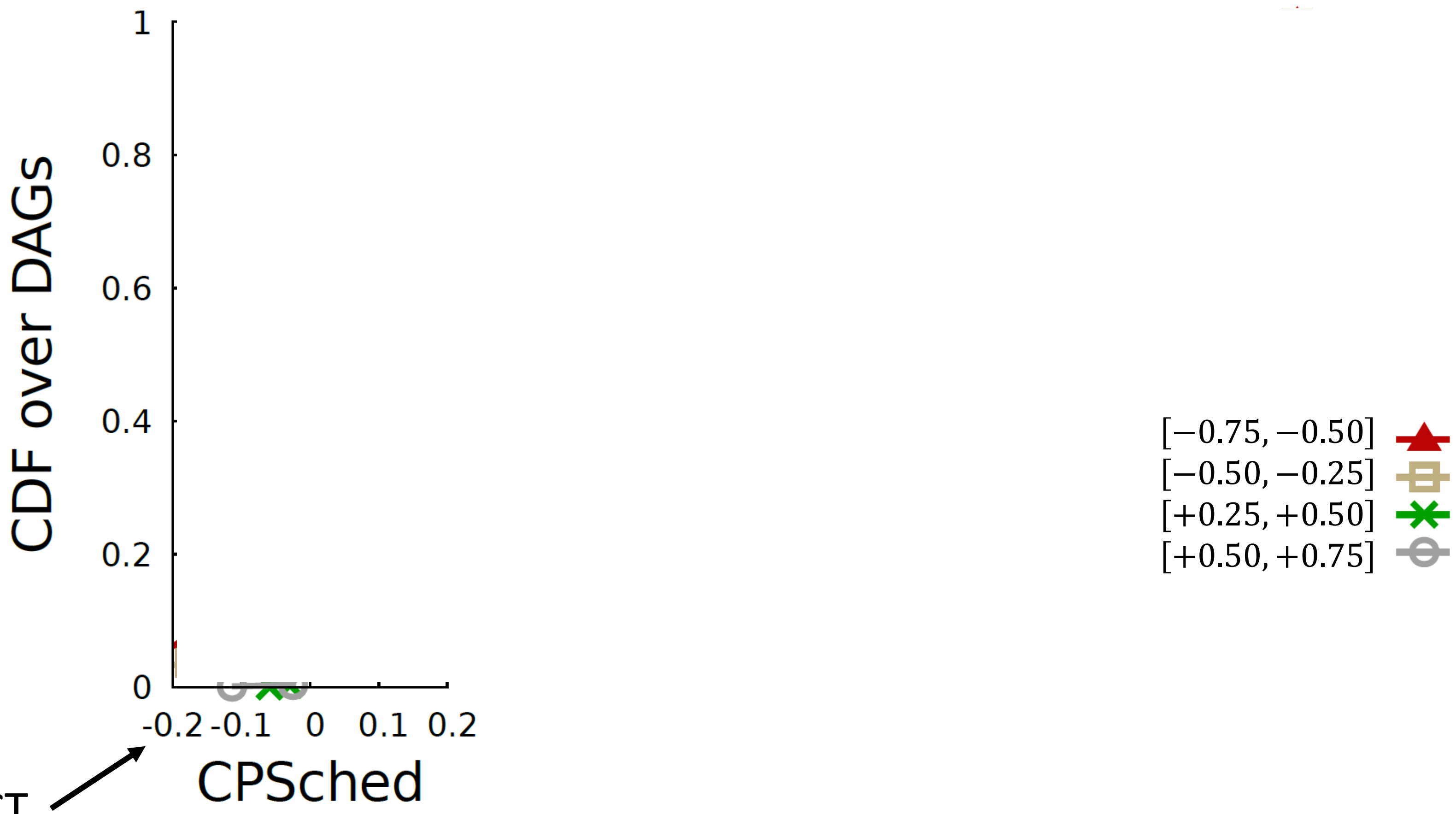
Graphene generalizes to DAGs in other settings

