Towards Network Systems that Improve with Experience

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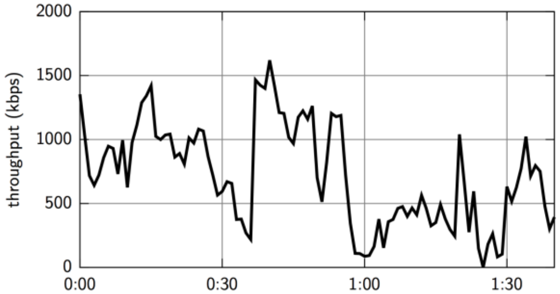
CSAIL

Network Control Systems



Congestion Control

Traffic Engineering

Cluster Scheduling

Adaptive Video Streaming

Internet Telephony

……

Two Paradigms in Network Control

Classical Paradigm (1960 – now)
[Specify & Build]

1. Specify operating environment & low-level design goals

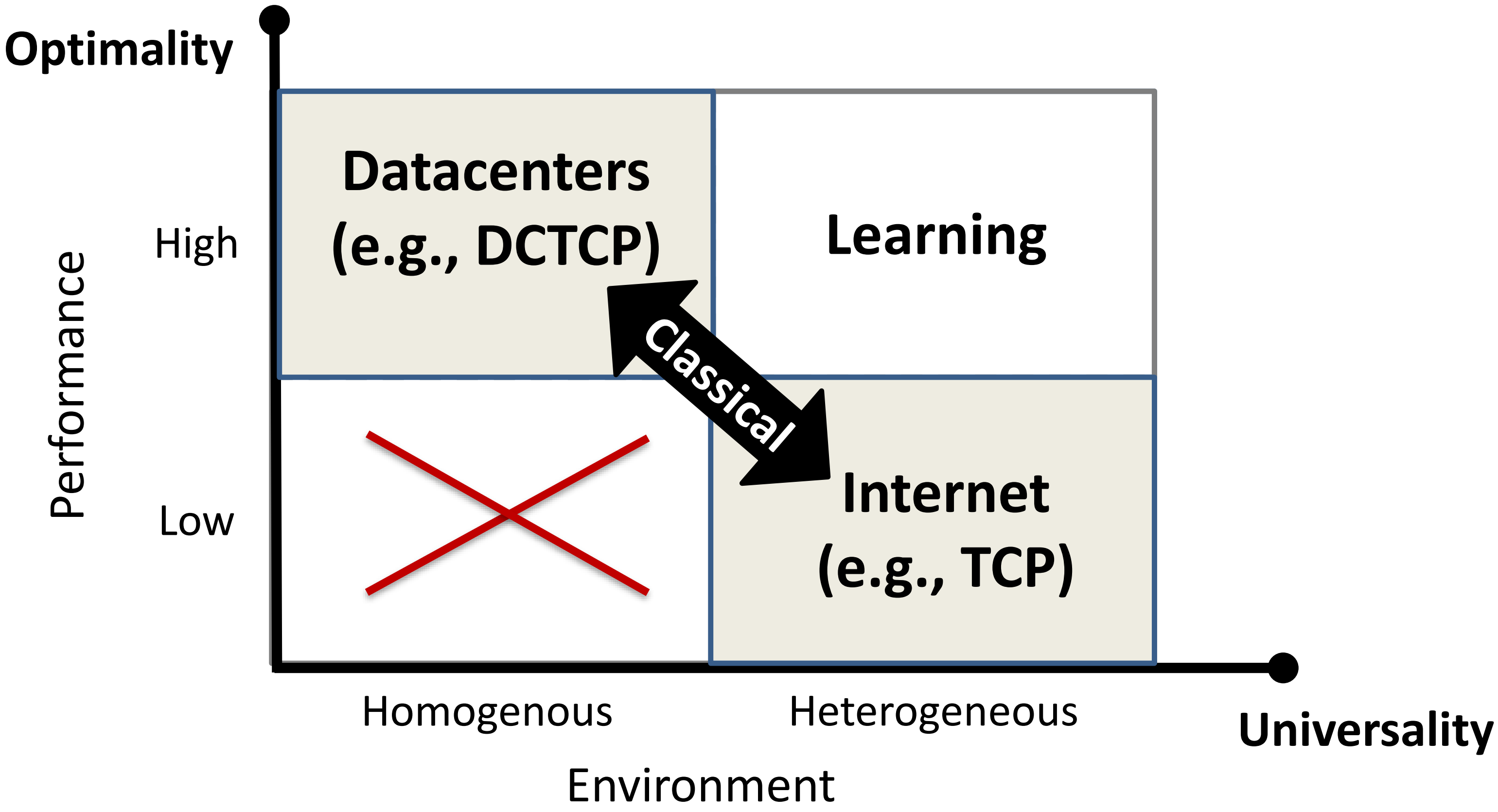
2. Build one algorithm that achieves goals in (most) cases of interest

Learning Paradigm
[Learn & Adapt]

1. Learn operating environment & low-level goals

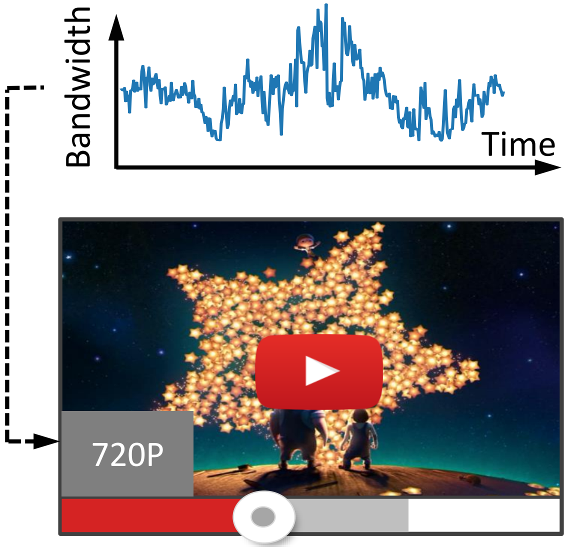
2. Learn algorithms that can adapt to network/workload conditions

Two Paradigms in Network Control

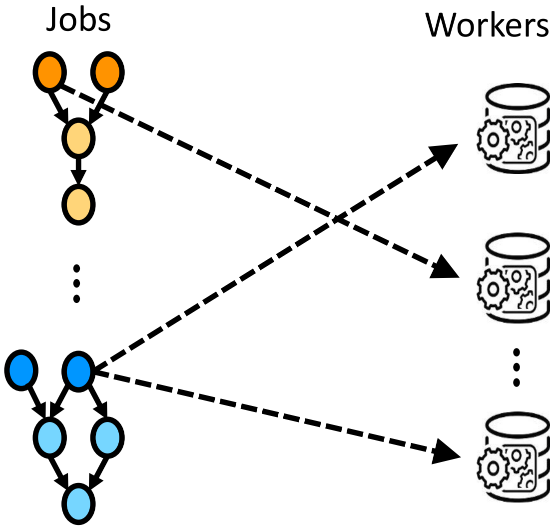


Our Work on Learning-Based Network Systems

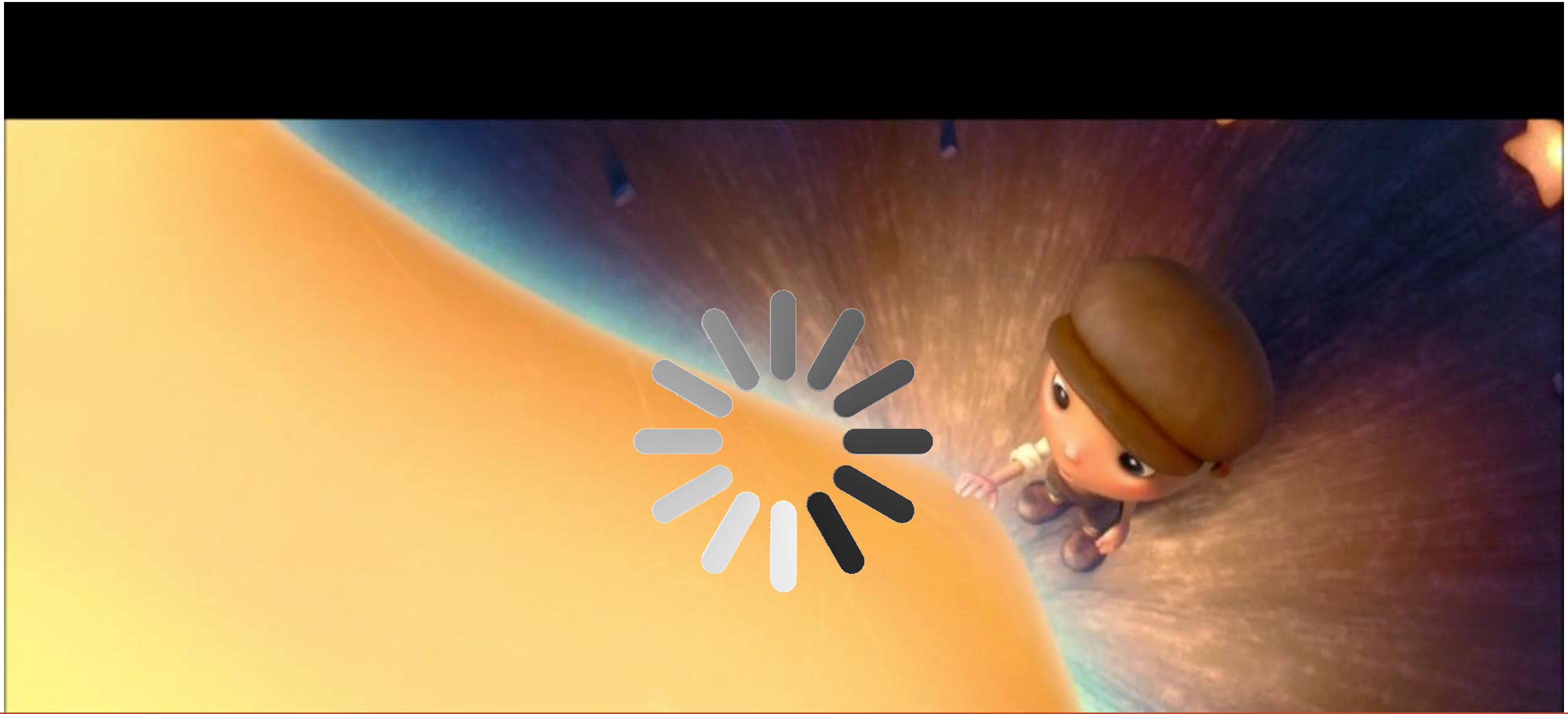
Adaptive video streaming
(Pensieve)



Cluster Scheduling
(Decima)



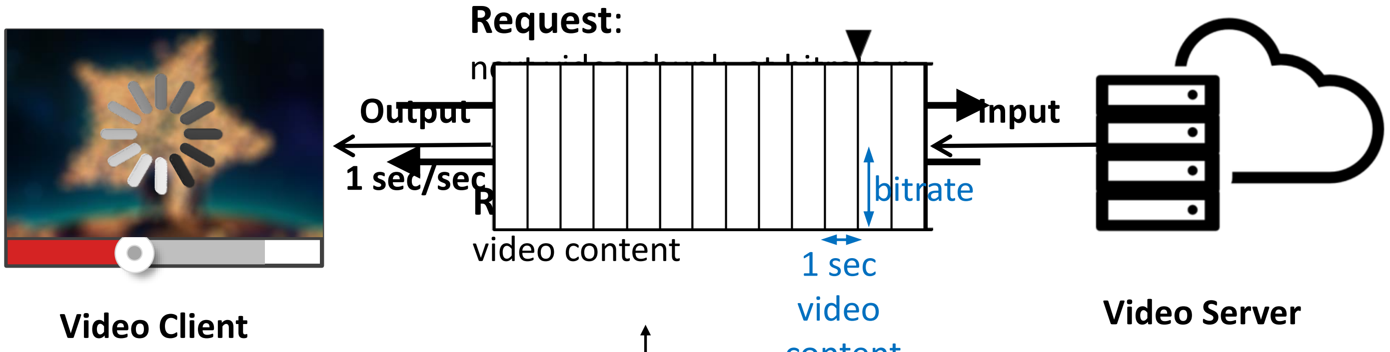
RL Techniques



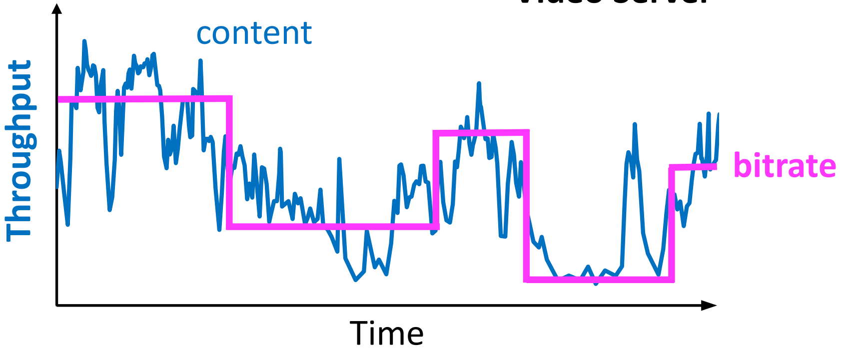
Users start leaving if video doesn't play in 2 seconds

https://gigaom.com/2012/11/09/online-viewers-start-leaving-if-video-doesnt-play-in-2-seconds-says-study/
Video: La Luna (Pixar 2011)

Dynamic Streaming over HTTP (DASH)

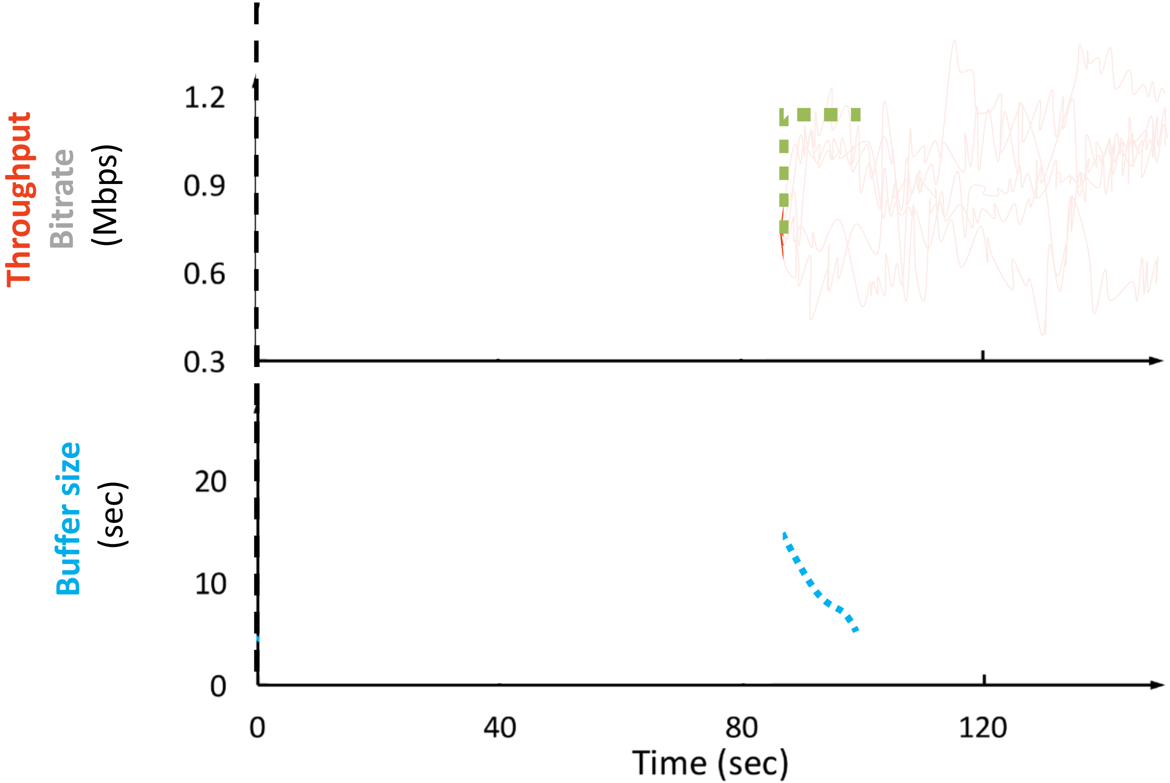


Adaptive Bitrate (ABR) Algorithms



Animation borrowed from Te-Yuan Huang (SIGCOMM '14) http://conferences.sigcomm.org/sigcomm/2014/doc/slides/38.pdf

Why is ABR Challenging?



