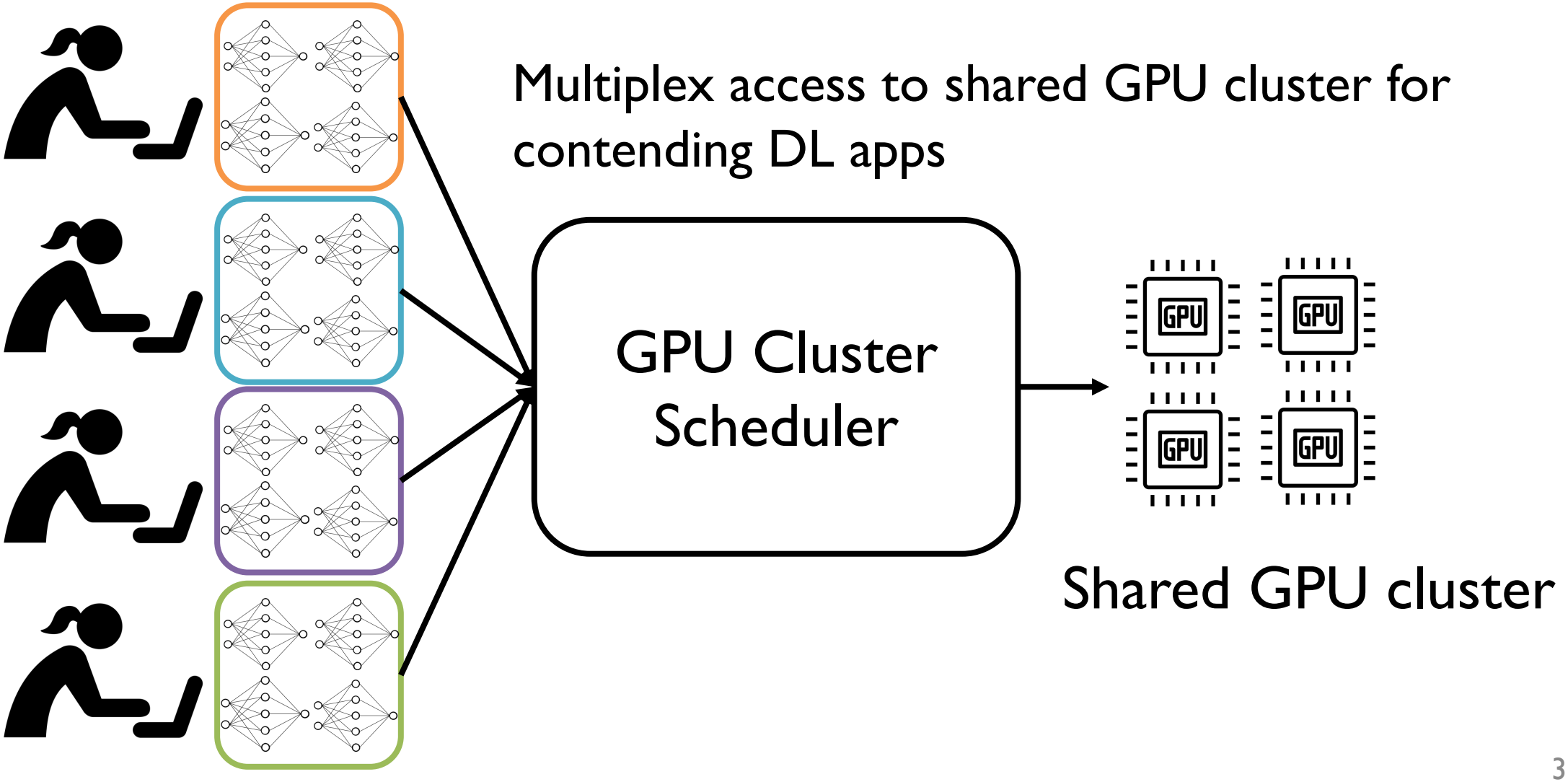
SHOCKWAVE: FAIR AND EFFICIENT GPU SHARING FOR DEEP LEARNING UNDER DYNAMIC ADAPTATION

Pengfei Zheng, Rui Pan, Tarannum Khan,
Shivaram Venkataraman, Aditya Akella

SHARED CLUSTERS FOR MACHINE LEARNING

GPU CLUSTER SCHEDULING



DYNAMIC ADAPTATION IN ML JOBS: GNS

Gradient Noise Scaling (GNS)

Adaptively double batch size based on gradient noise

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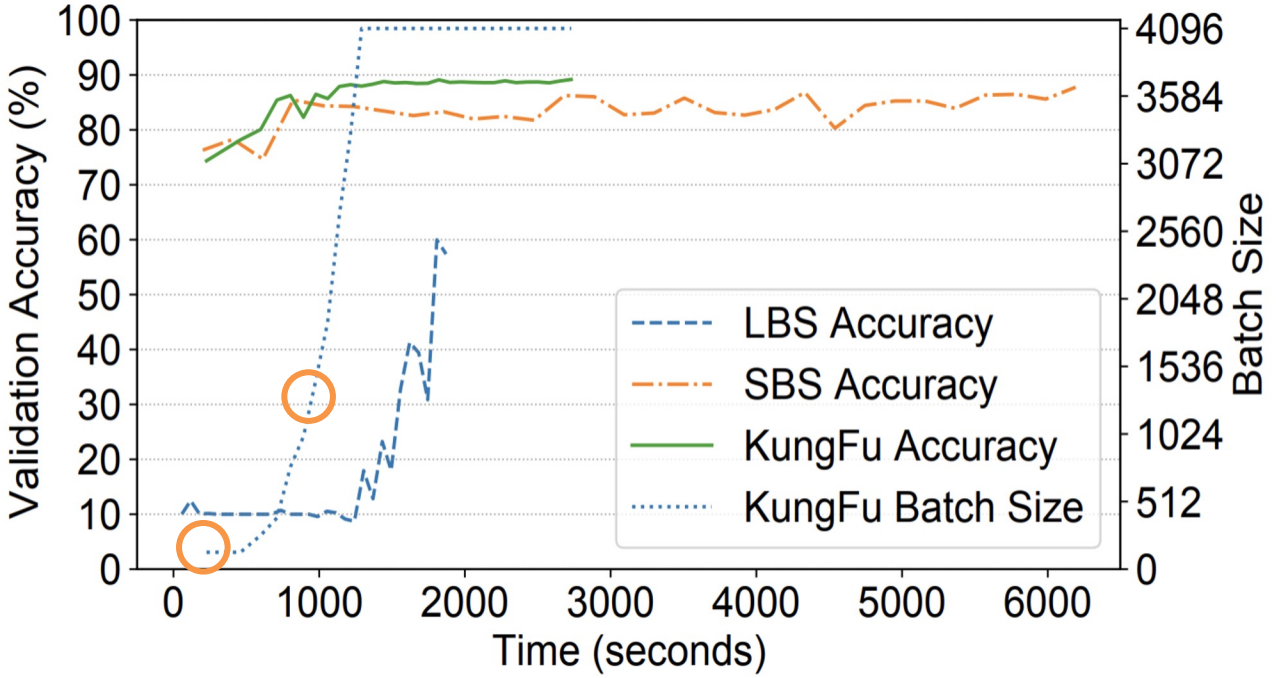
Small Batch Size (16),