When scheduler works with erroneous task profiles



Amount of error

Fractional change in JCT

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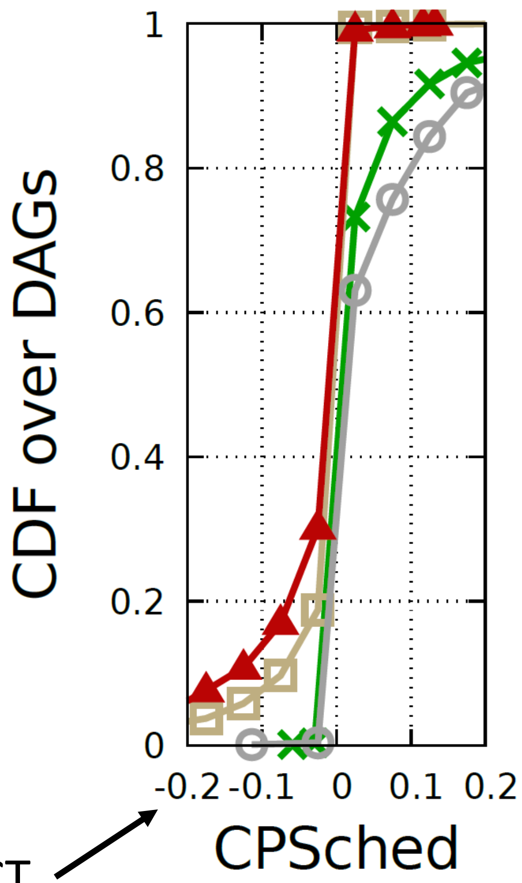

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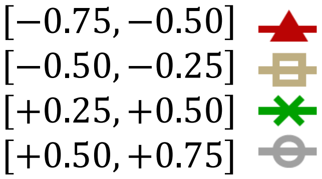

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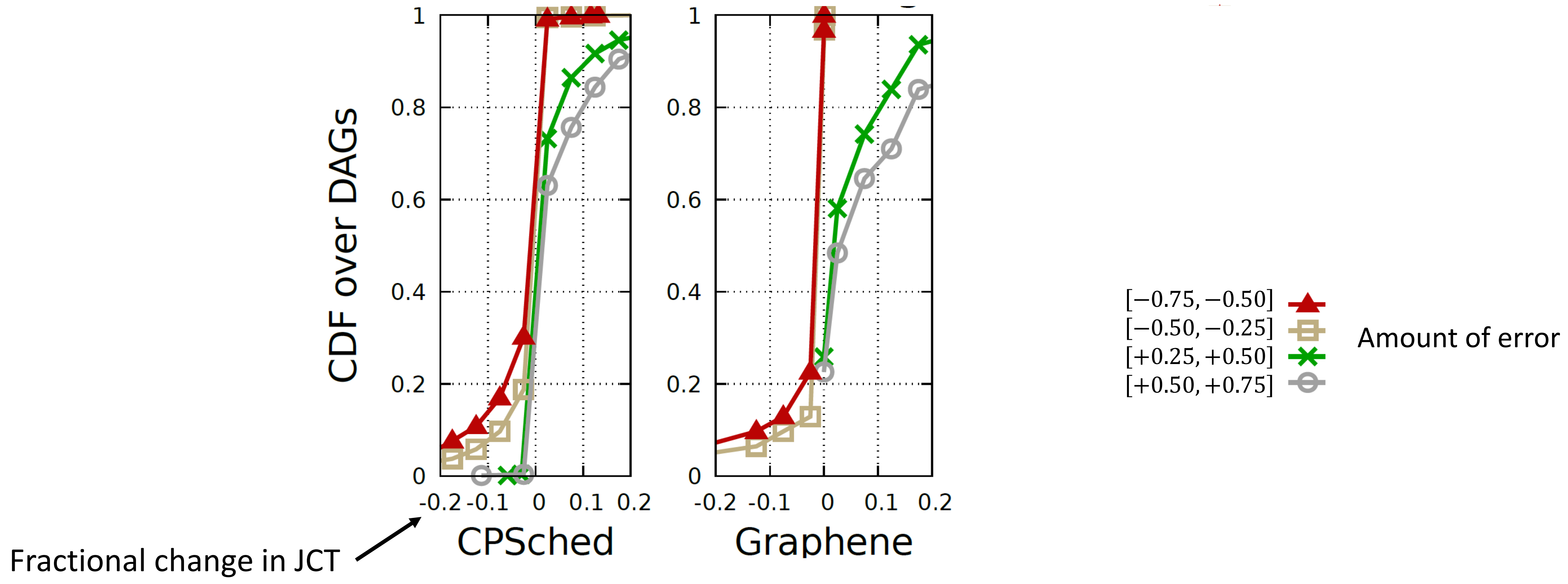