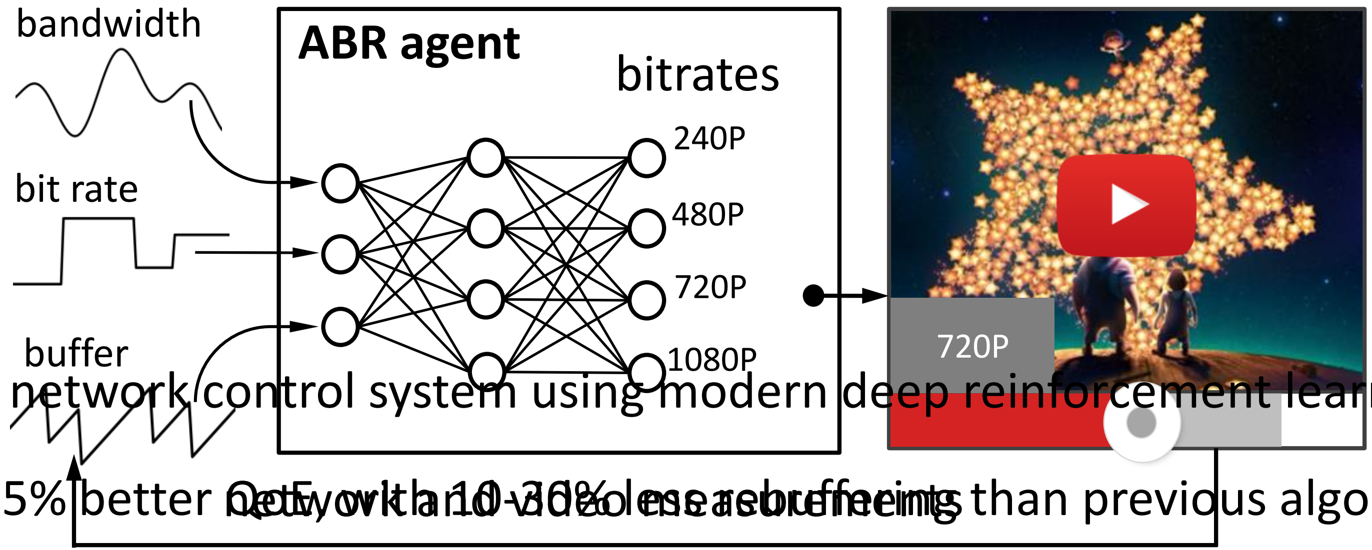
Network throughput is variable & uncertain

Conflicting QoE goals

- Bitrate
- Rebuffering time
- Smoothness

Cascading effects of decisions

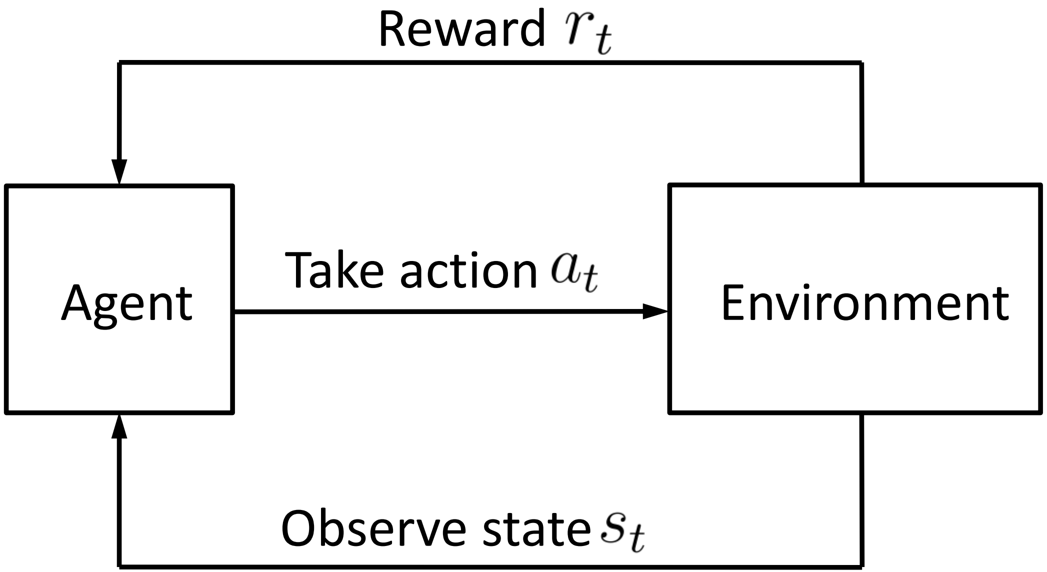
Our System: Pensieve



1. First network control system using modern deep reinforcement learning
2. 12-25% better QoE with 10-30% less rebuffering than previous algorithms
3. Tailors ABR decisions specifically for different network conditions

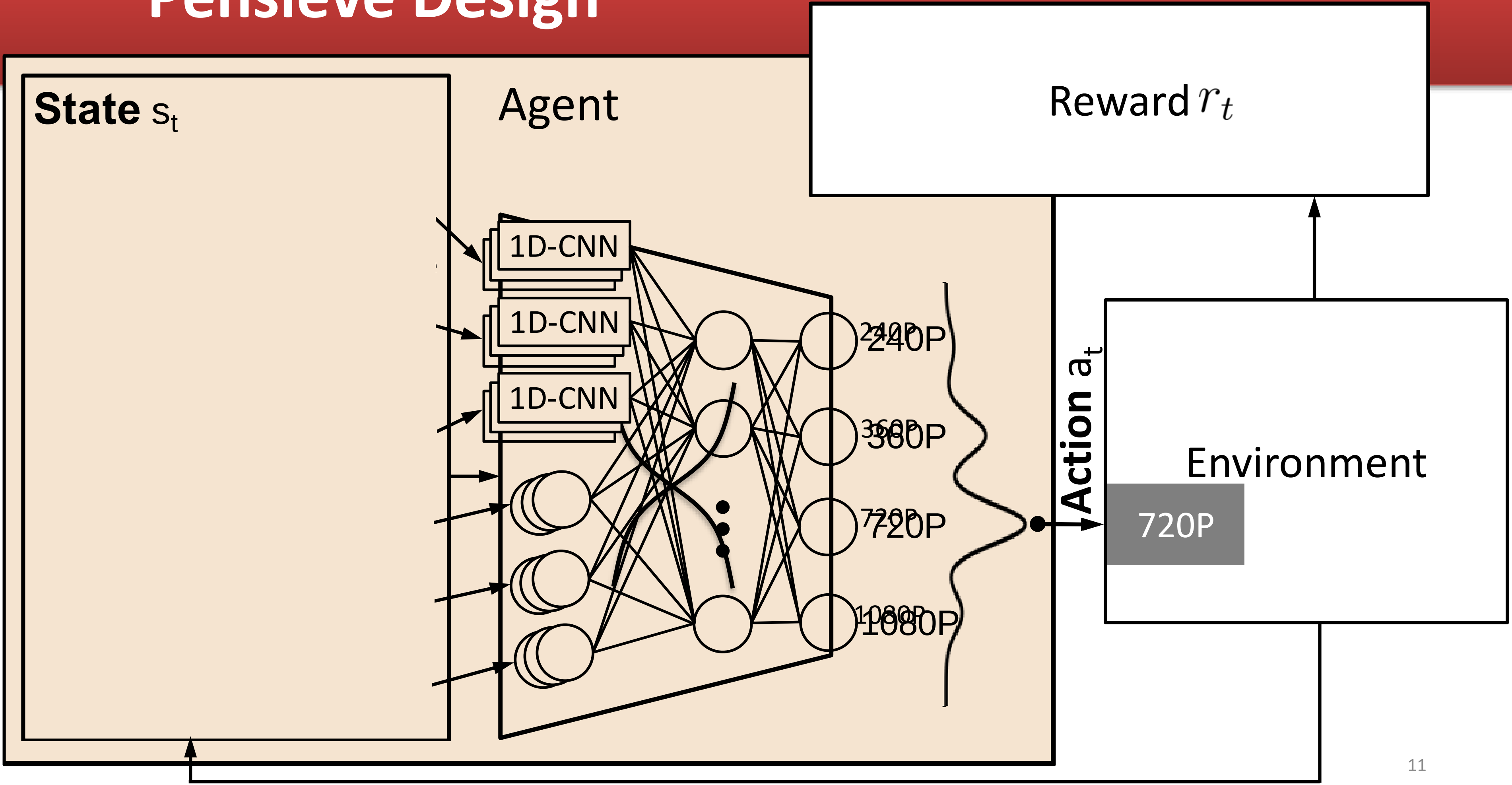
Pensieve learns ABR algorithms automatically through experience

Reinforcement Learning



Goal: maximize expected total future reward $\mathbb{E}\left[\sum_t r_t\right]$

Pensieve Design

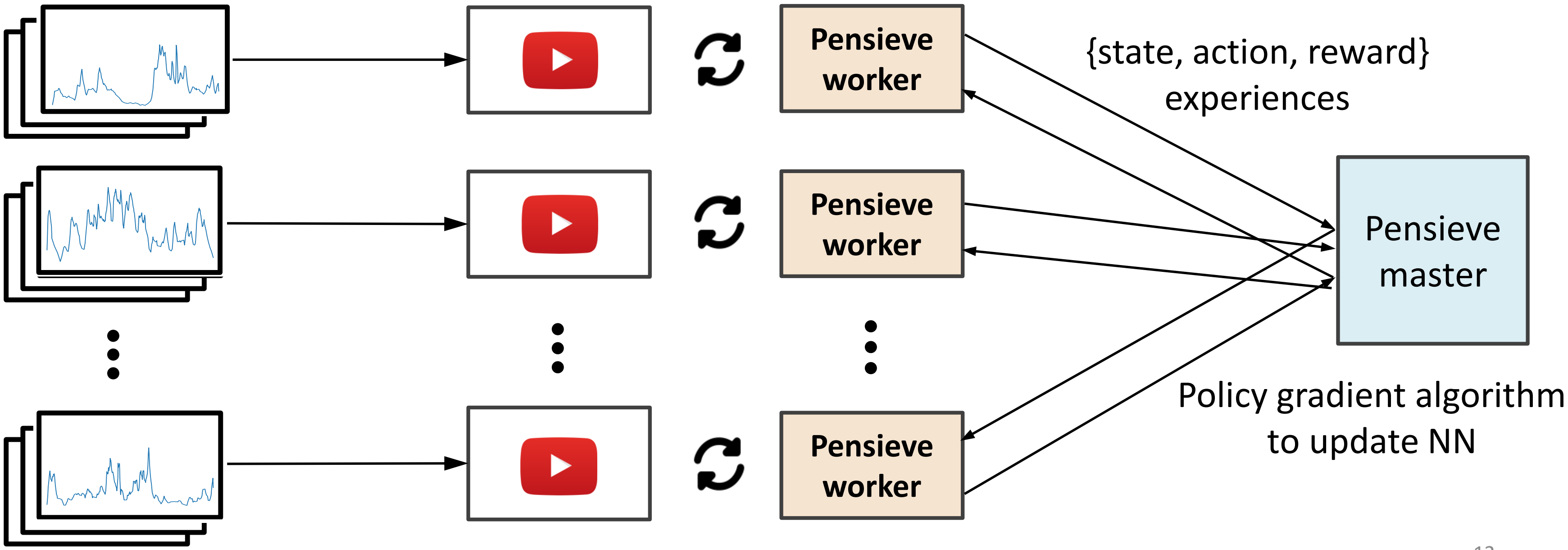


Pensieve Training System

Large corpus of network traces
cellular, broadband, synthetic

Video playback
Fast chunk-level simulator

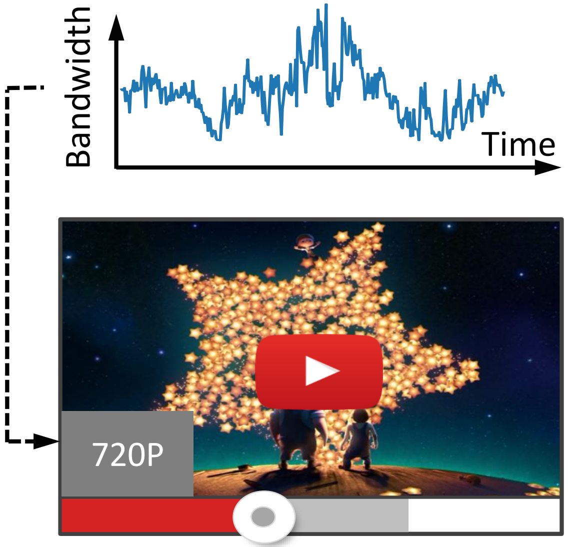
Model update



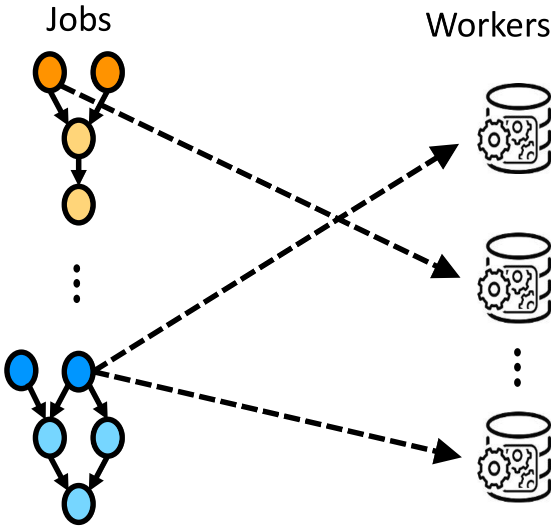
Pensieve
MPC
240P
240P
Pensieve
buffer (sec)
Throughput
(mbps)
MPC
buffer (sec)
chances of outage
Rebuffering
Time