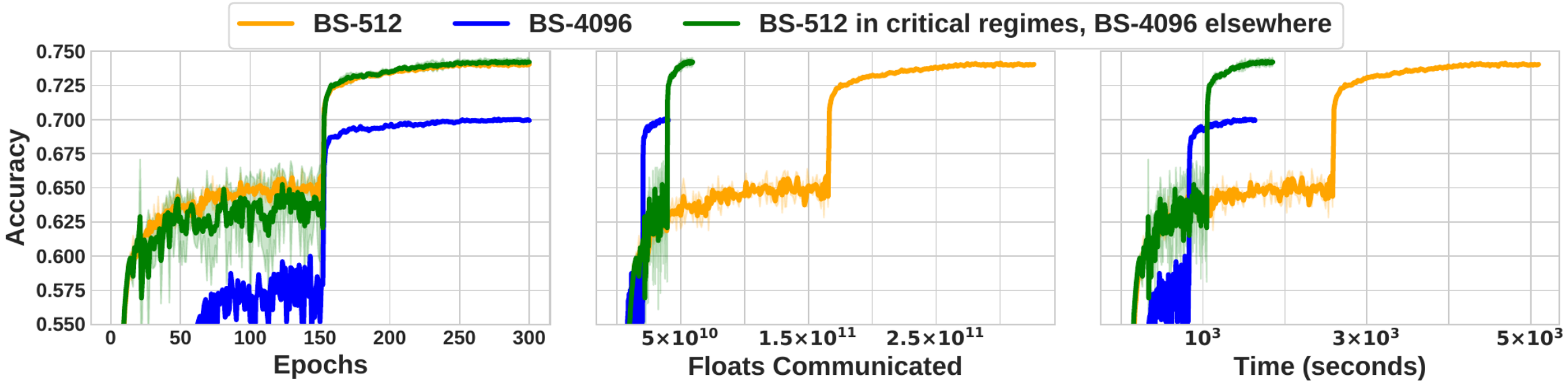
Large Batch Size (4096)

Batch size 16 → 32 → … → 4096



KungFu (OSDI 2020)

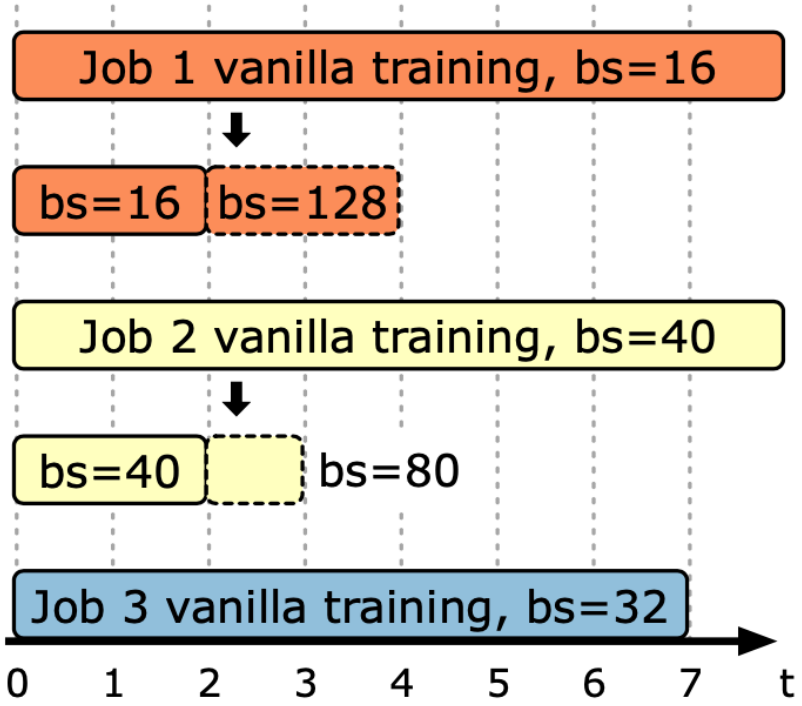
DYNAMIC ADAPTATION IN ML JOBS: ACCORDION



Use small batch size in critical regimes, large batch size elsewhere

Accordion (MLSys 2021)

SCHEDULING WITH DYNAMIC ADAPTATION



Dynamic adaptation can affect Efficiency

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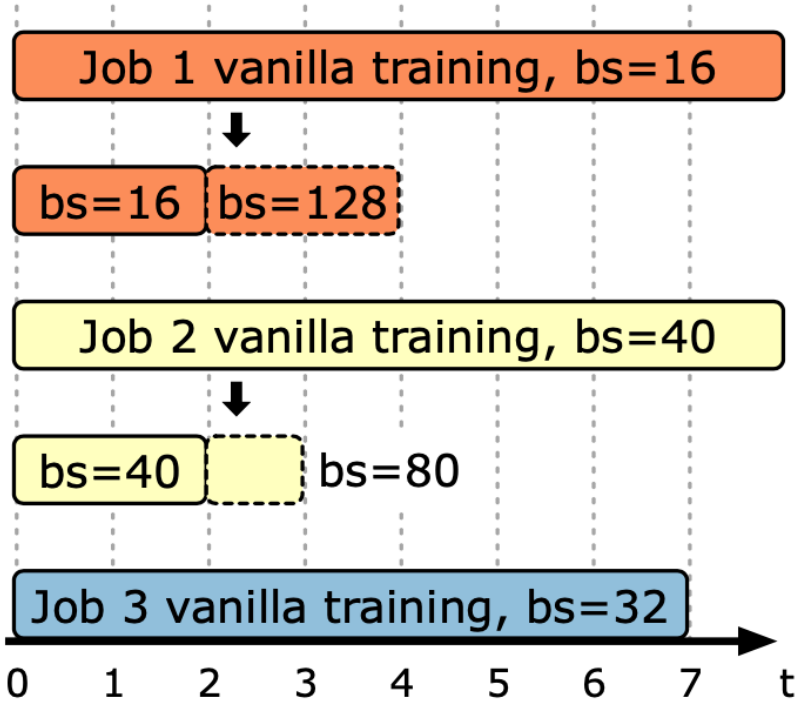