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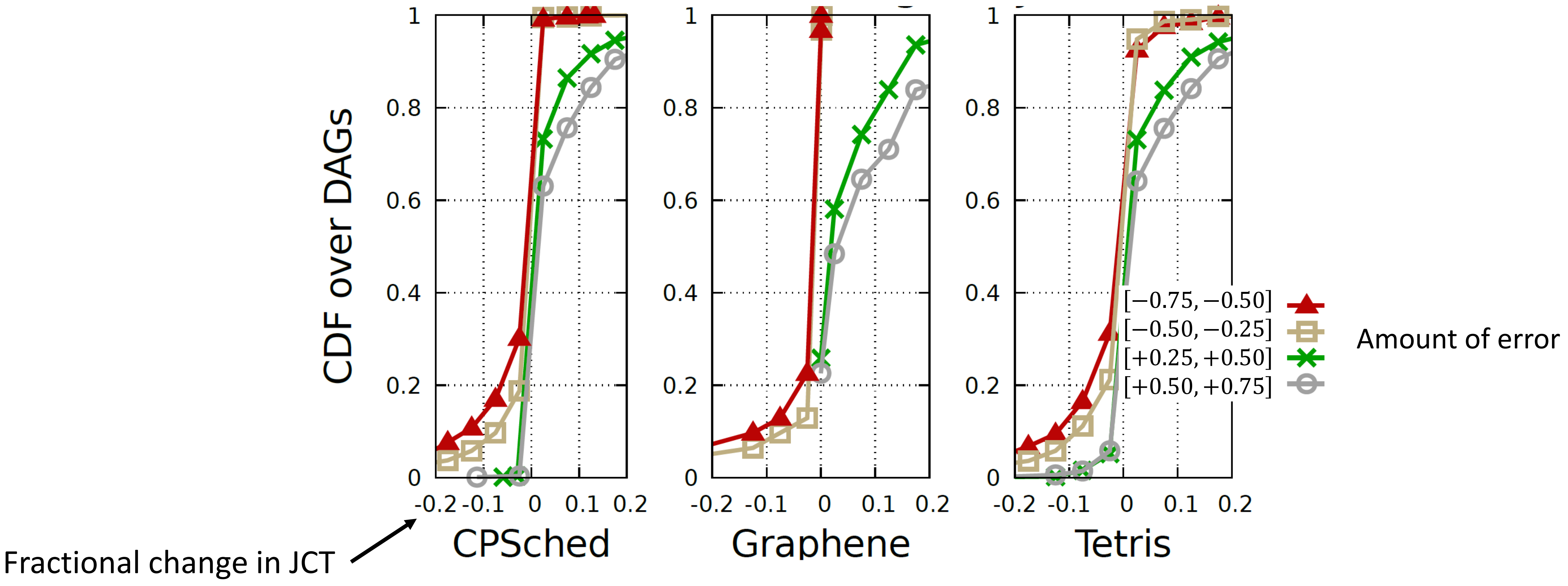