Our Work on Learning-Based Network Systems

Adaptive video streaming
(Pensieve)



Cluster Scheduling
(Decima)

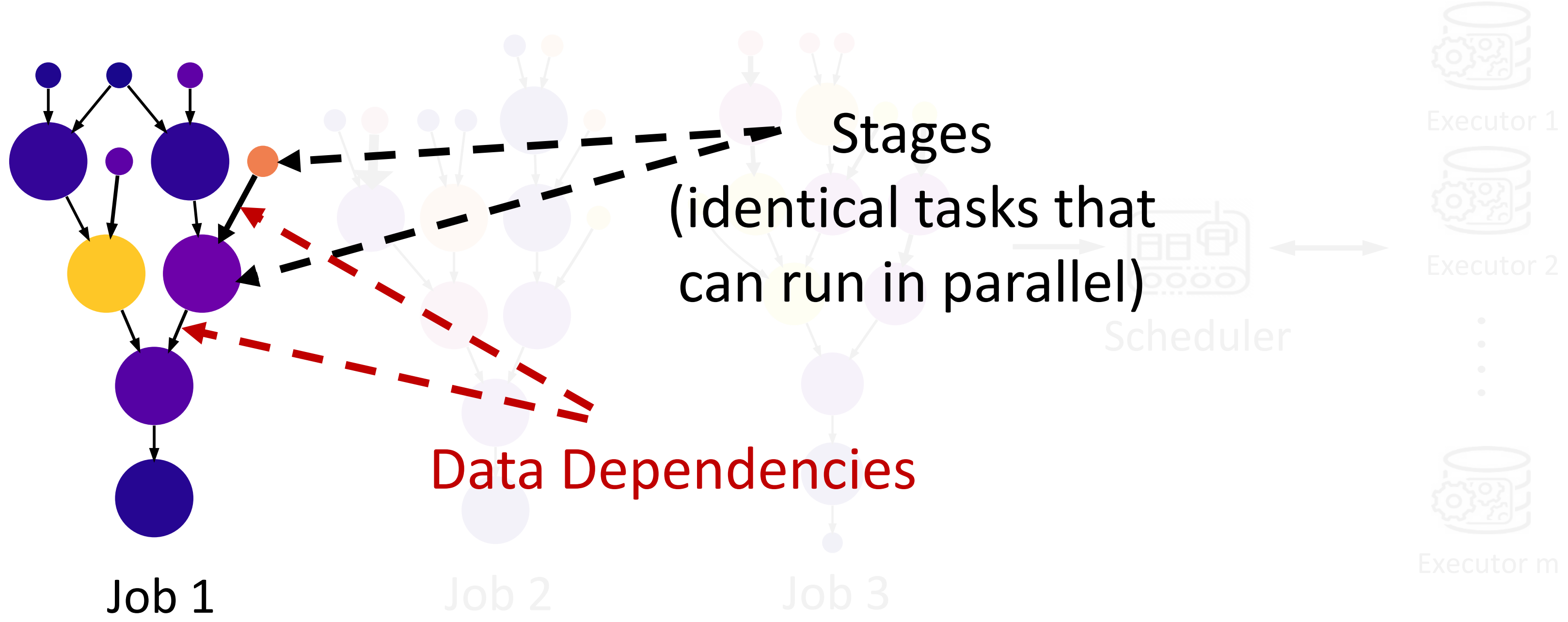


RL Techniques

Scheduling Graph-Structured Workloads

Many systems encode jobs as directed acyclic graphs (DAGs)

- Data processing (e.g., Spark, Hadoop), ML training (e.g., TensorFlow), ...



Designing Optimal Schedulers is Intractable

A lot of considerations for optimal performance:

- Job dependency structure
- Degree of parallelism
- Scheduling order
- Locality
- …

No "one-size-fits-all" solution:

Best algorithm depends on specific workload and system

Decima: Technical Challenges

Challenge: Huge state and action space

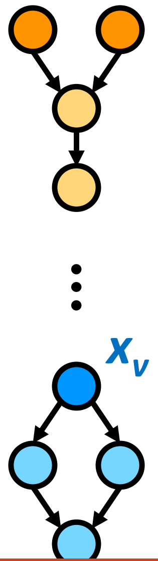
→ Scalable Graph CNN to process any number of job DAGs

Challenge: Variance caused by stochastic job arrival process

→ Variance reduction technique for RL in input-driven systems

Decima Design

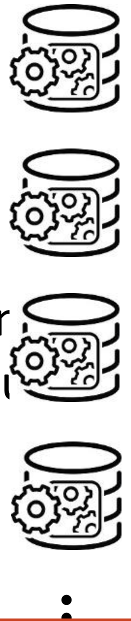
Job DAG 1



Job DAG n

Node features:

- # of tasks
- avg. task duratior
- # of current execı



Executor 1

Executor 2

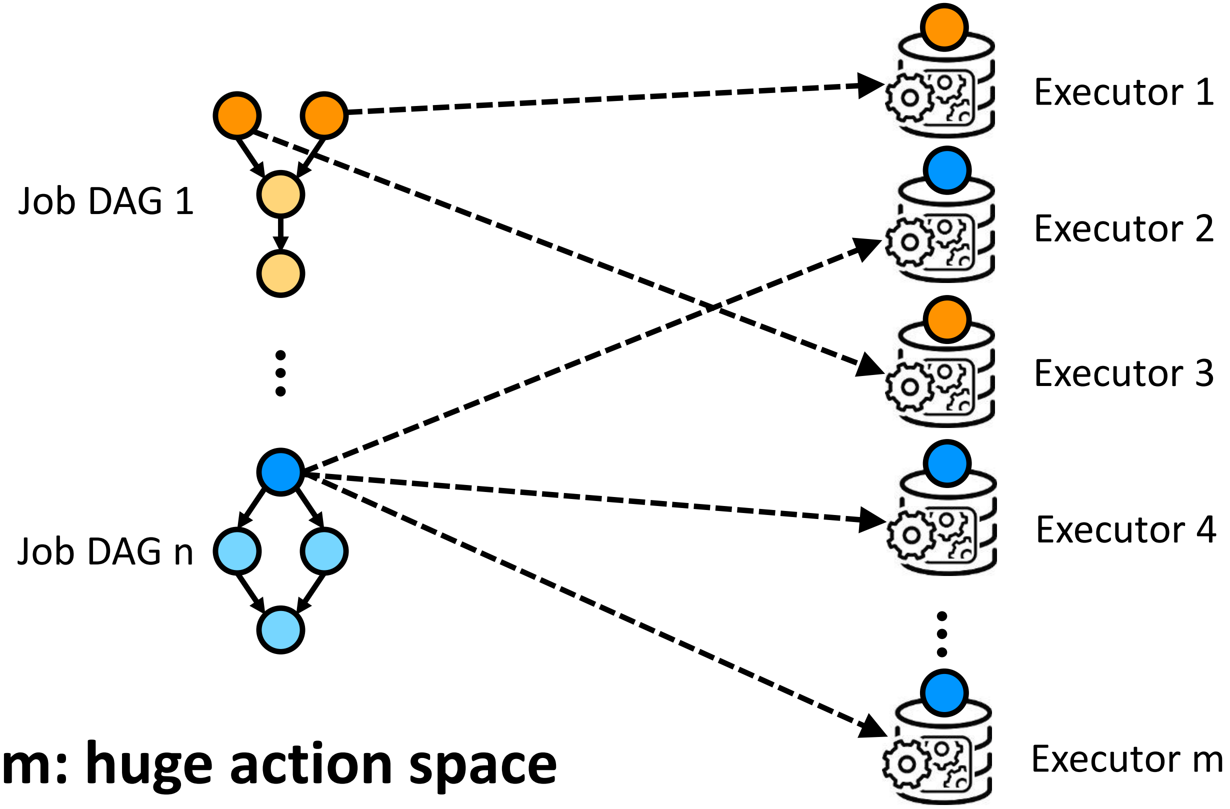
Executor 3

Executor 4

Set of identical free executors

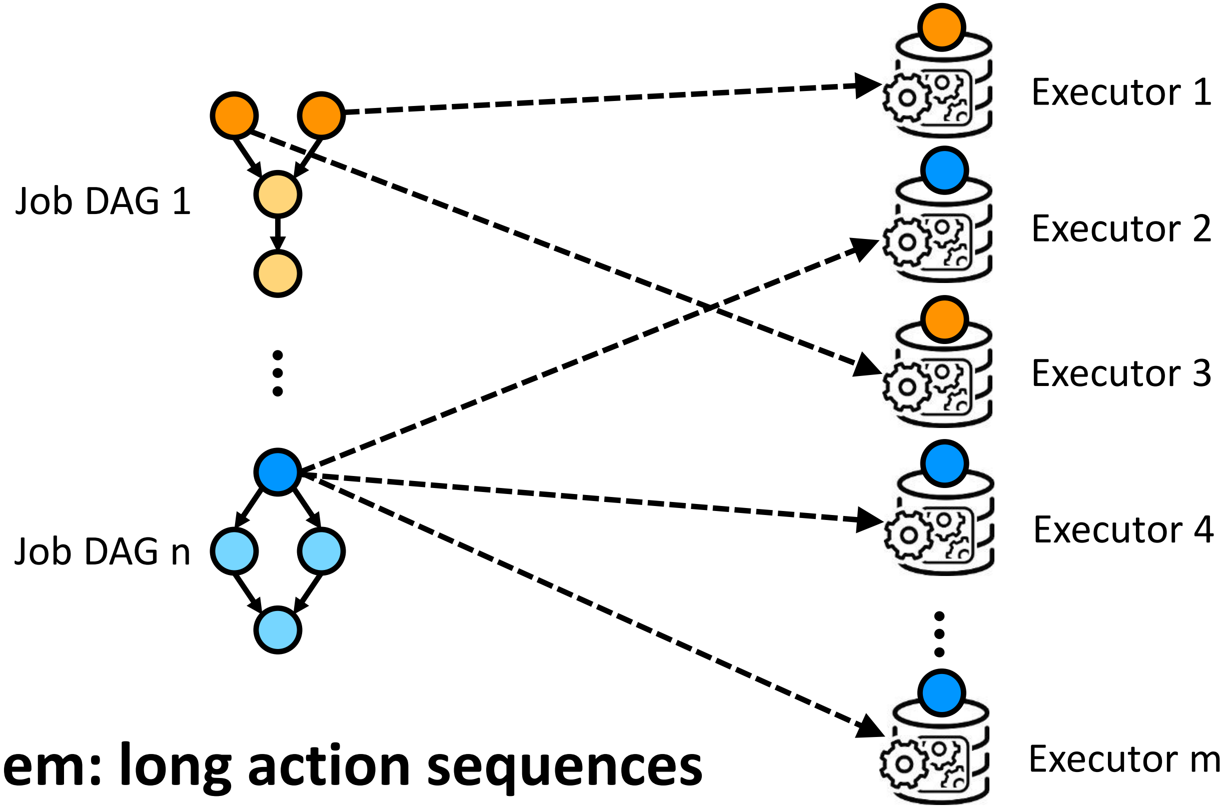
How to encode scheduling decisions as actions?