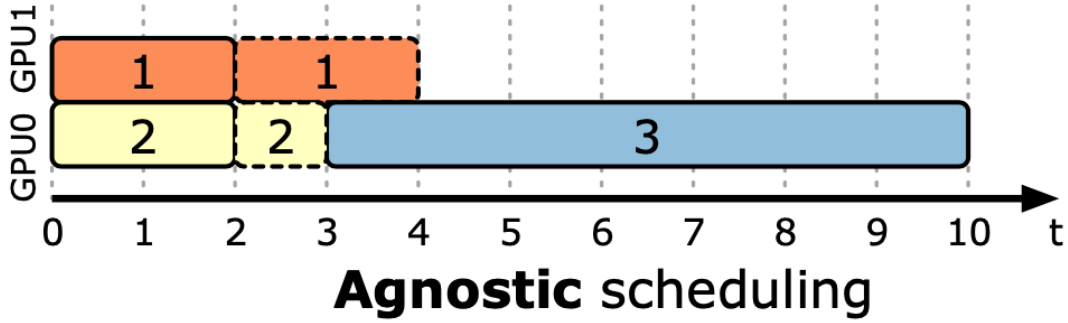

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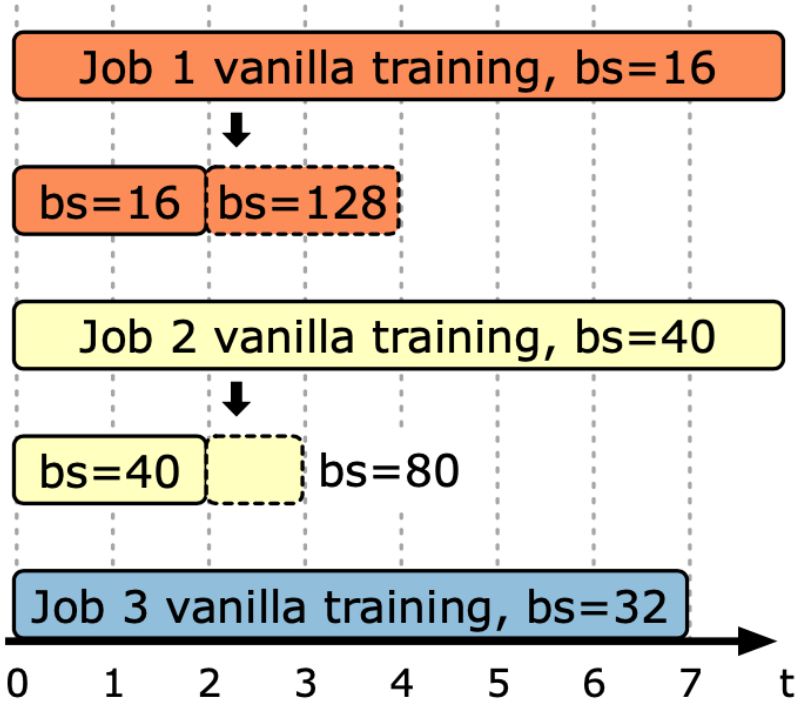

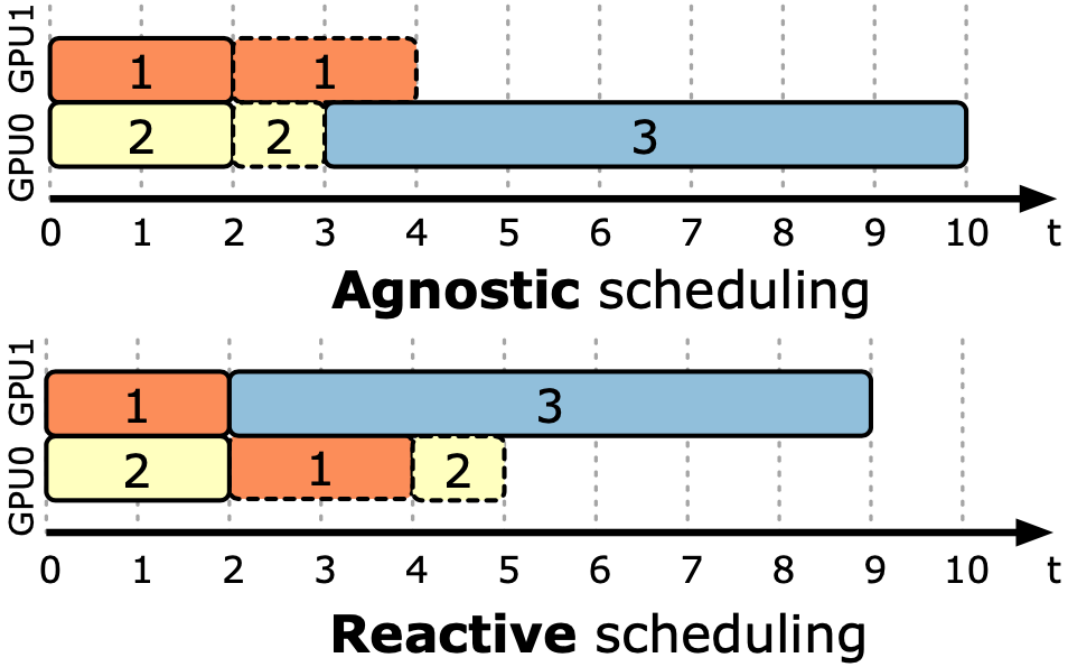

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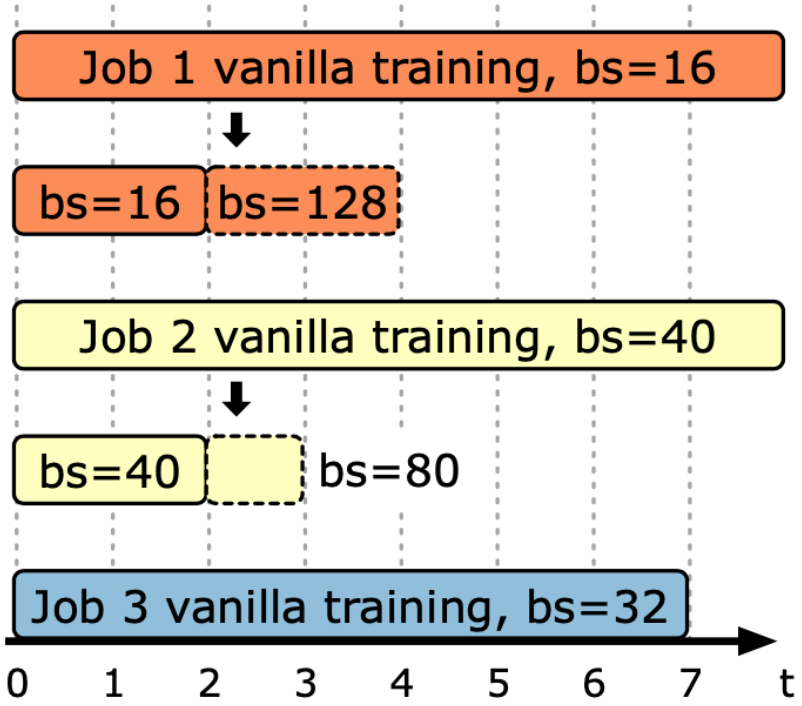