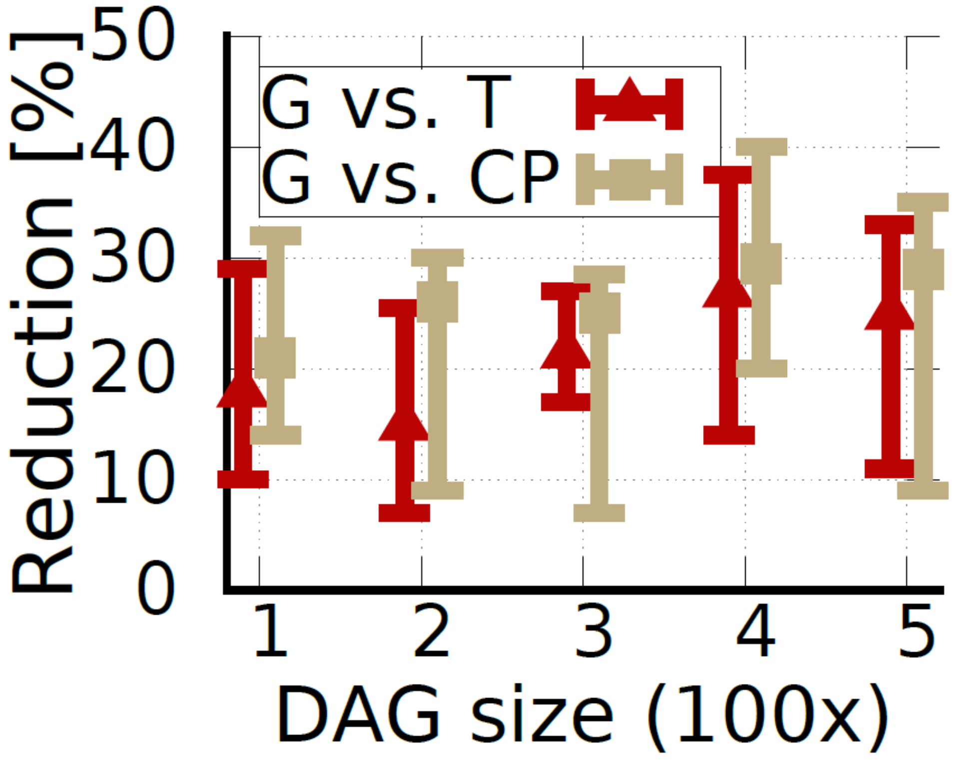
DAG annotations

G uses per-stage average duration and demands of {cpu, mem, net. disk}

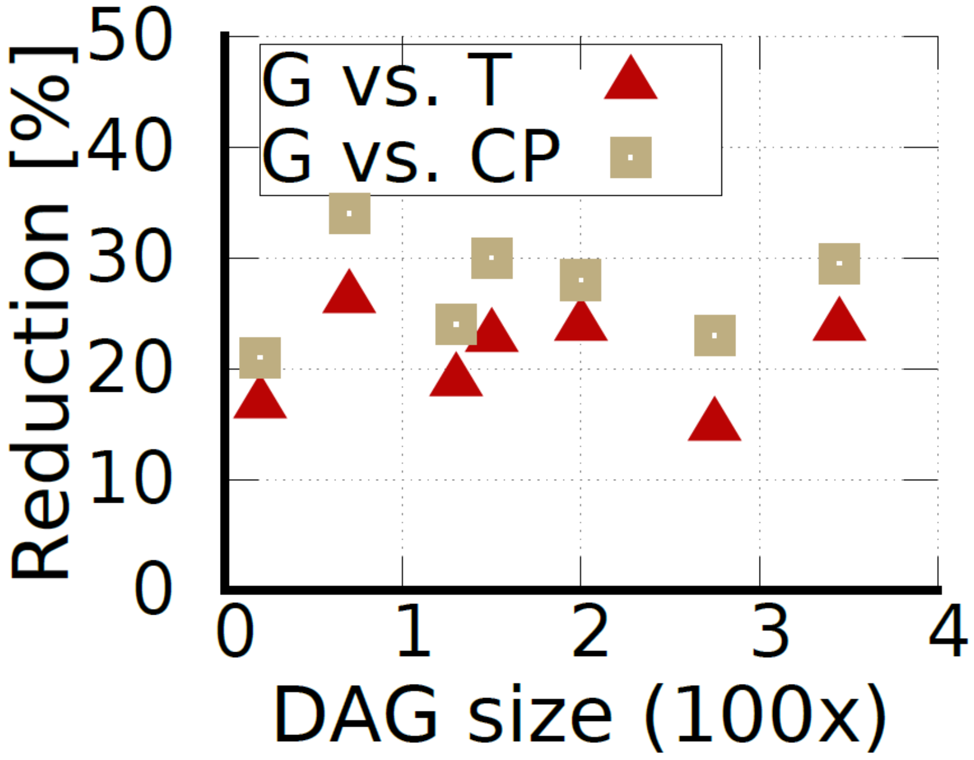
1) Almost all frameworks have user's annotate cpu and mem
2) Recurring jobs[1] have predictable profiles (correcting for input size)
3) Ongoing work on building profiles for ad-hoc jobs
    - Sample and project[2]
    - Program analysis[3]