Option 1: Assign all Executors in 1 Action



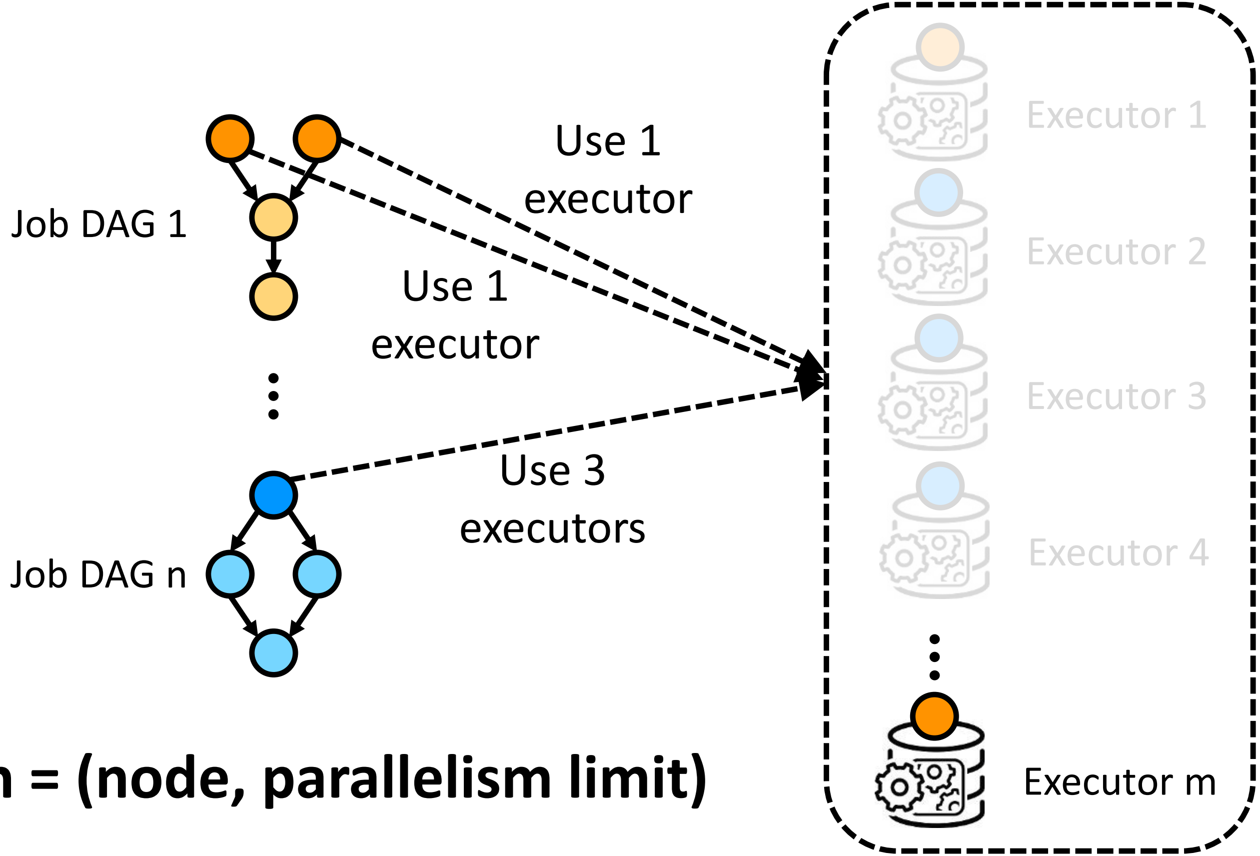
Problem: huge action space

Option 2: Assign 1 Executor per Action



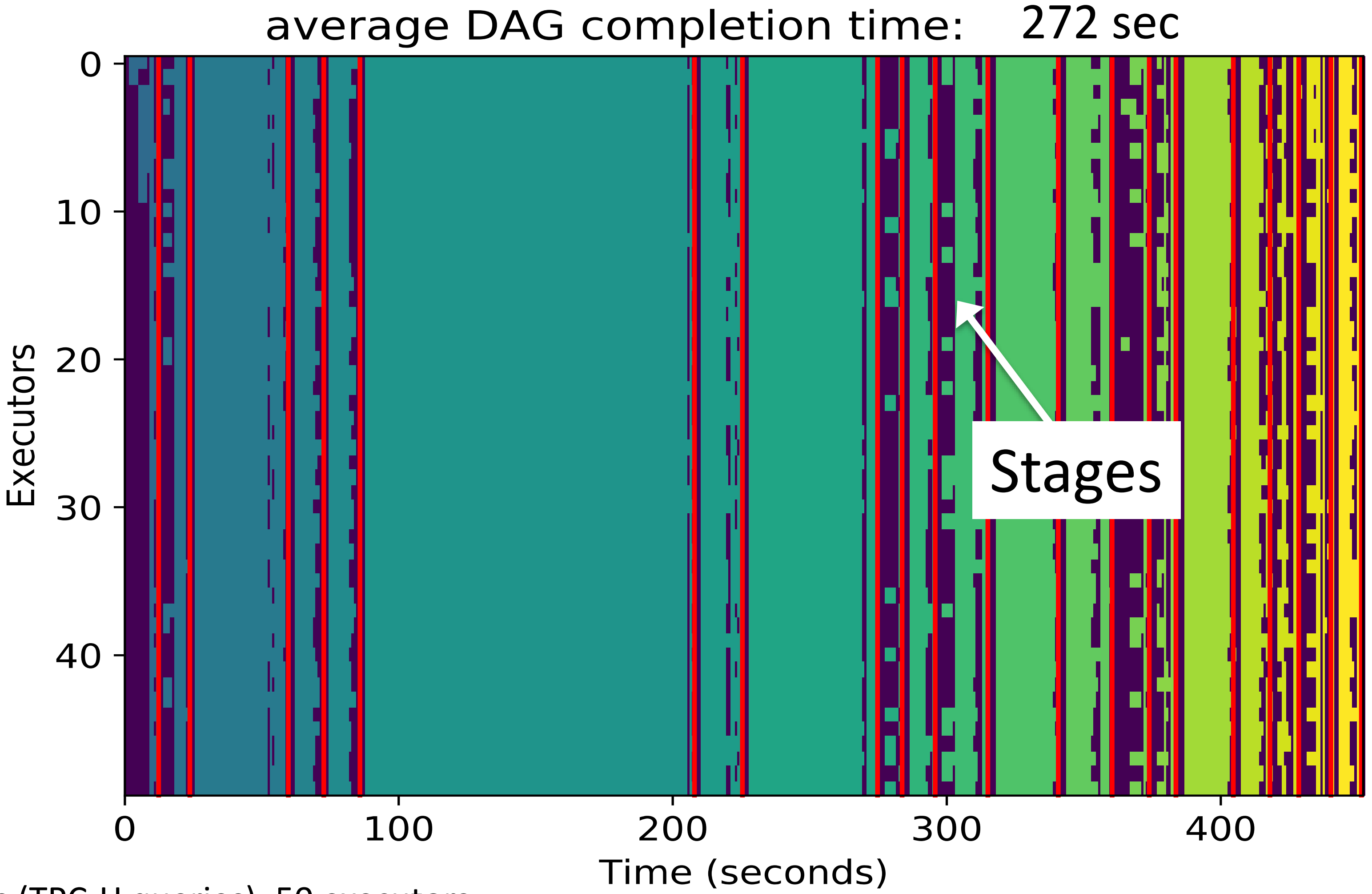
Problem: long action sequences

Decima: Assign Groups of Executors per Action



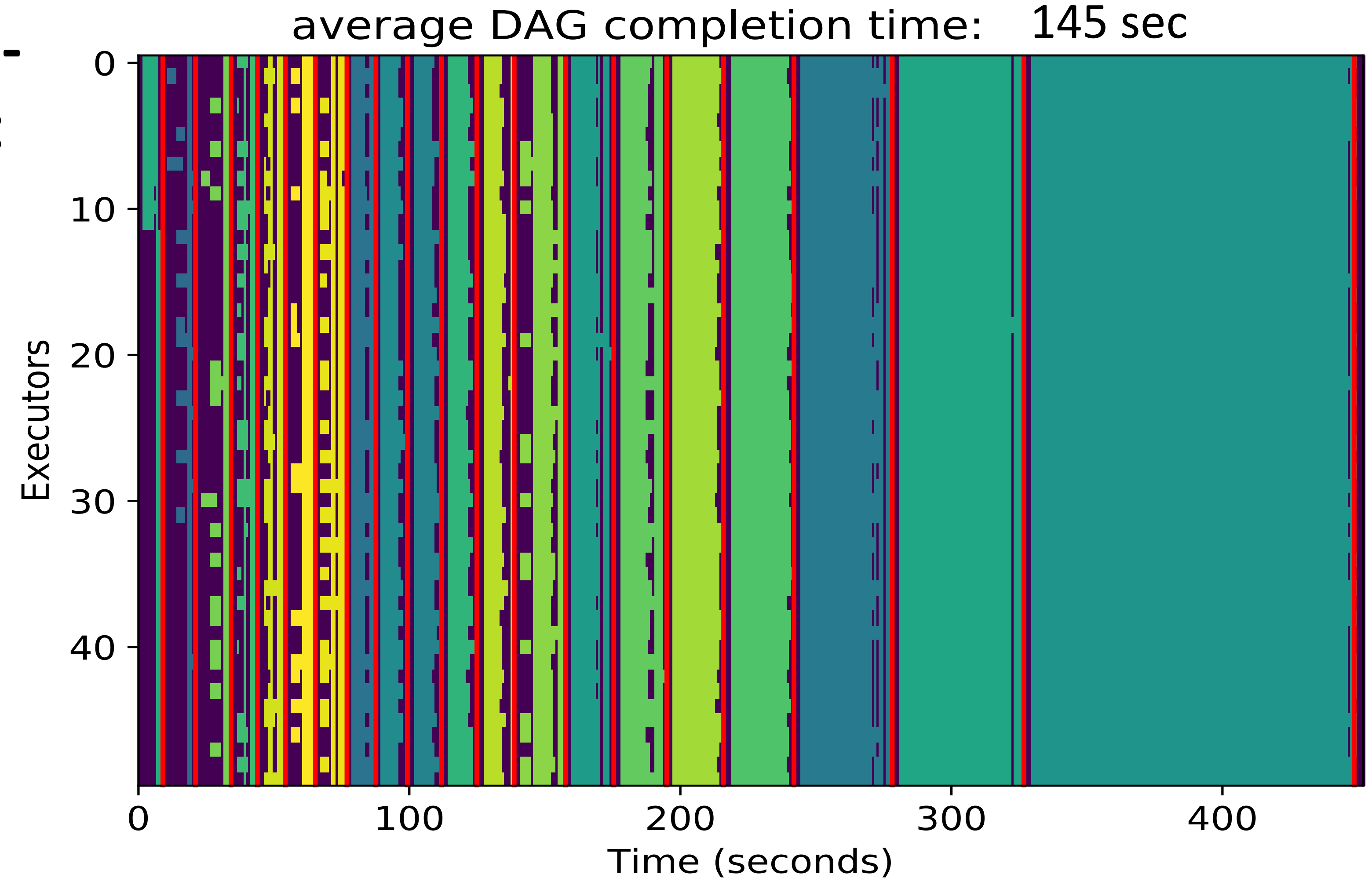
Action = (node, parallelism limit)

FIFO

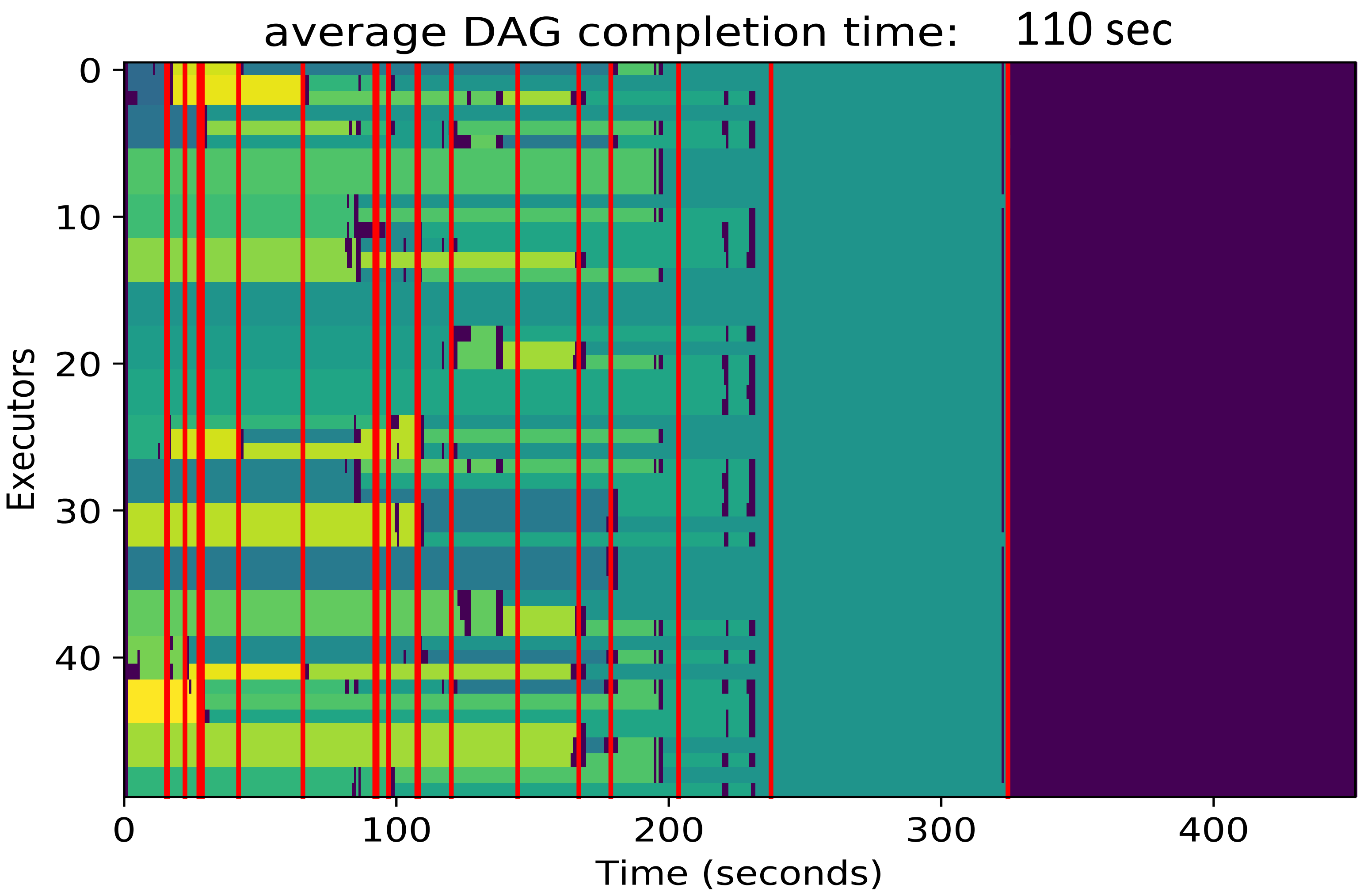


✧ 20 Spark jobs (TPC-H queries), 50 executors

Shortest-Job-First

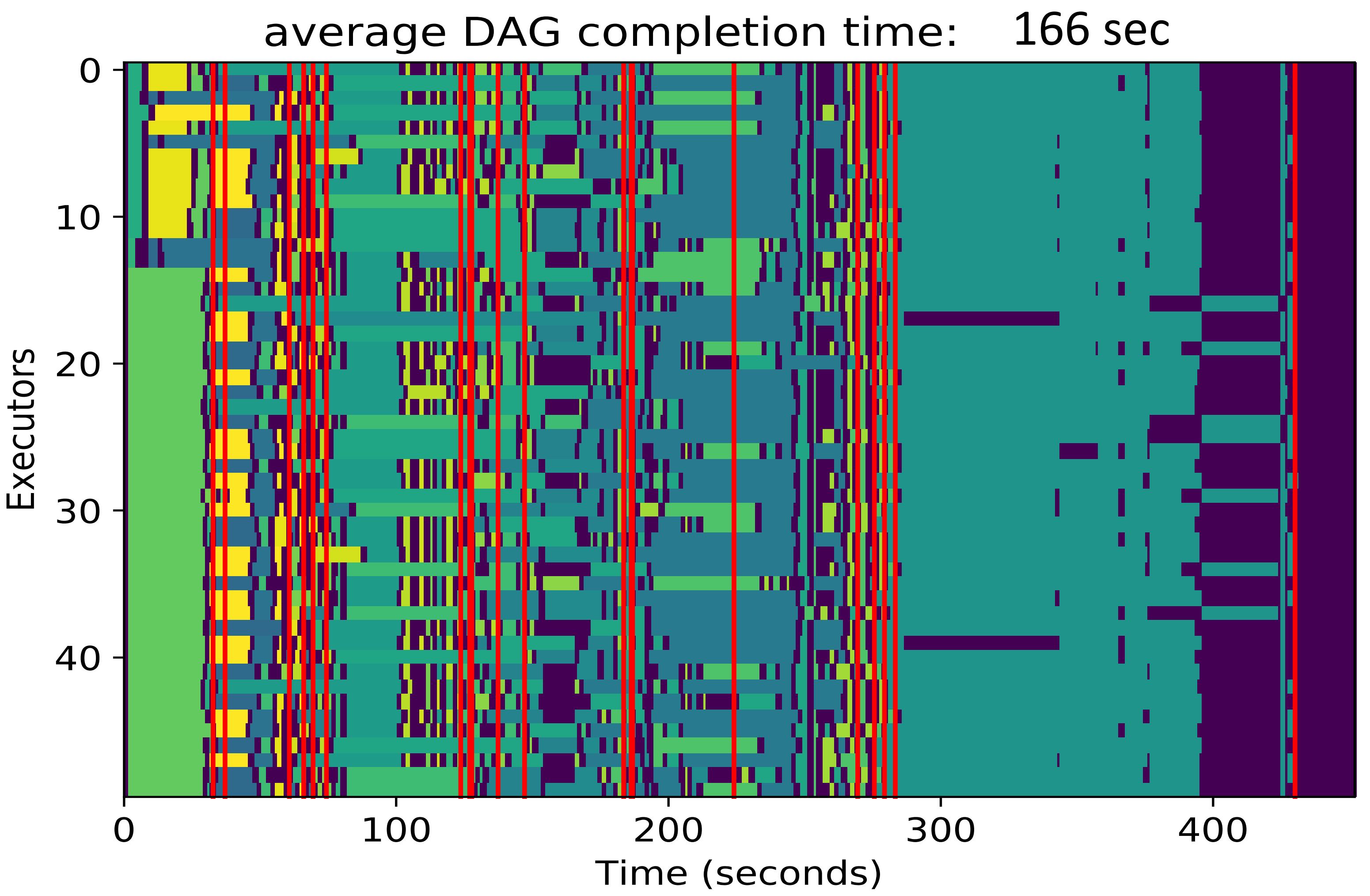


Fair


average DAG completion time: 110 sec
Executors
0
10
20
30
40
0
100
200
300
400
Time (seconds)