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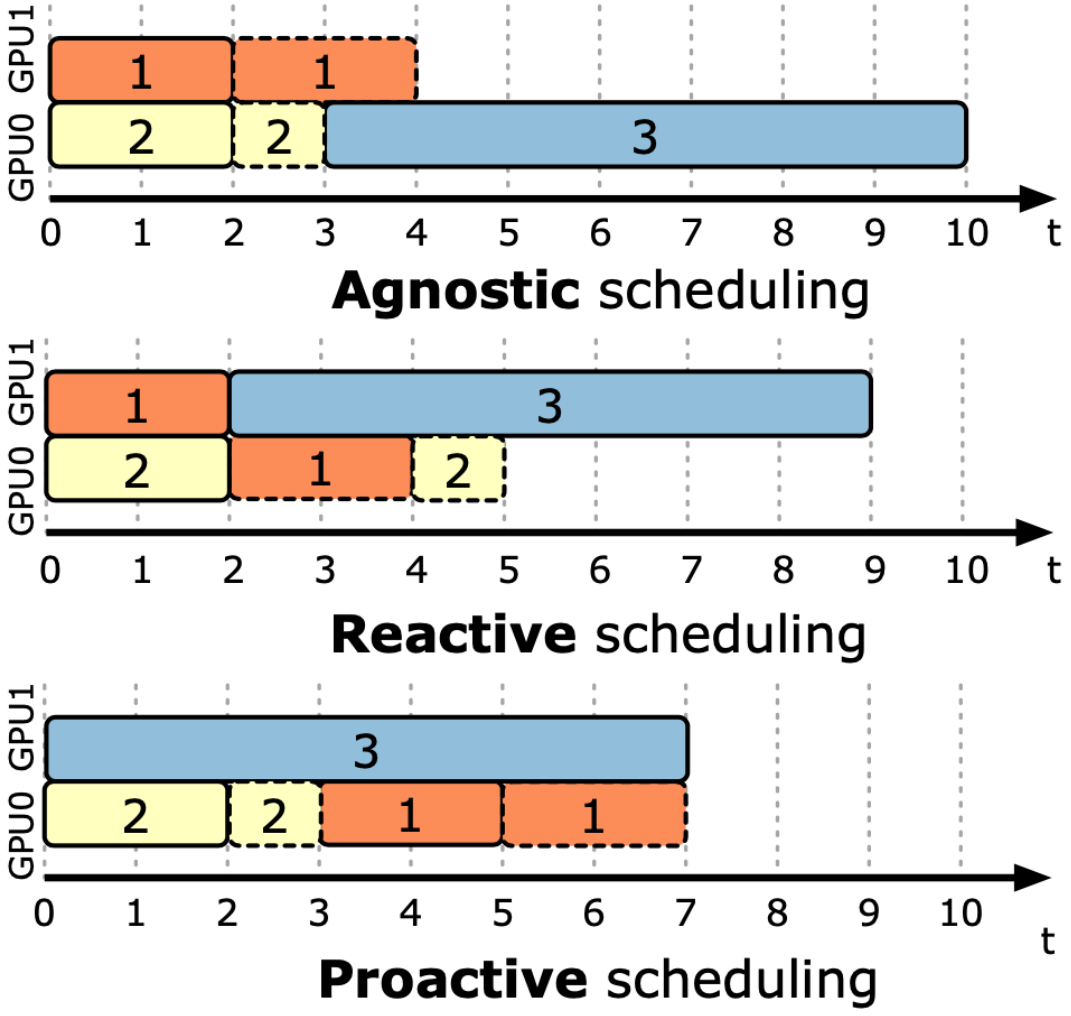
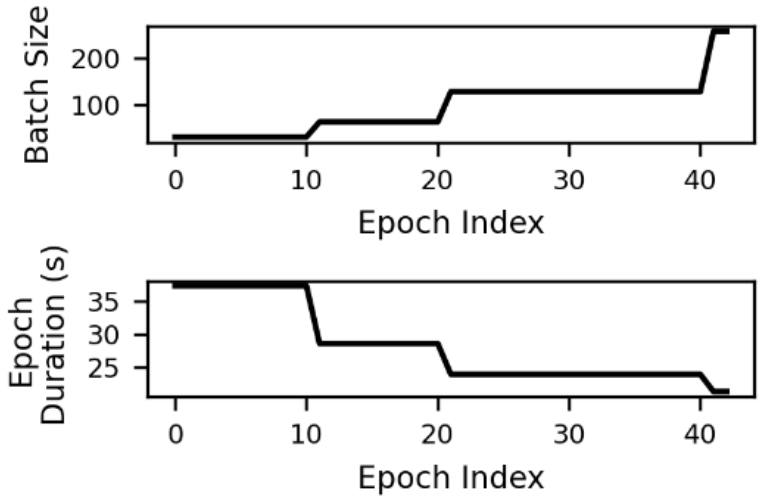
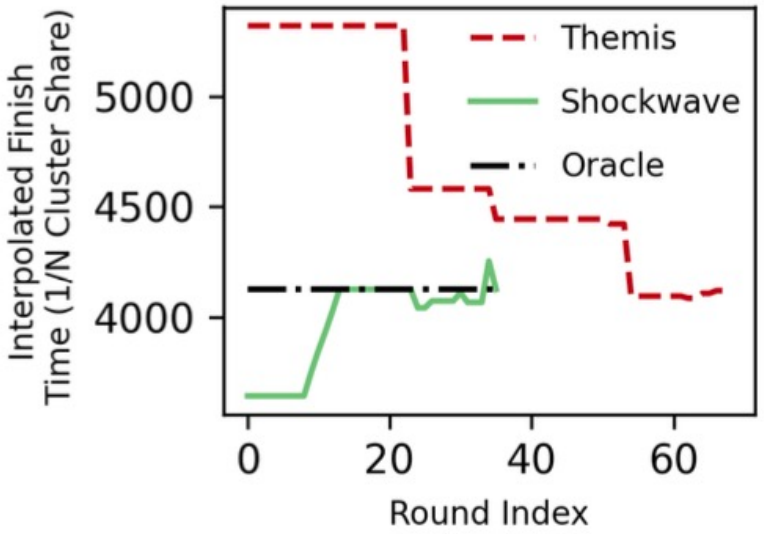


SCHEDULING WITH DYNAMIC ADAPTATION

Dynamic adaptation can affect Fairness





Leads to 2x worse than fair finish time

SCHEDULING WITH DYNAMIC ADAPTATION

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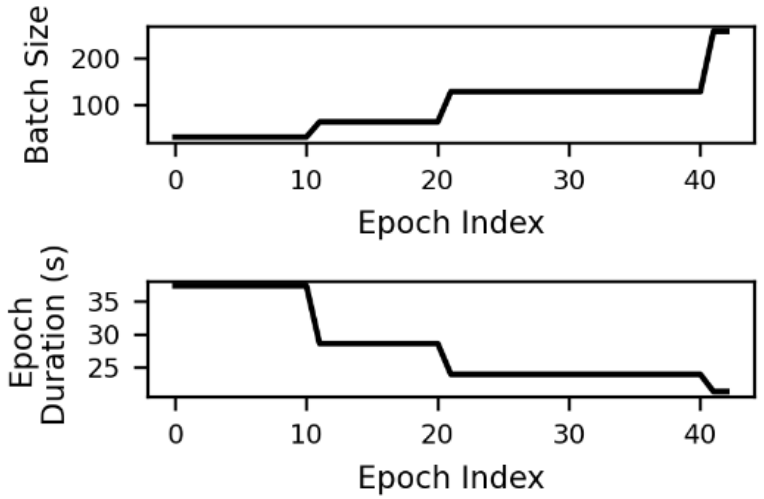
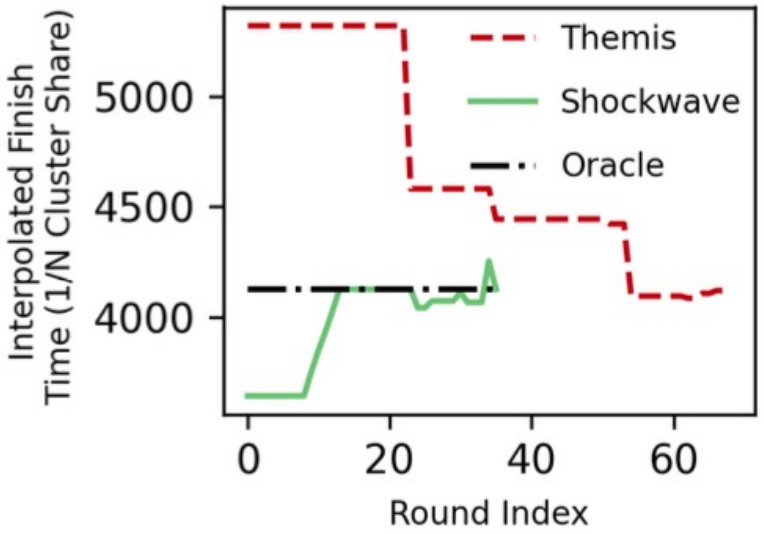




Leads to 2x worse than fair finish time

How do we achieve efficiency with long term fairness for dynamic ML jobs?