[1] RoPE, NSDI'12; …
[2] Perforator, SOCC'16; …
[3] SPEED, POPL'09; …

Using Graphene to schedule other DAGs

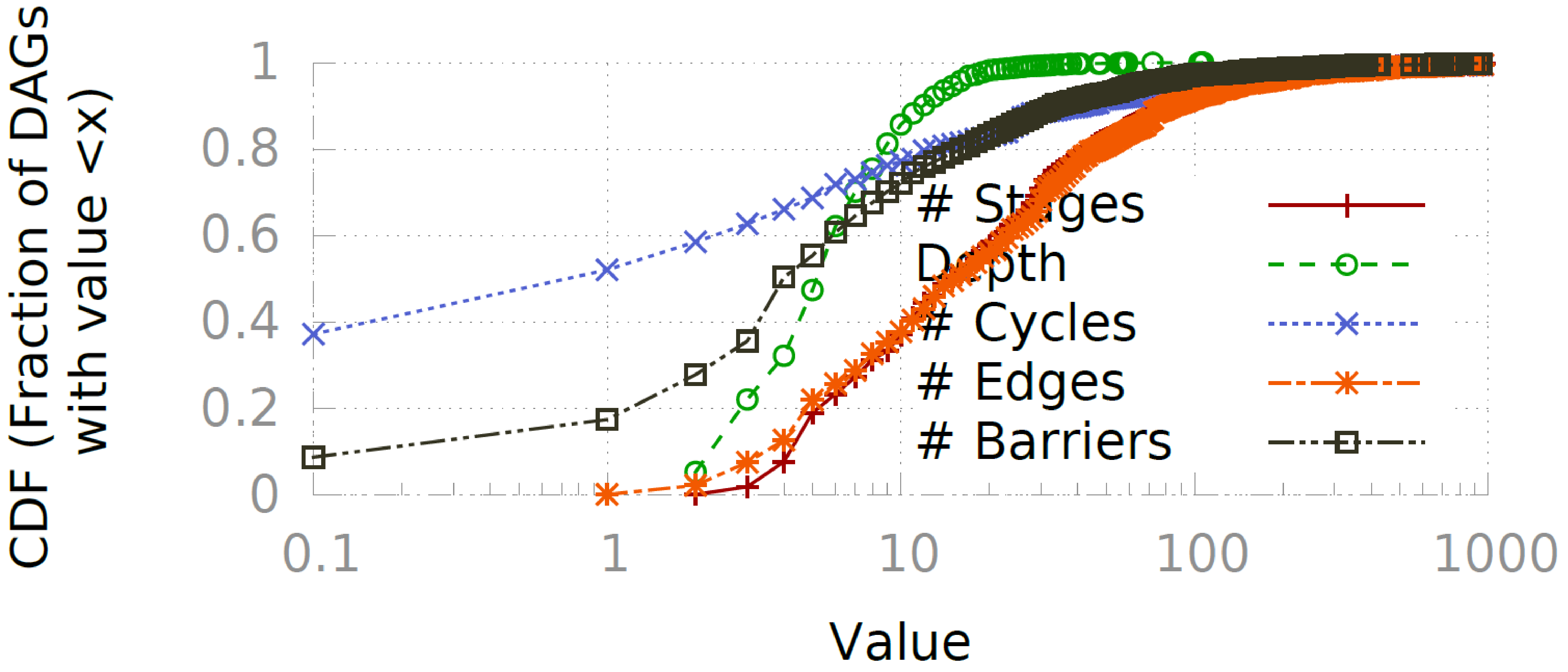


(a) Distributed Build Systems: Compilation time

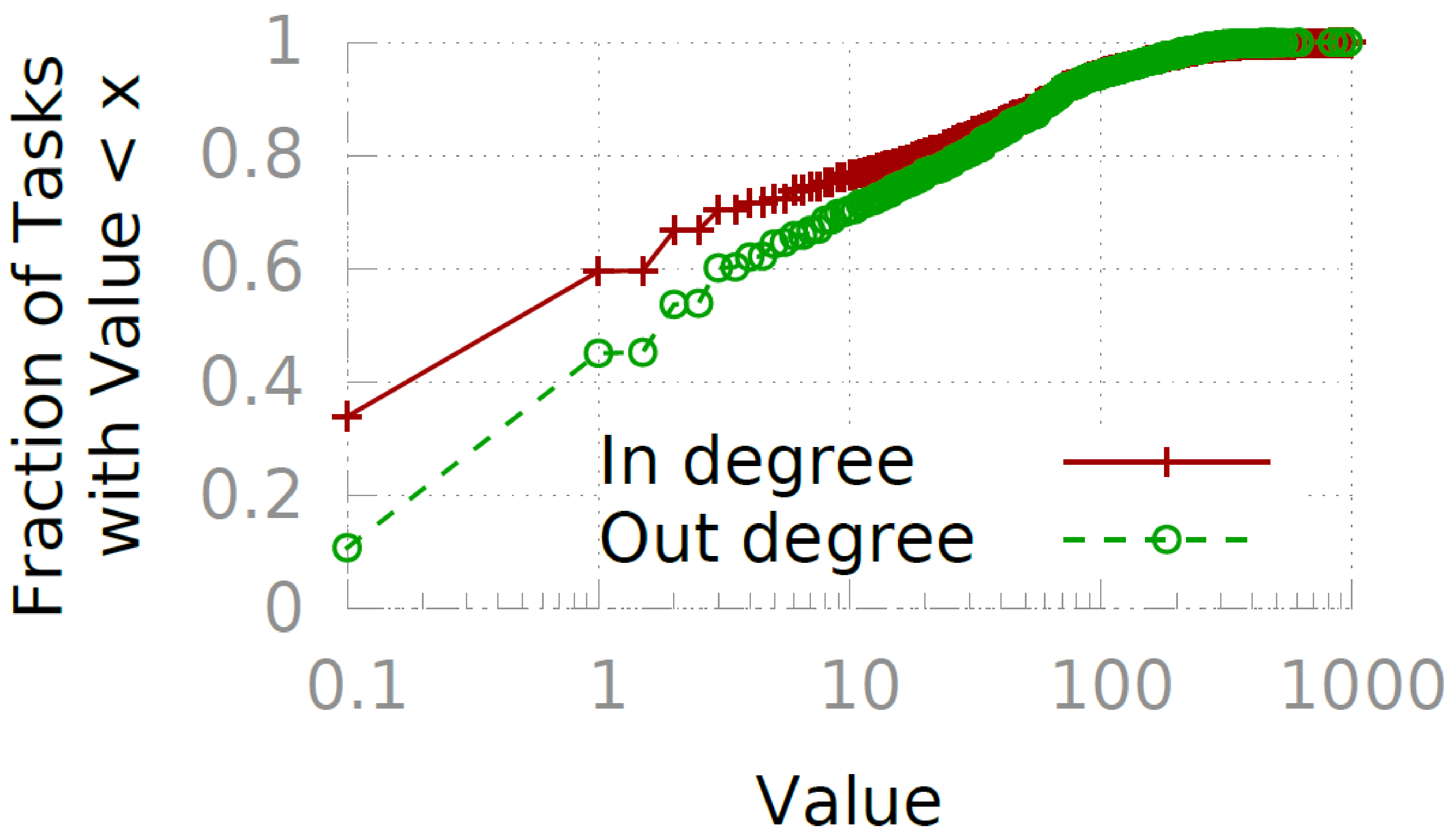