Decima

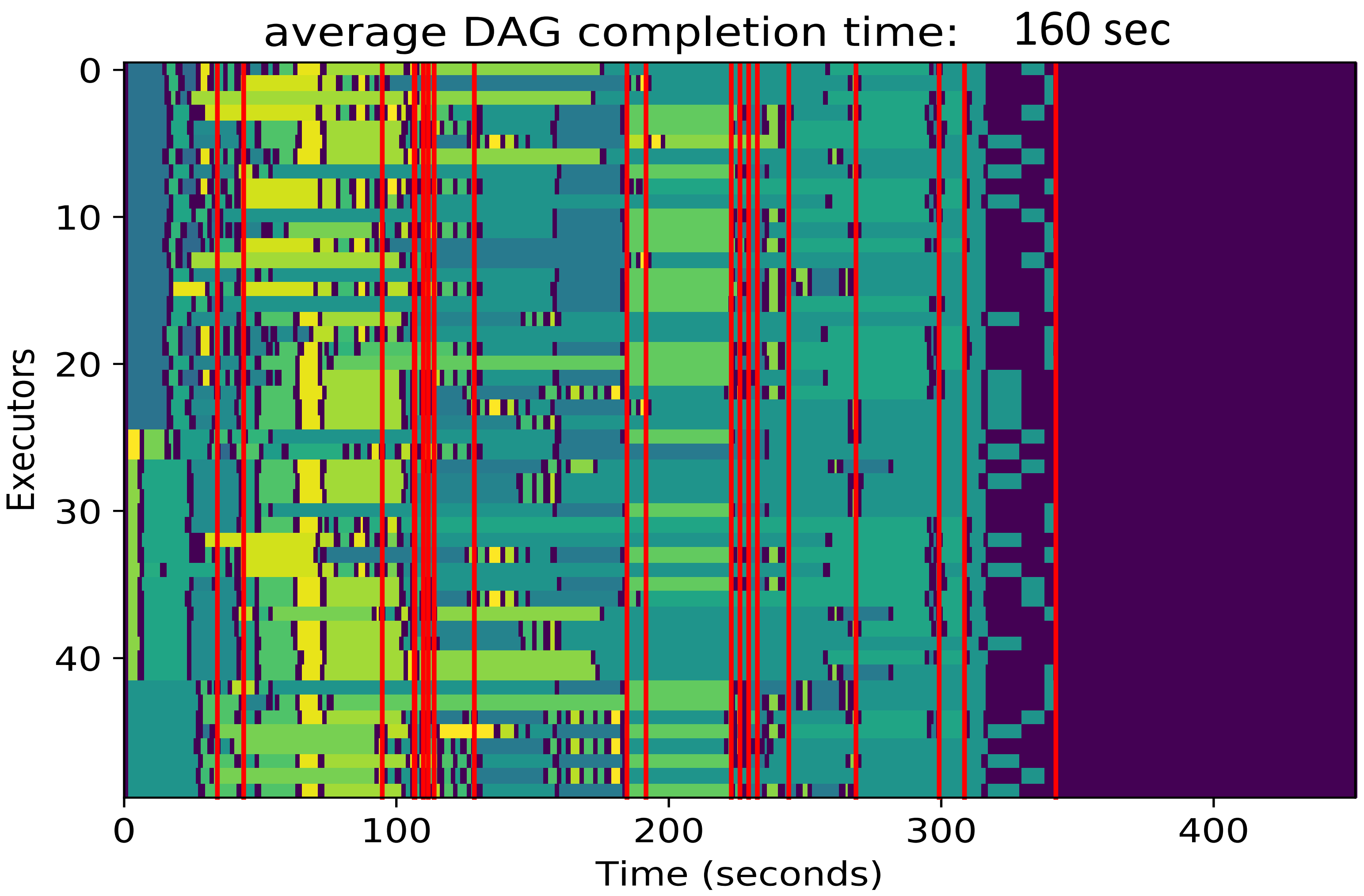
it=0



average DAG completion time: 166 sec
Executors
Time (seconds)
0
10
20
30
40
0
100
200
300
400