SHOCKWAVE

Shockwave: Fair and Efficient Scheduler under Dynamic Adaptation

Key contributions

- Predictive model for Dynamic Adaptation
- Market-based formulation with time-varying utility
- Improves makespan by ~1.3x and fairness by ~2x

OUTLINE

Problem statement

Related work, Challenges

Shockwave Design

Evaluation

SOME PRIOR DL SCHEDULERS

Improve Cluster Utilization:

Gandiva (OSDI 2018), AntMan (OSDI 2020), HiveD (OSDI 2020)

Reduce Job-completion Time

Tiresias (NSDI 2019), Optimus (Eurosys 2019)

Optimize Goodput through Elasticity

SLAQ (SoCC 2017), Optimus (Eurosys 2019), Pollux (OSDI 2021)

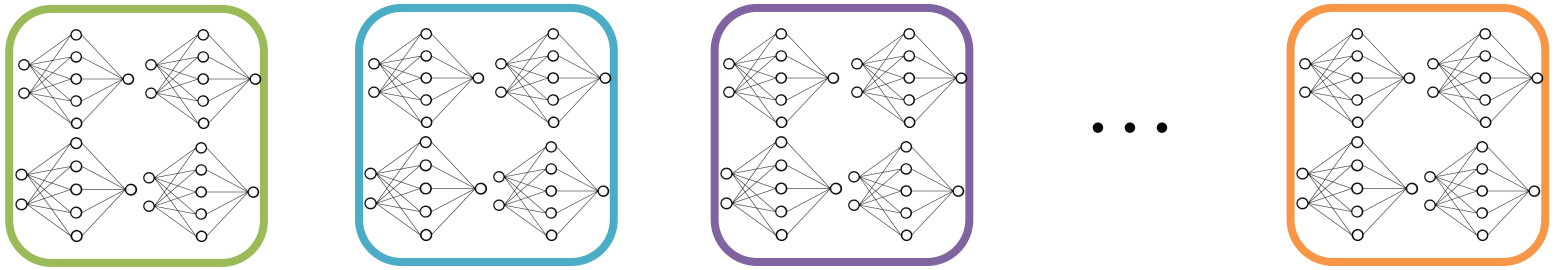
Fair sharing across users:

Themis (NSDI 2020), $\text{Gandiva}_{\text{fair}}$ AlloX(Eurosys 2020), Gavel (OSDI 2020)

CHALLENGE: INACCURATE ESTIMATES

Themis Objective: min (max ρ)

Interface: Get finish time fairness (ρ) estimates from all apps



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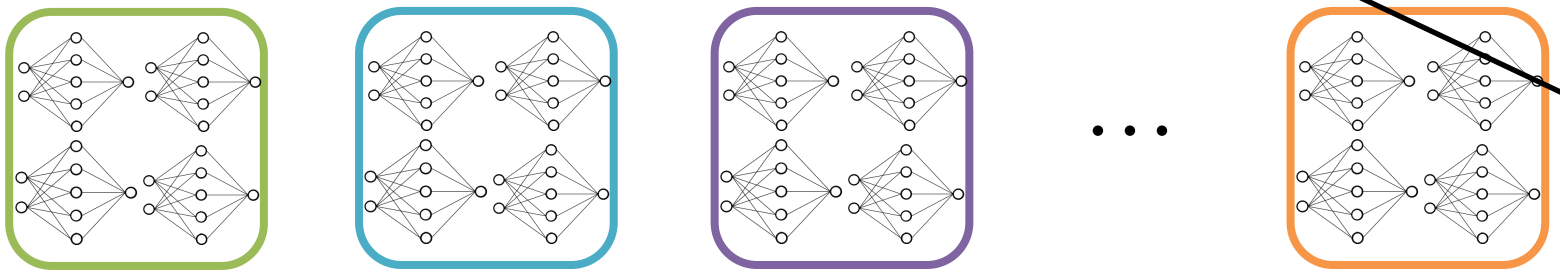
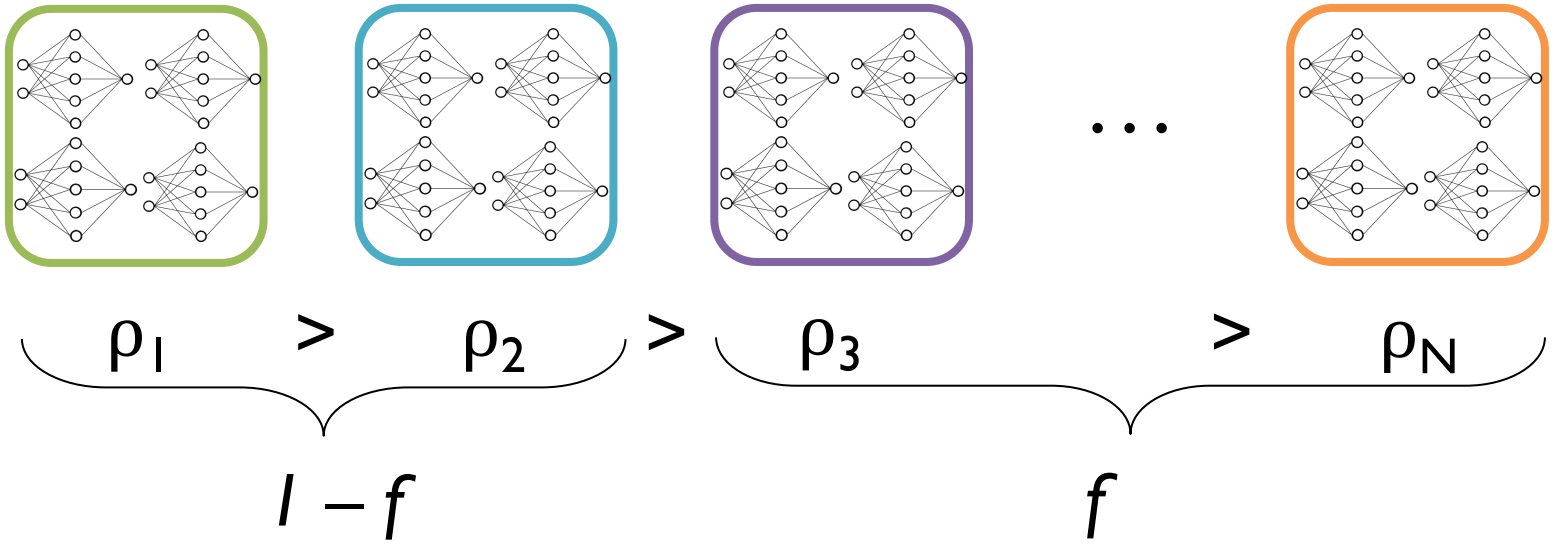