(b) Request-response workflows: Query latency

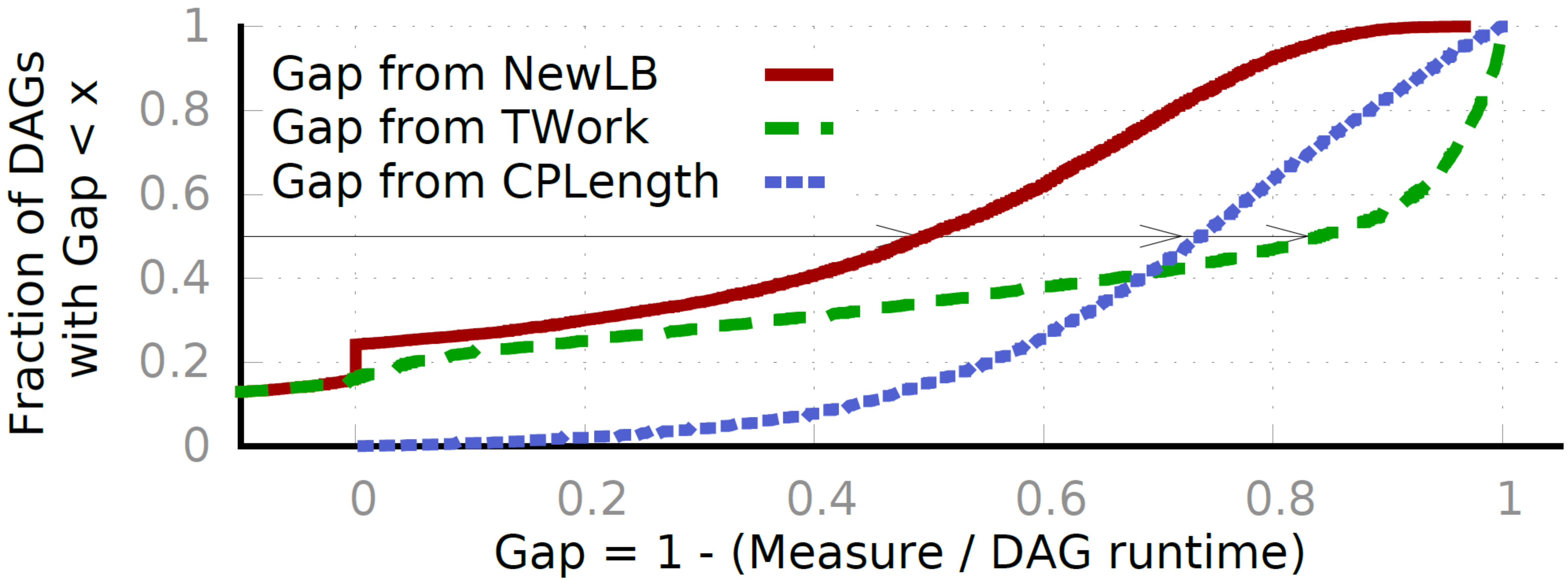
Characterizing DAGs in Cosmos clusters



Characterizing DAGs in Cosmos clusters – 2



Runtime of production DAGs



Job completion times on different workloads

Workload	50th percentile G	50th percentile T+C	50th percentile T+T	75th percentile G	75th percentile T+C	75th percentile T+T
TPC-DS	**27.8**	4.1	6.5	**45.7**	8.9	16.6
TPC-H	**30.5**	3.8	8.9	**48.3**	7.7	15.0
BigBench	**25.0**	6.4	6.2	**33.3**	21.7	18.5
E-Hive	**19.0**	1.0	5.8	**29.7**	4.5	14.2