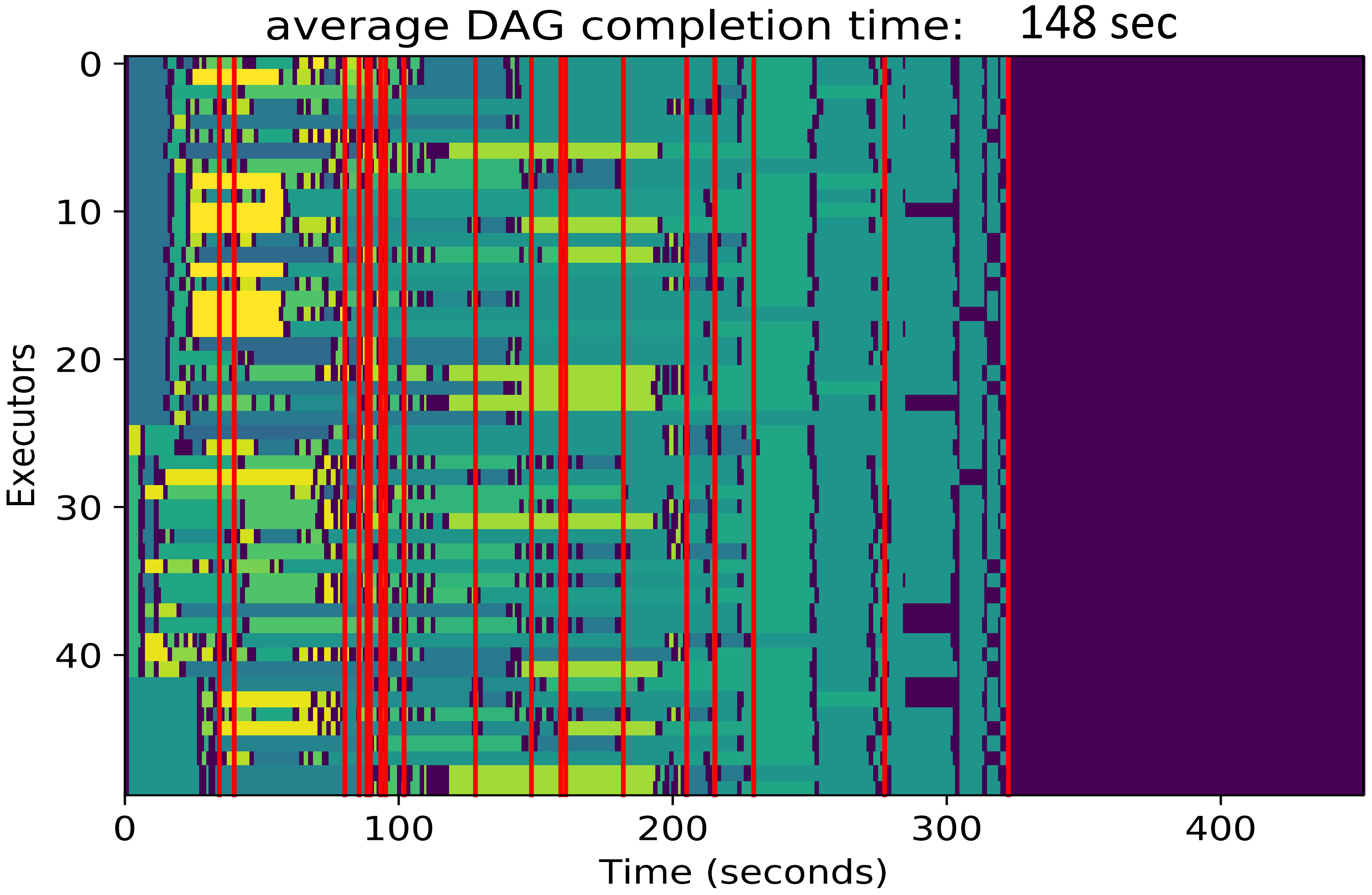
Decima

it=3000



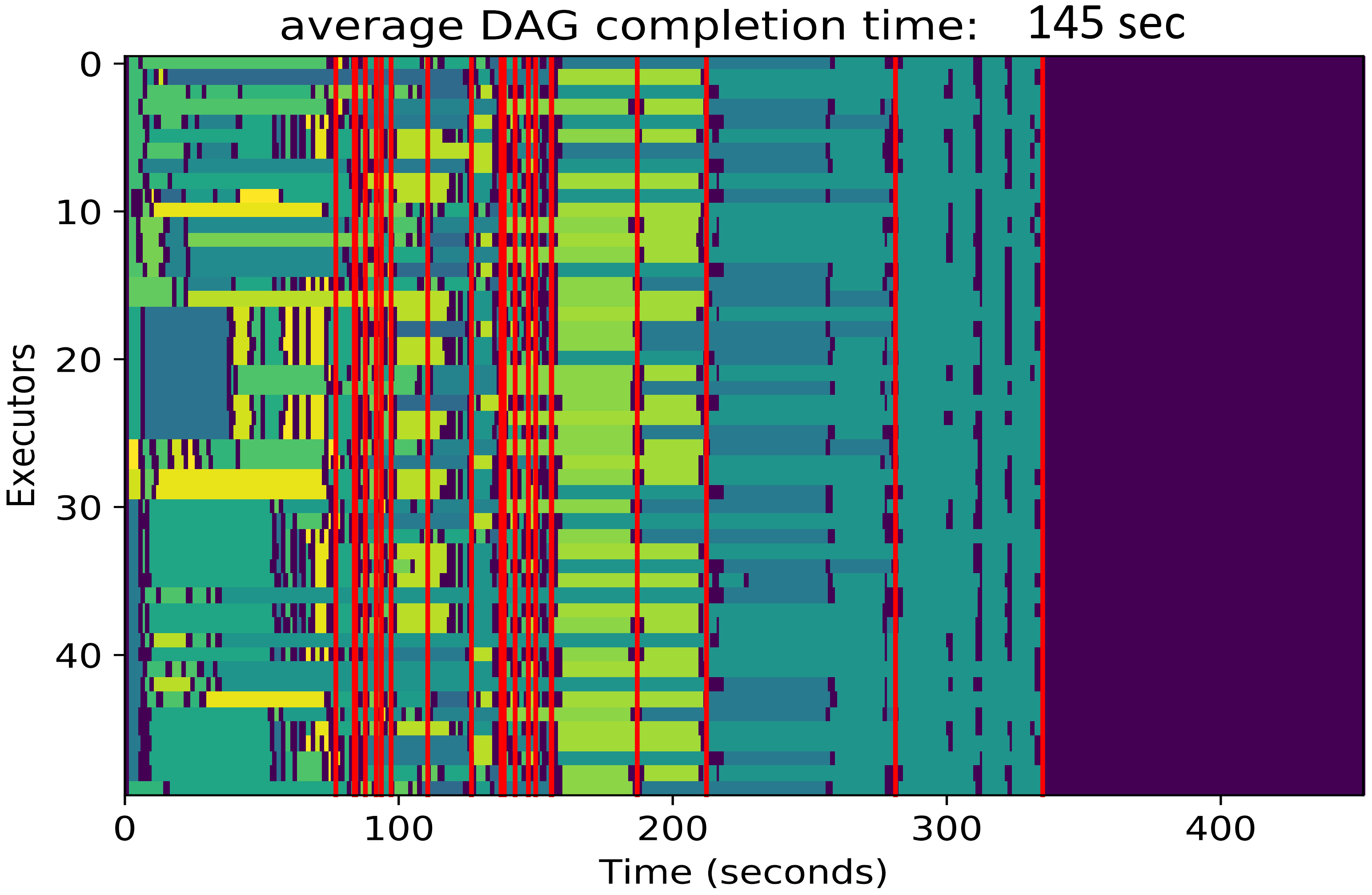
Decima

it=6000



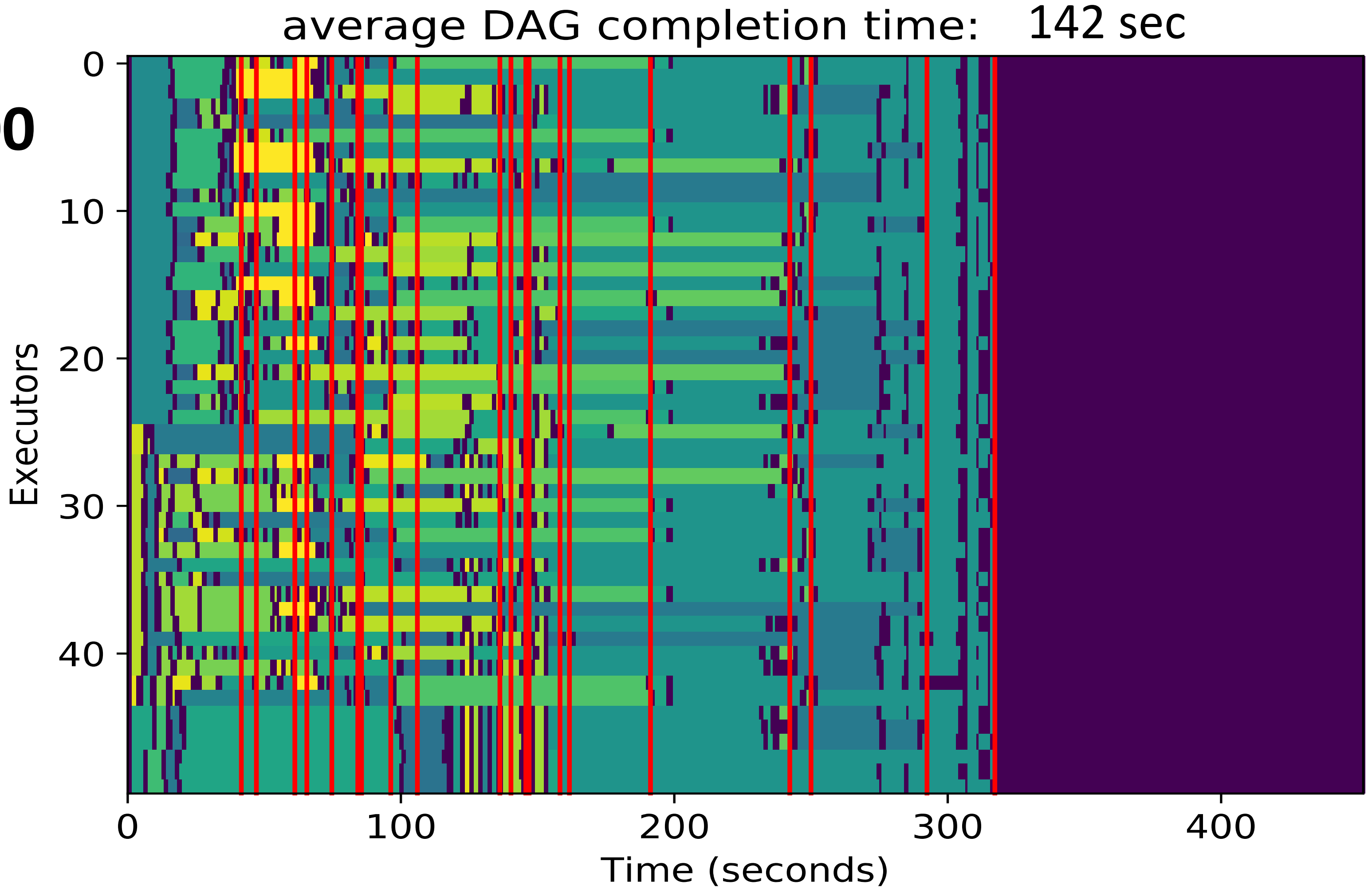
Decima

it=9000

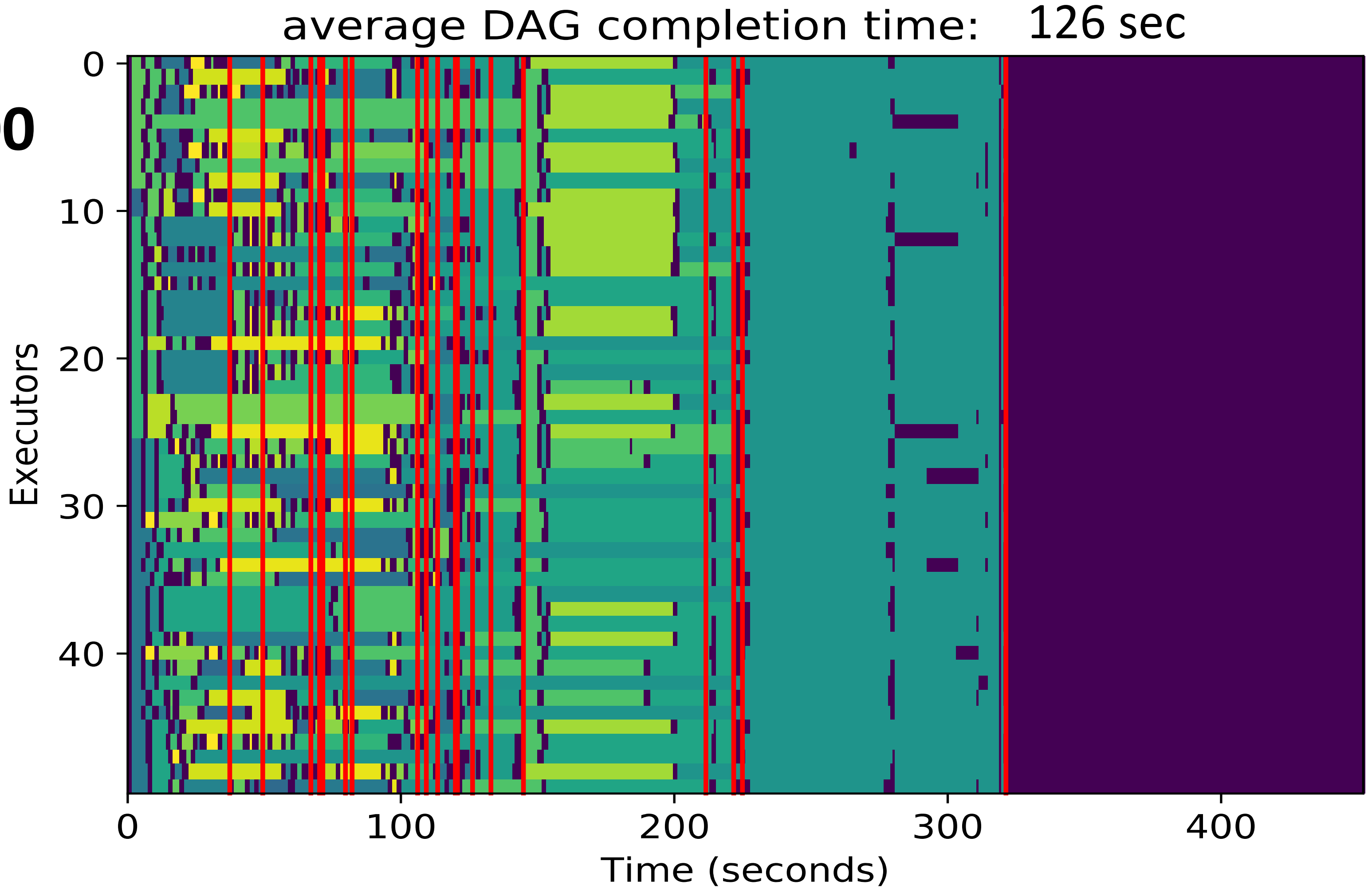


Decima

it=12000

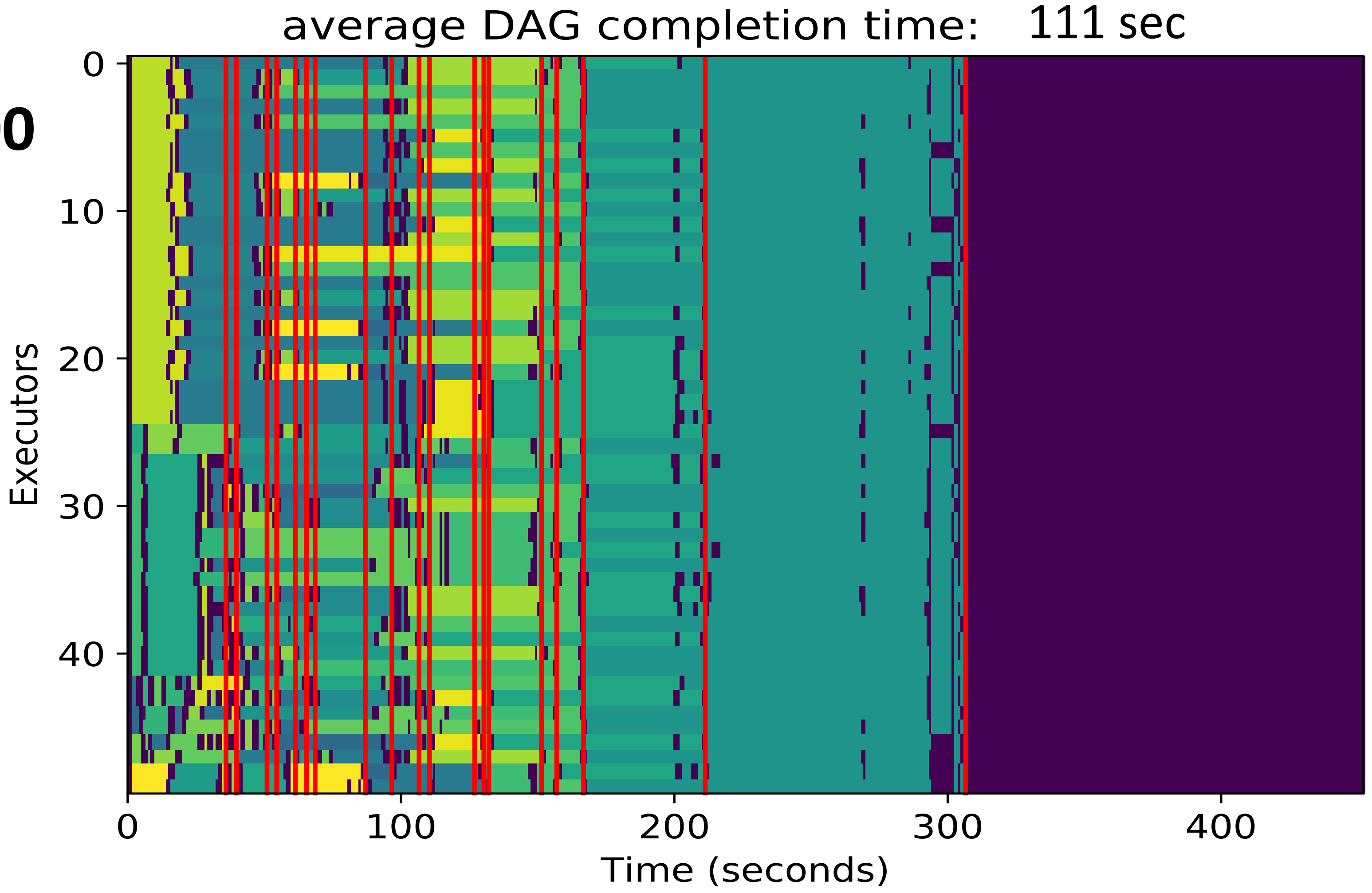


Decima
it=15000



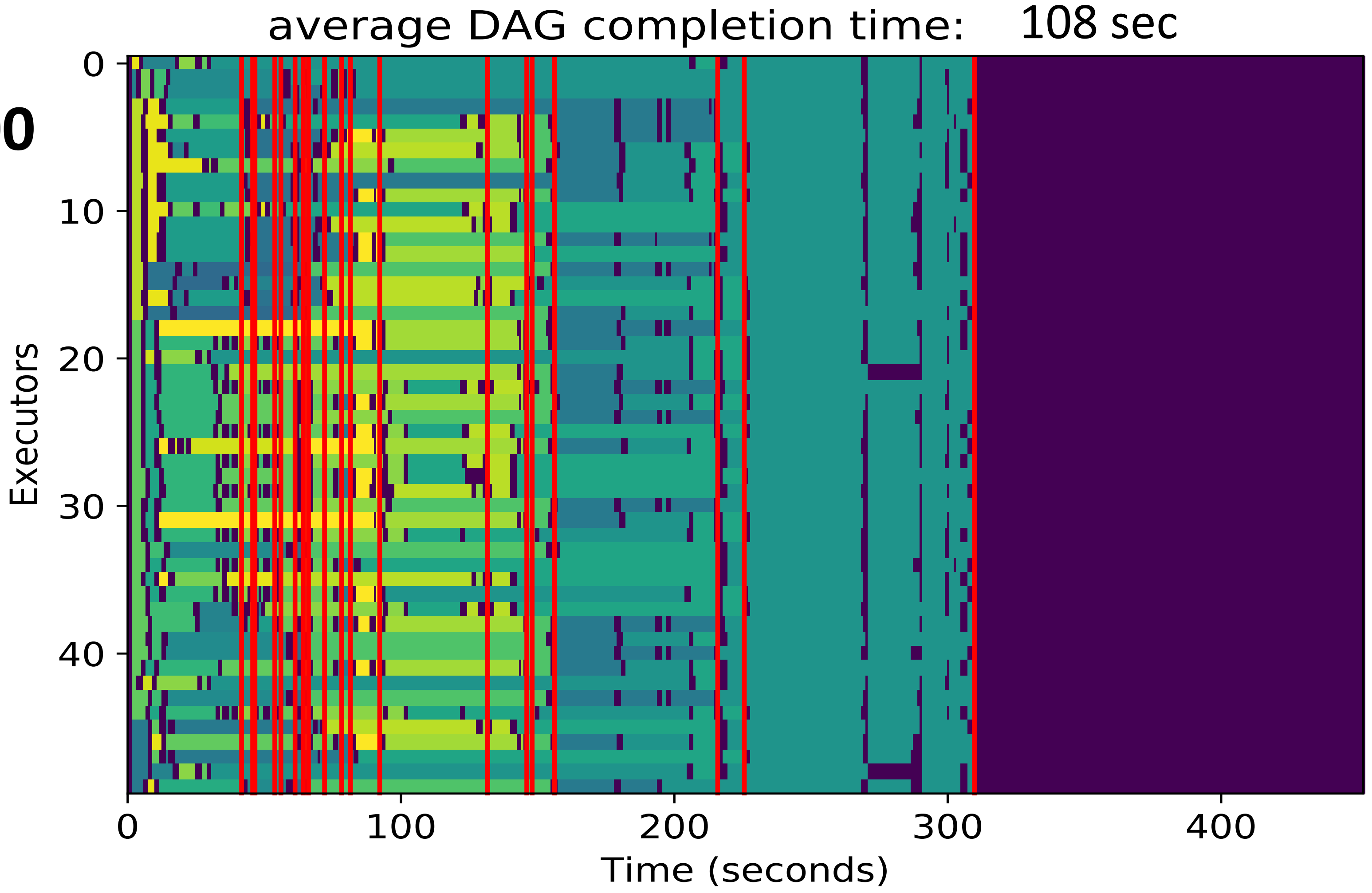
Decima

it=18000



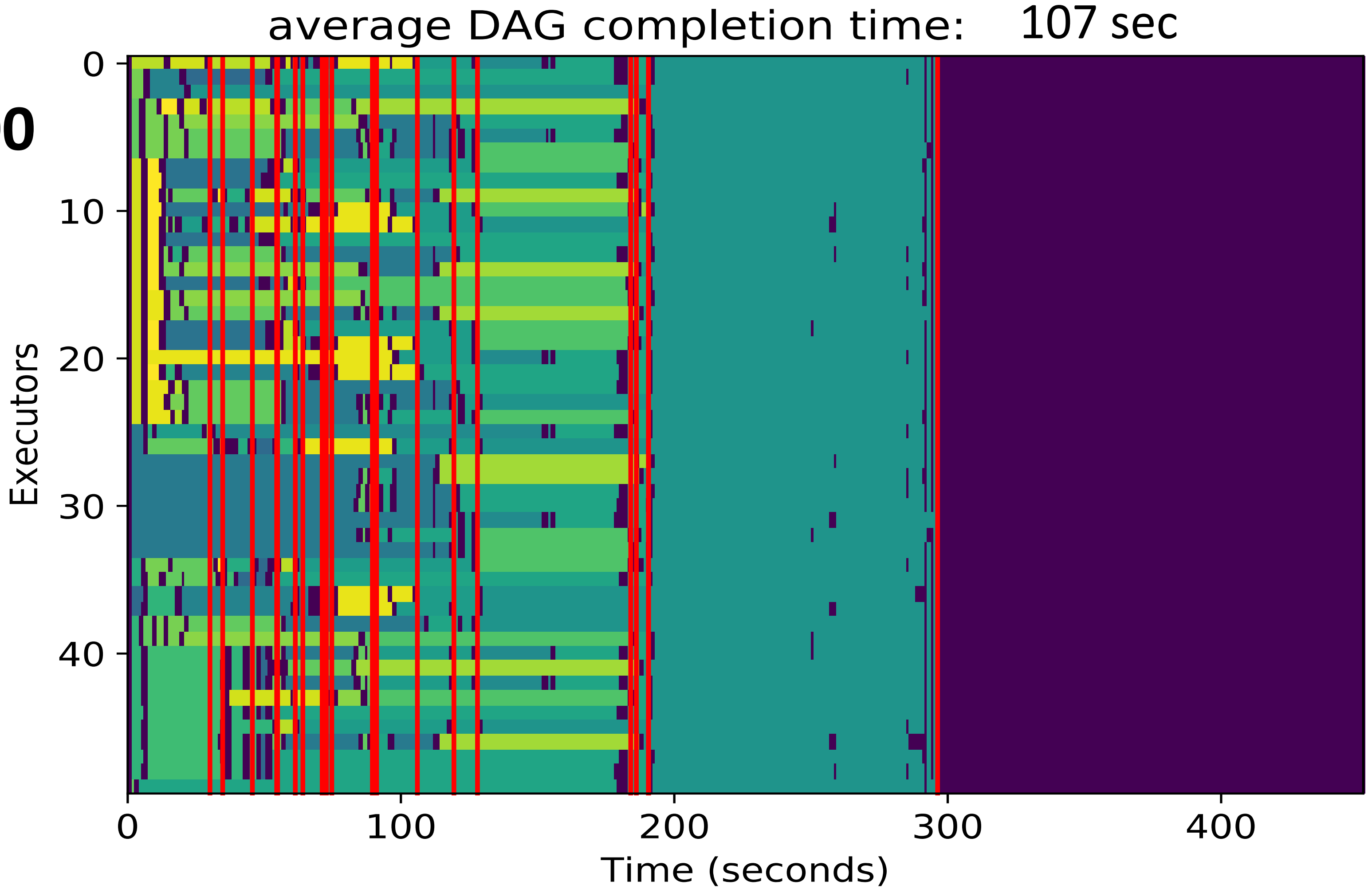
Decima

it=21000



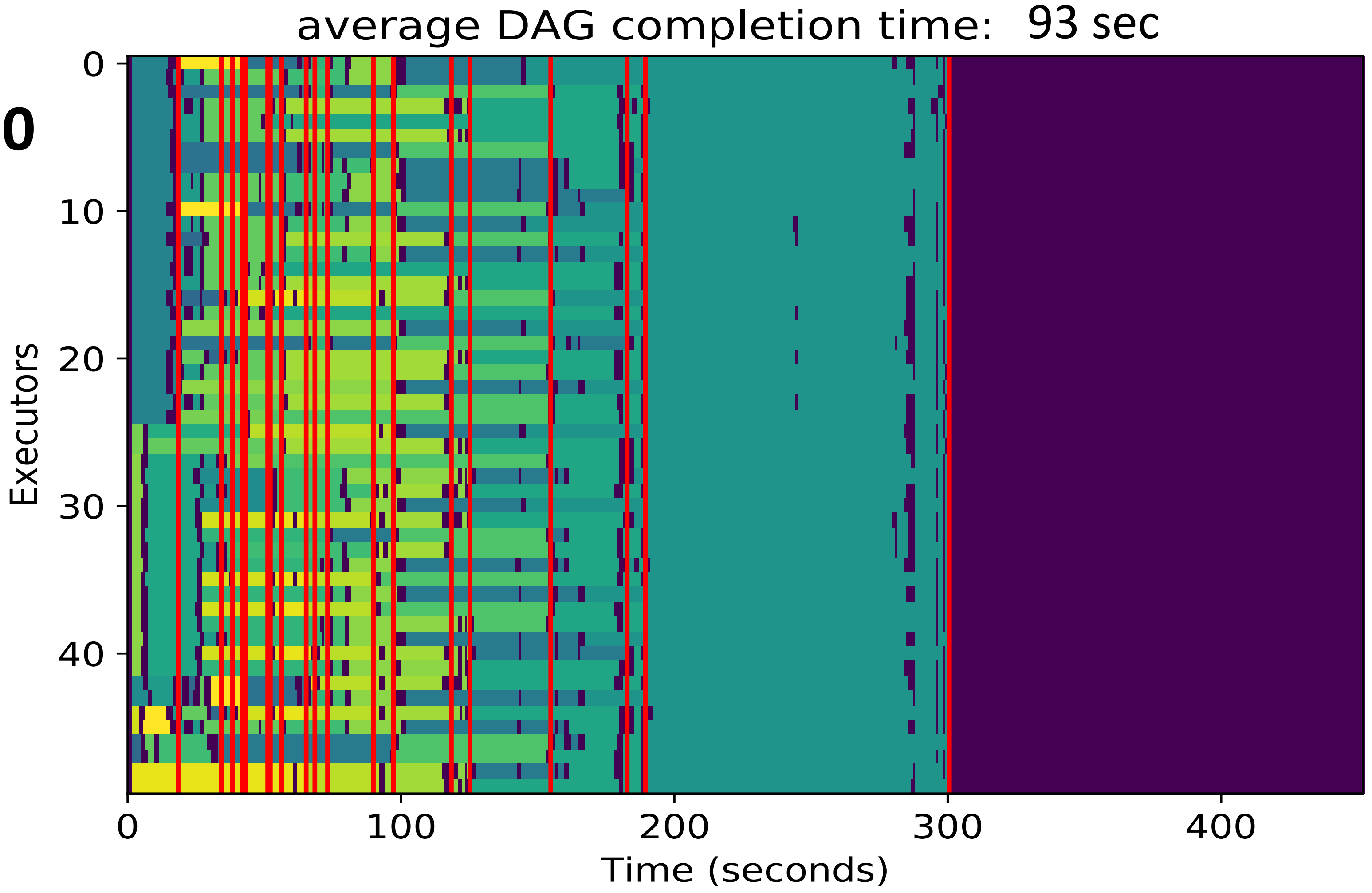