Dynamism → Inaccurate Estimates

CHALLENGE: FILTERING ON PAST ALLOCATIONS

Themis objective – min (max ρ)



1. Filter *1 – f* apps with worst ρ values
2. Allocate to one or more of *1 – f* apps for *next round* using partial auctions

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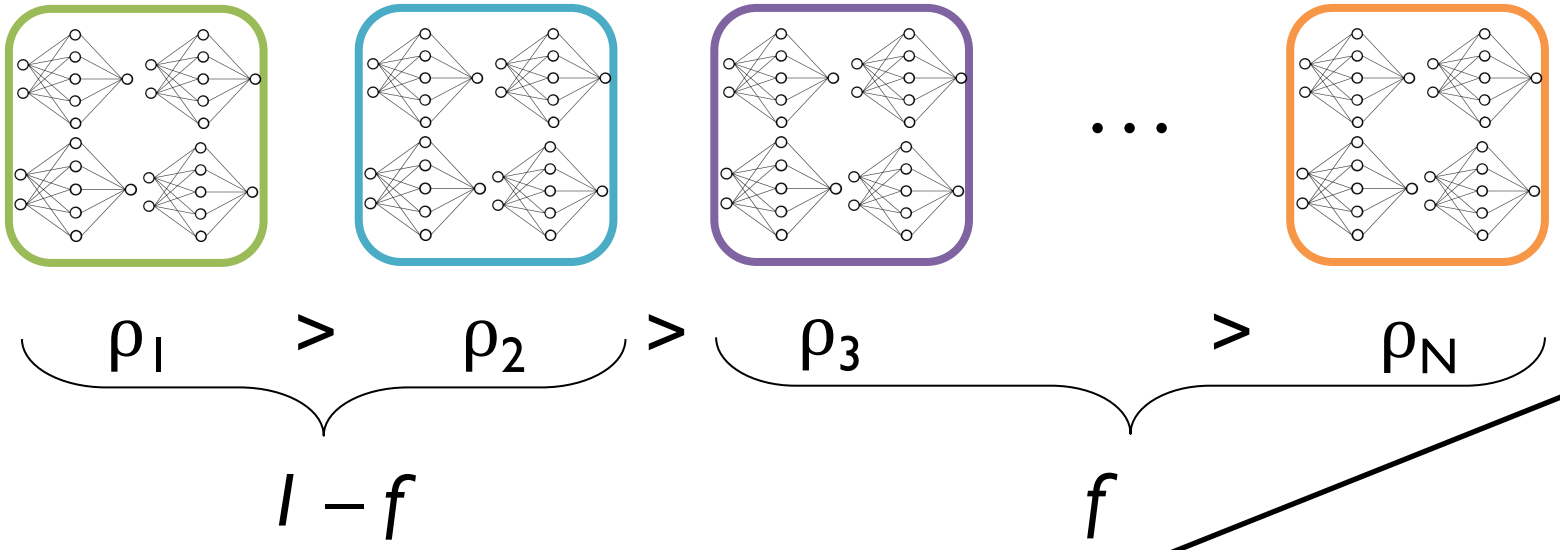

Filter only looks at past allocations

1. Filter *1 – f* apps with worst ρ values
2. Allocate to one or more of *1 – f* apps for *next round* using partial auctions

SHOCKWAVE DESIGN

Approach

- Prediction-based approach that captures long-term fairness and efficiency
- Mechanism for allocations that accounts for future rounds

Key Design Components

- Bayesian model to predict utility under dynamic adaptation
- Input to a market-based solver that gives us provable guarantees.

SHOCKWAVE: PREDICTING DYNAMIC ADAPTATION

Challenge: Predict utility of future epochs in presence of dynamic adaptation

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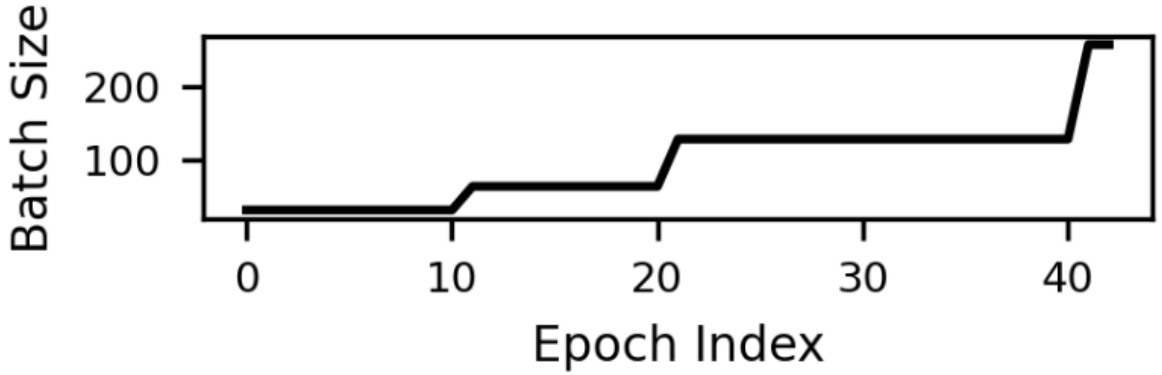
Handful of patterns used for dynamic adaptation

- Accordion: Alternating batch sizes over epochs
- GNS: Doubling batch size over epochs



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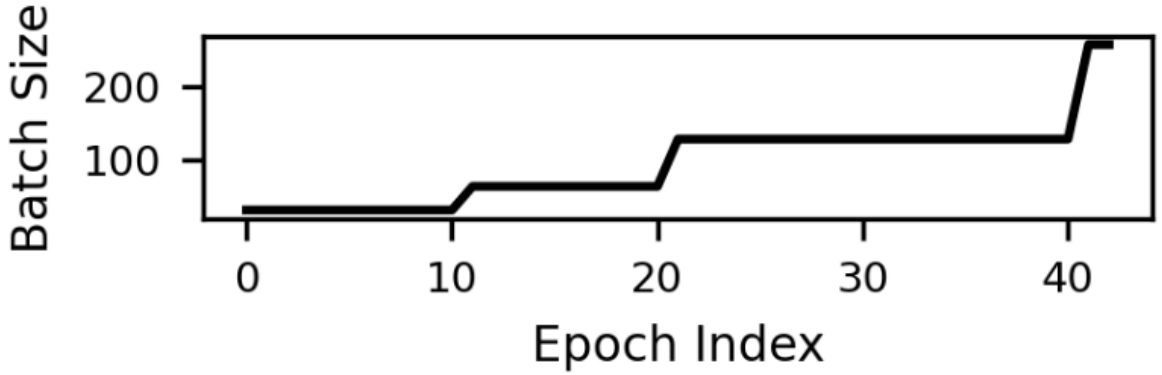

Approach: Model dynamic adaptation as a mixture of regimes

- Use profiles for each batch size regime

SHOCKWAVE: PREDICTING DYNAMIC ADAPTATION

Mixture of regimes with different batch sizes

- ✓ Example - Job *i* 100 epochs:

  30 epochs (30%) for BS-512,

  70 epochs (70%) for BS-4096

SHOCKWAVE: PREDICTING DYNAMIC ADAPTATION

Mixture of regimes with different batch sizes

- ✓ Example - Job *i* 100 epochs:
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Use a Dirichlet prior to model the mixture

- ✓ Job *i* Prior: Dir(50%, 50%): 50 epochs BS512,
  50 epochs BS-4096

Observe batch scaling and update the posterior

- ✓ Job *i* Posterior: Dirichlet (65%, 35%): 65 epochs for BS512, 35 epochs for BS-4096

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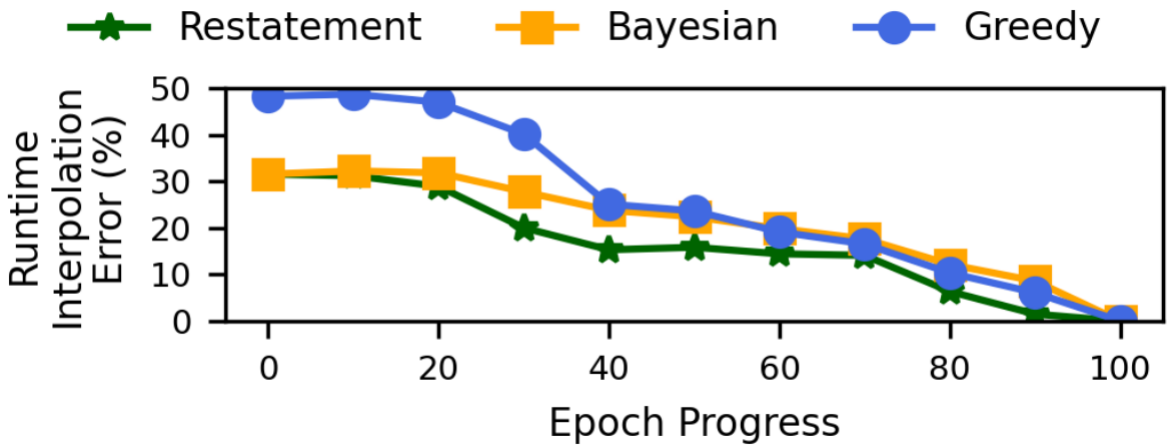

Temporal-dependence across epochs

Restatement rule: only updates parameters for completed epochs

SHOCKWAVE: DYNAMIC MARKETS

Goal: Scheduling policy that accounts for the past and future utilities

Market theory: Provable guarantees for efficiency, fairness.

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Market theory: Provable guarantees for efficiency, fairness.

Static market: Every training job has a known**, time-invariant** utility *U(x)*

- Utility *U(x):* map allocated GPU-time to training throughput for a job

Volatile Fisher Market (VFM) in Shockwave

- Operate at discrete time intervals (rounds)
- Every training job has **a time-variant utility $U_t(x)$** for each round (t)
- Solve for allocation that leads to market equilibrium

SHOCKWAVE: DYNAMIC MARKET PROPERTIES

Maximizes Nash Social Welfare over time

$$U_i(X_i) = \sum_t u_{it}(\boldsymbol{x}_{it})$$

$$\text{NSW}_{\text{OT}}(U_1(\boldsymbol{X_1}), \ldots, U_N(\boldsymbol{X_N})) = \prod_i U_i(\boldsymbol{X_i})^{\frac{B_i}{\sum_i B_i}},$$

Maximizes cluster-wide utility

Efficiency

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Efficiency

Minimizes product of FTF over time

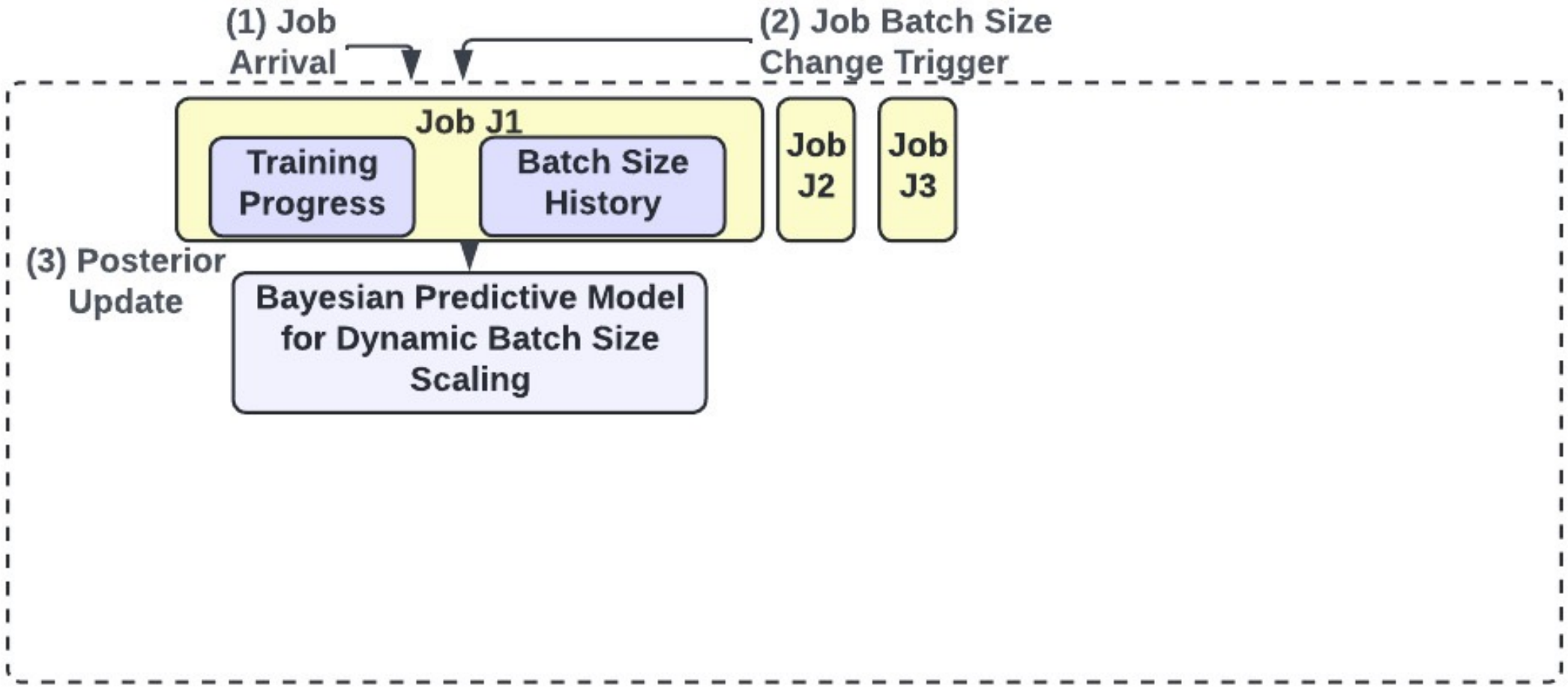
Minimize $\prod_i \rho_i$

$$\rho_i = \frac{\text{(Finish time in a shared cluster)}}{\text{(Finish in an 1/N exclusive cluster)}}$$