G stands for GRAPHENE. T+C and T+T denote `Tez + CP` and `Tez + Tetris` respectively (see §7.1). The improvements are relative to `Tez`.

Makespan

Workload	Tez+CP	Tez+Tetris	GRAPHENE
TPC-DS	+2.1%	+8.2%	+30.9%
TPC-H	+4.3%	+9.6%	+27.5%

Fairness

Workload	Scheme	2Q vs. 1Q Perf. Gap	Jain's fairness index		
			10s	60s	240s
TPC-DS	Tez	−13%	0.82	0.86	0.88
	Tez+DRF	−12%	0.85	0.89	0.90
	Tez+Tetris	−10%	0.77	0.81	0.92
	GRAPHENE	+2%	0.72	0.83	0.89

Comparison with other alternatives

		25^{th}	50^{th}	75^{th}	90^{th}
GRAPHENE		**7**	**25**	**57**	**74**
Random		−2	0	1	4
Crit.Path	Fit cpu/mem	−2	0	2	1
	Fit all	1	4	13	16
Tetris	Fit all	0	7	29	42
Strip Part.	Fit all	0	1	12	27
Coffman-Graham.	Fit all	0	1	12	26
	Fit cpu/mem	−2	0	0	2

Online Pseudocode

Func: FindAppropriateTasksForMachine:
Input: $\mathbf{m}$: vector of available resources at machine; $\mathcal{J}$: set of jobs with task details$\{t_{\text{duration}}, \mathbf{t}_{\text{demands}}, t_{\text{priScore}}\}$; `deficit`: counters for fairness;
Parameters: κ: unfairness bound; rp: remote penalty
Output: S, the set of tasks to be allocated on the machine

```
S ← ∅
while true do
    foreach task t do
        {pScore_t, oScore_t} ← {0, 0}
        rPenalty_t ← t is locality sensitive ? rp : 1
        if t_demands ≤ m // fits? then
            pScore_t ← (m · t_demands) rPenalty_t // dot product
        else
            // what-if analysis: "overbook or wait".
            ∀tasks t′ affected by t running at m, let before(t′),
            after(t′) be expected completion times before and
            after placing t at m
            benefit = nextSchedOpp + t_duration − after(t)
            cost = Σ_{aff. tasks t′} (after(t′) − before(t′))
            if benefit > cost then oScore_t = benefit − cost;
        job j ∋ t, srpt_j ← Σ_{pending u∈j} u_duration * |u_demands|
        ┌──────────────────────────────────────────────────────────┐
        │ perfScore_t ← t_priScore {pScore_t, oScore_t} − η srpt_j │
        └──────────────────────────────────────────────────────────┘
    t^best ← arg max{perfScore_t | t} // task with highest perf score
    if t^best = ∅ then break // no new task can be scheduled on this machine;
    g′ ← jobgroup with highest deficit counter
    ┌──────────────────────────────────────────────────────────────────────┐
    │ if deficit_g′ ≥ κC then t^best ← arg max{perfScore_t | t ∈ g′};      │
    └──────────────────────────────────────────────────────────────────────┘
    S ← S ∪ t^best
    m ← [m − t^best_demands]_0+
    deficit_g ← deficit_g +
    ┌──────────────────────────────────────────────────────────────────────┐
    │ factor(t^best_demands) * { fairShare_g − 1   t ∈ jobgroup g          │
    │                          { fairShare_g       otherwise               │
    └──────────────────────────────────────────────────────────────────────┘
```