Decima

it=24000

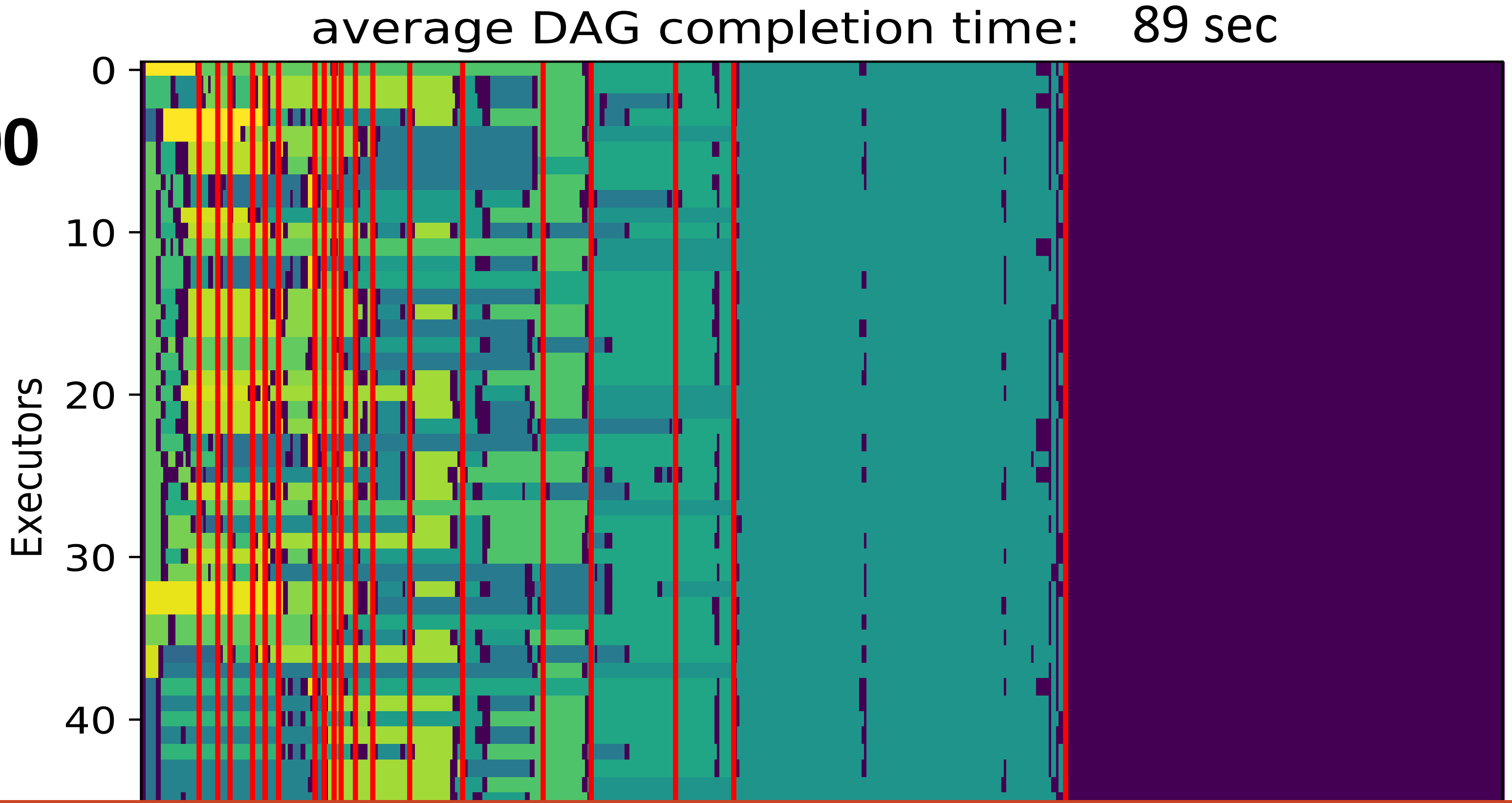


Decima

it=27000



Decima
it=30000



Decima improves average job completion time by >2x over existing schedulers, and 19-31% over best hand-crafted heuristics

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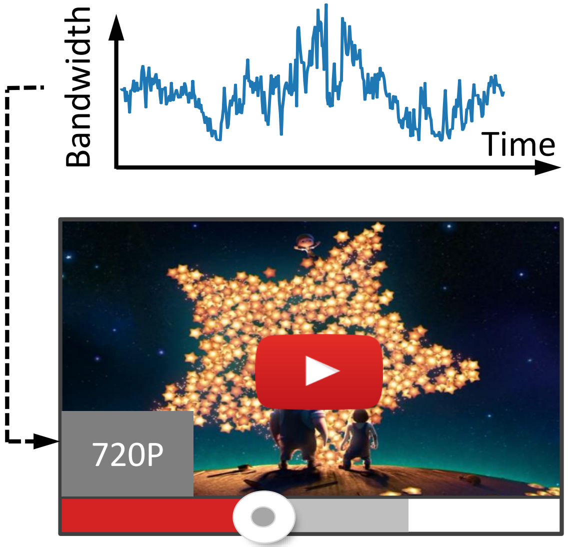
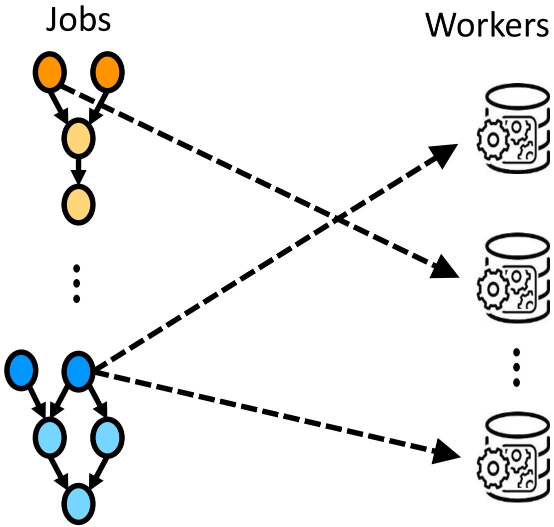
(Pensieve)



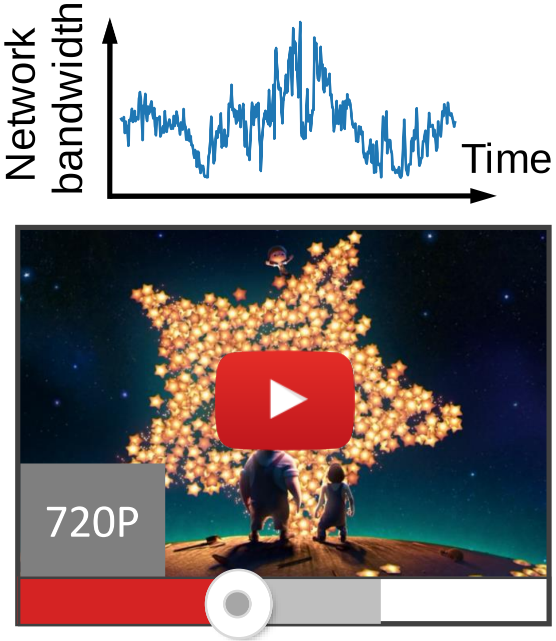
Cluster Scheduling
(Decima)

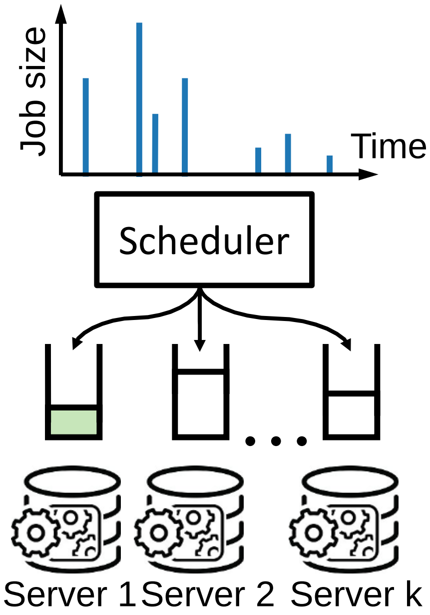


RL Techniques

Input-Driven Environments

Dynamics driven by an exogenous stochastic **input process**





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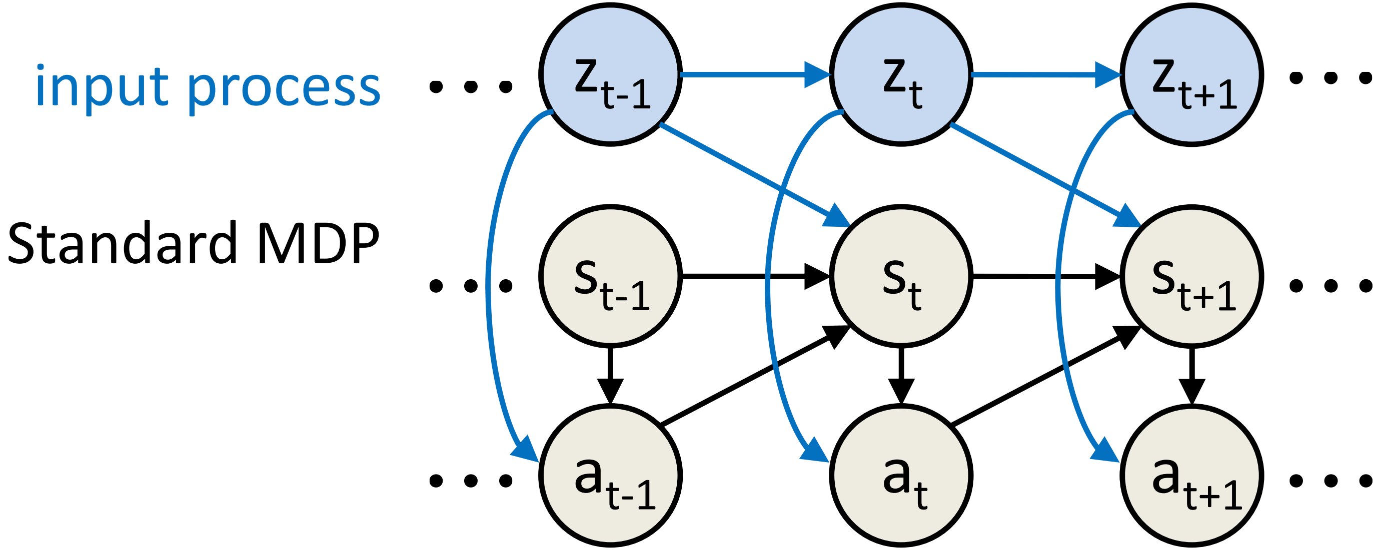
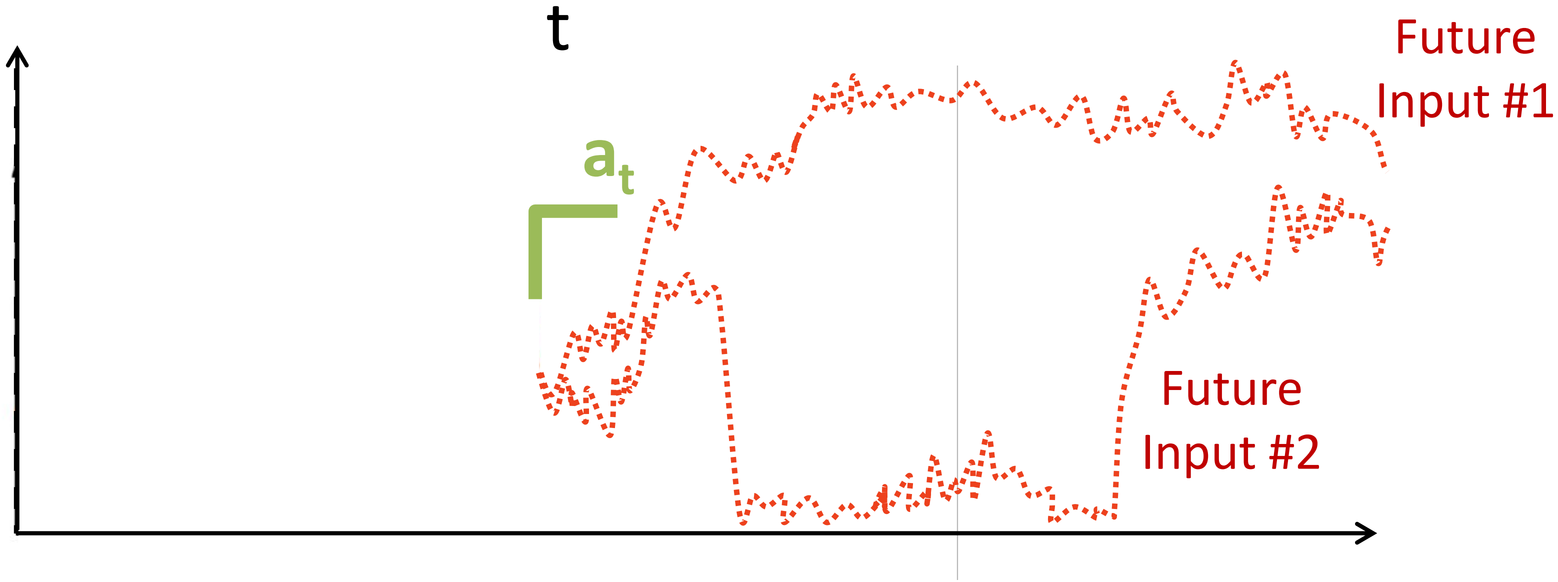
Dynamics driven by an exogenous stochastic **input process**



The input does not depend on the states and actions

Reinforcement Learning for Input-Driven MDPs



Must take the future input into account when evaluating actions

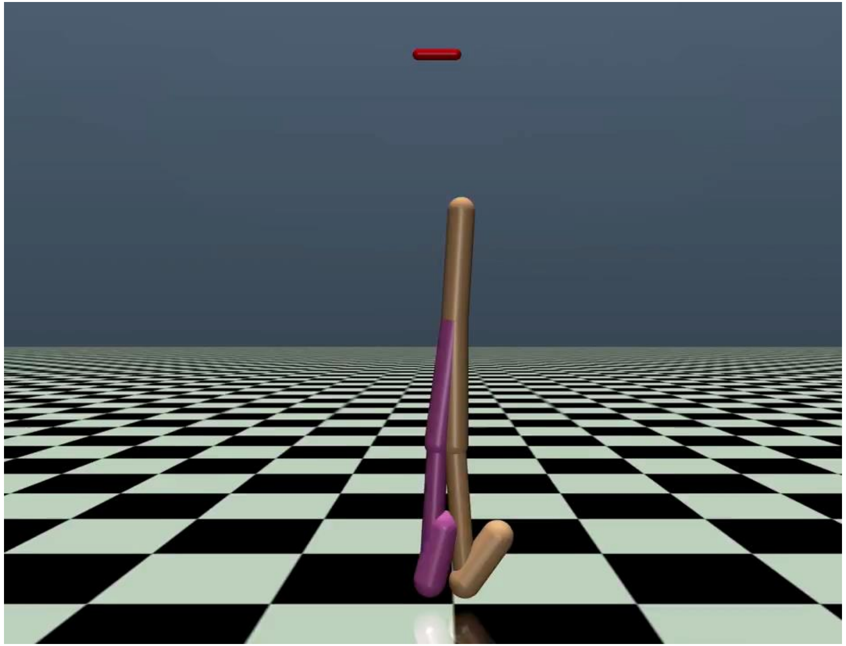
Input-Dependent Baseline

Score for action a_t = $\sum_{t'=t}^{T-1} r_{t'}$ $-$ $b(s_t, z_t, z_{t+1}, \ldots)$

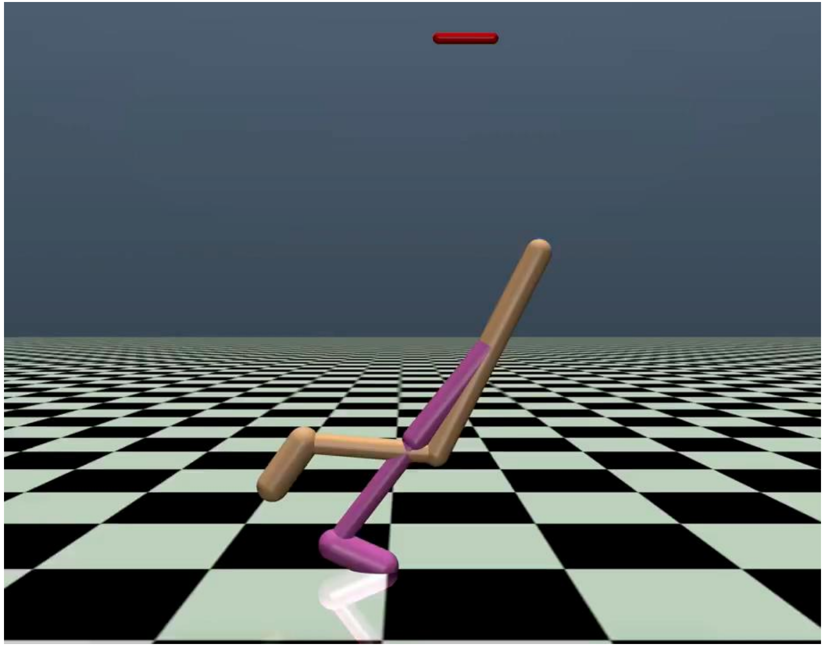
Expected return for trajectories from state s_t
with input sequence z_t, z_{t+1}, …

- Input-dependent baselines reduce variance without bias
- We use meta-learning to learn baseline efficiently

Walker2d with Wind

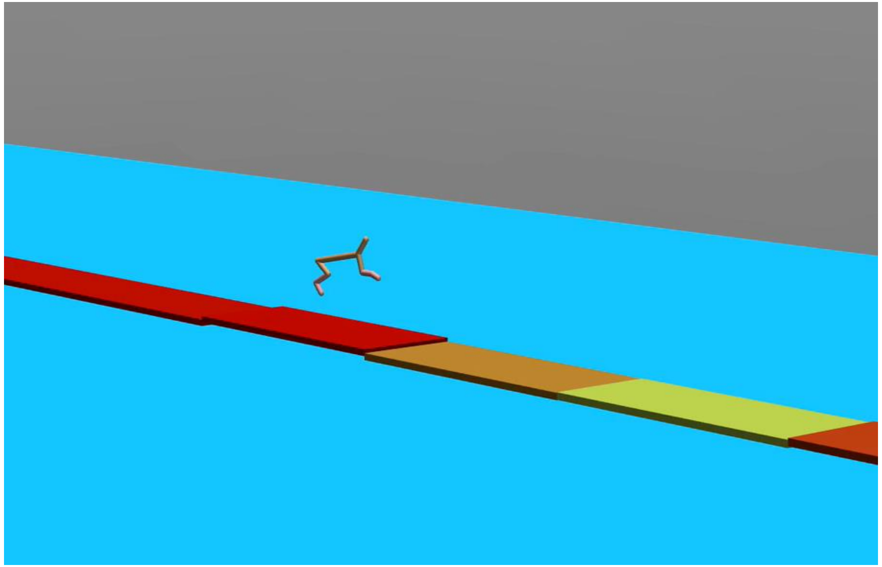


TRPO with standard baseline

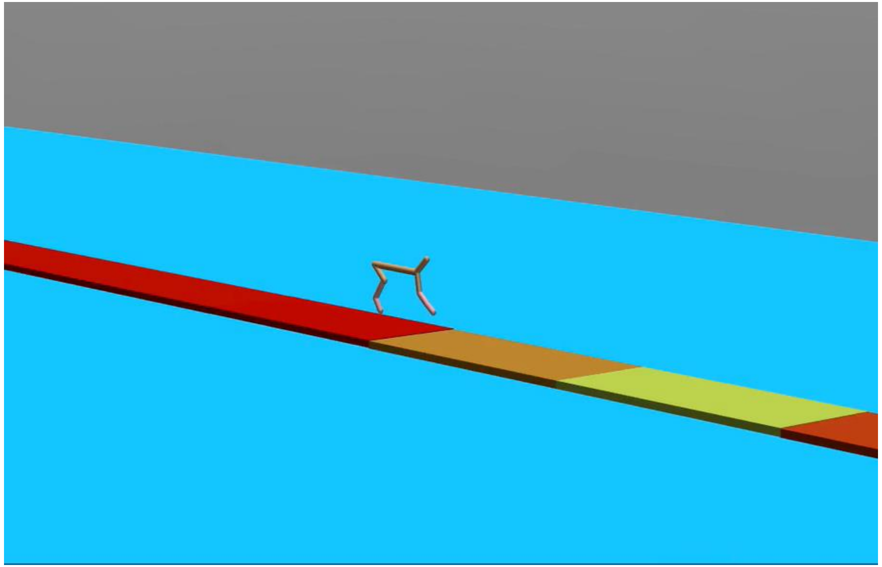


TRPO with input-dependent baseline

Half-Cheetah on Floating Tiles

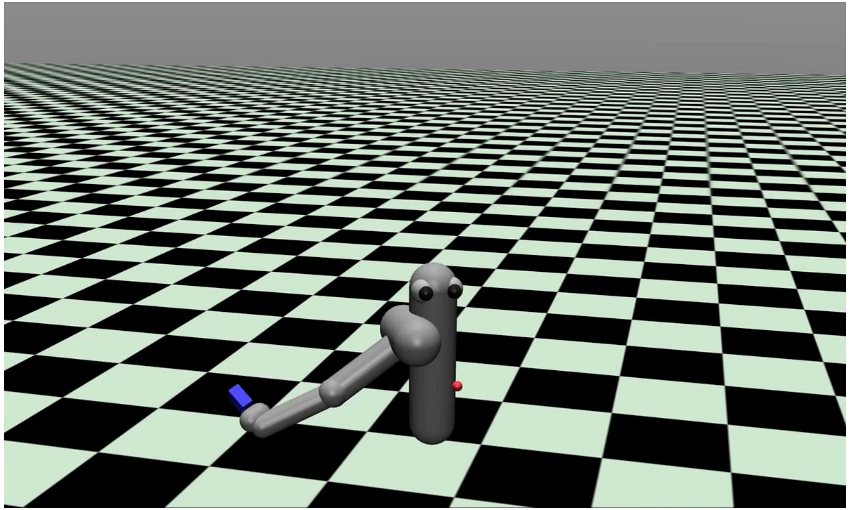


TRPO with standard baseline

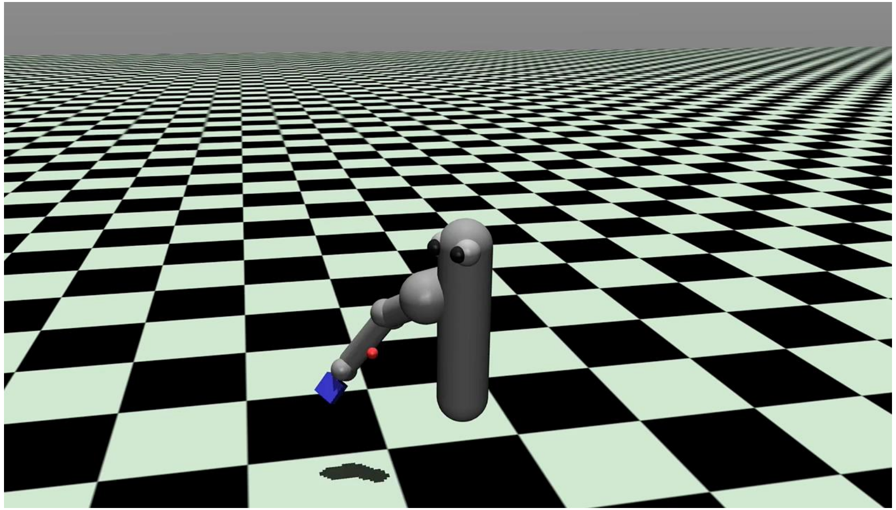


TRPO with input-dependent baseline

7-DoF Arm Tracking Moving Object



TRPO with standard baseline



TRPO with input-dependent baseline

Summary

- Significant opportunity to build smarter networks that can adapt to workload and environment
- Network systems are an exciting domain for ML/AI; can lead to new techniques with broad applications
- Many challenges remain for learning-based systems
  - Safe training & exploration
  - Interpretability
  - …