Provides sharing incentive

Fairness

SHOCKWAVE ARCHITECTURE



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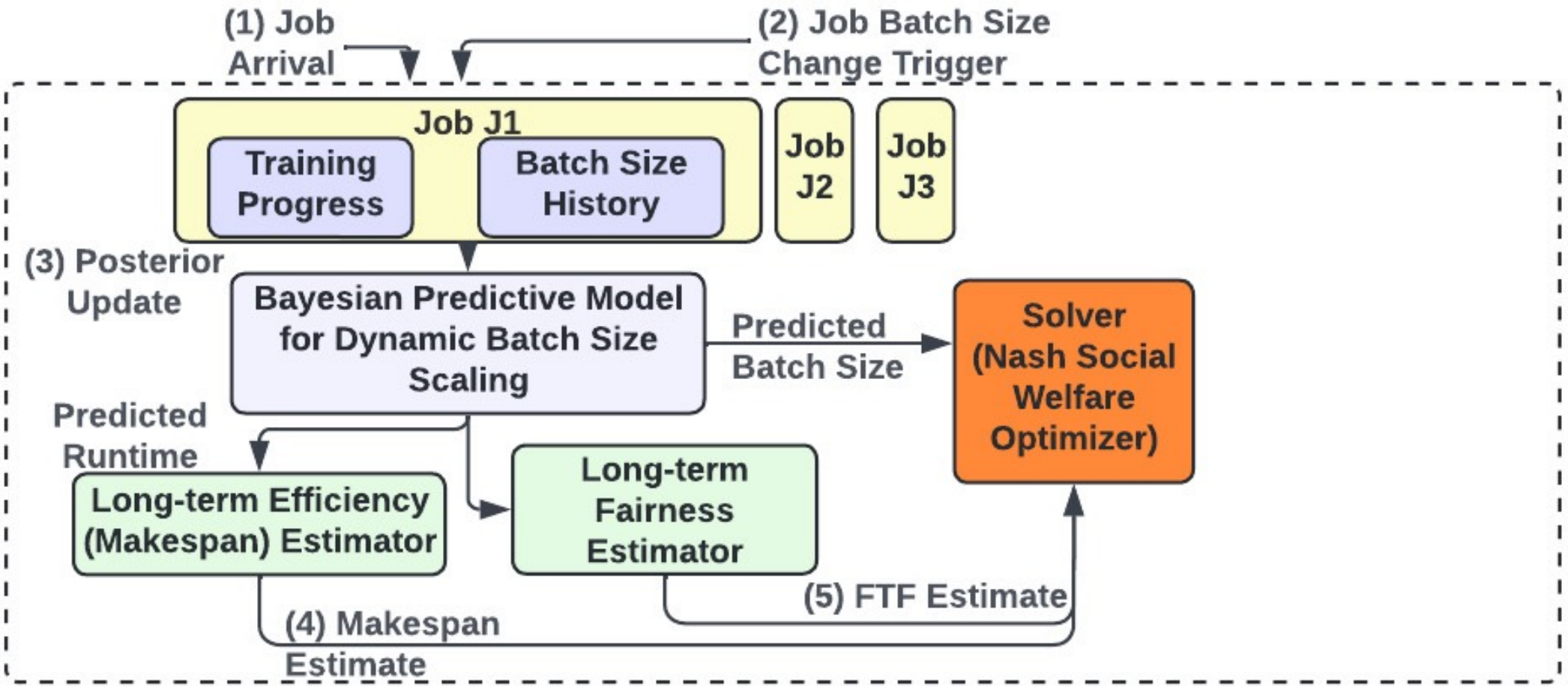

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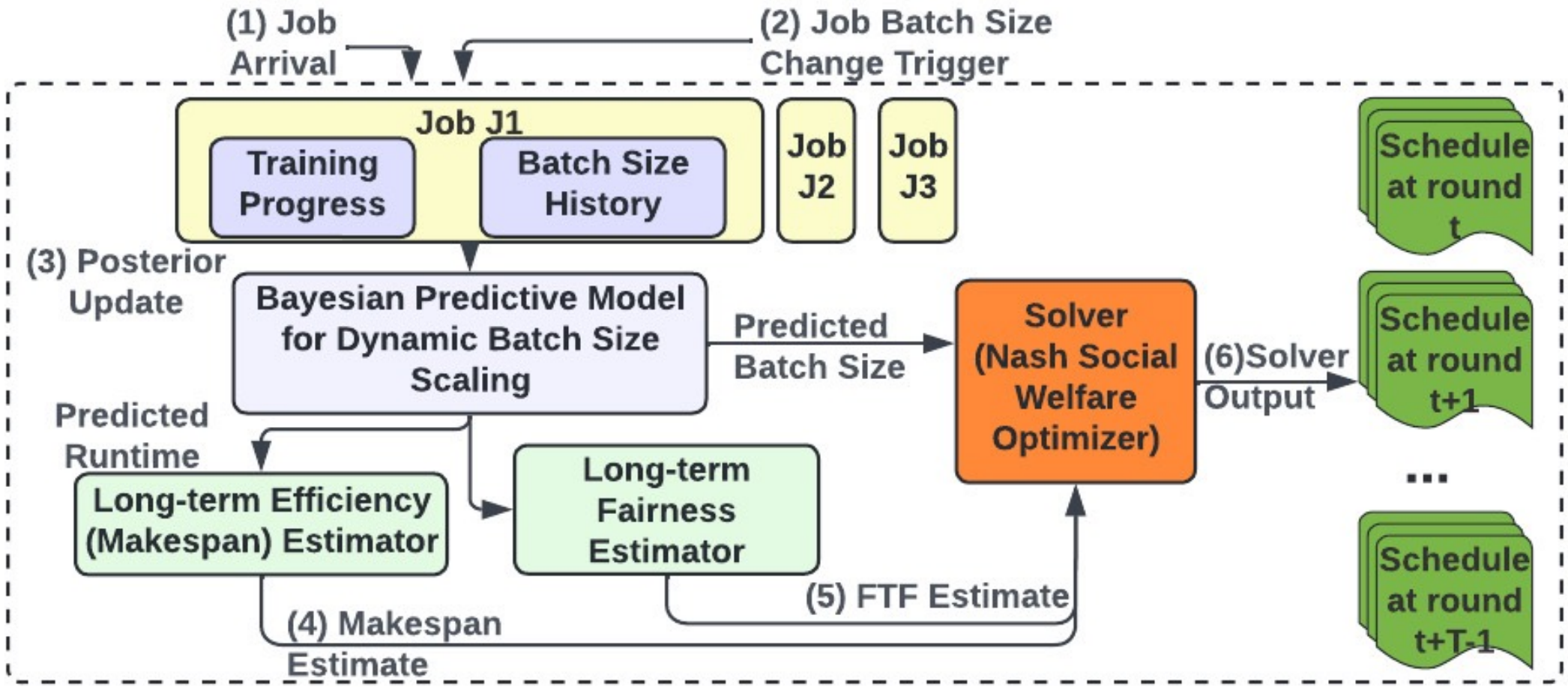


EVALUATION

- **Testbeds**
  - 32 Nvidia Quadro RTX5000 GPUs (16GB) at TACC
  - Simulated clusters with 64-256 GPUs
  - High simulation fidelity (<5% deviation)

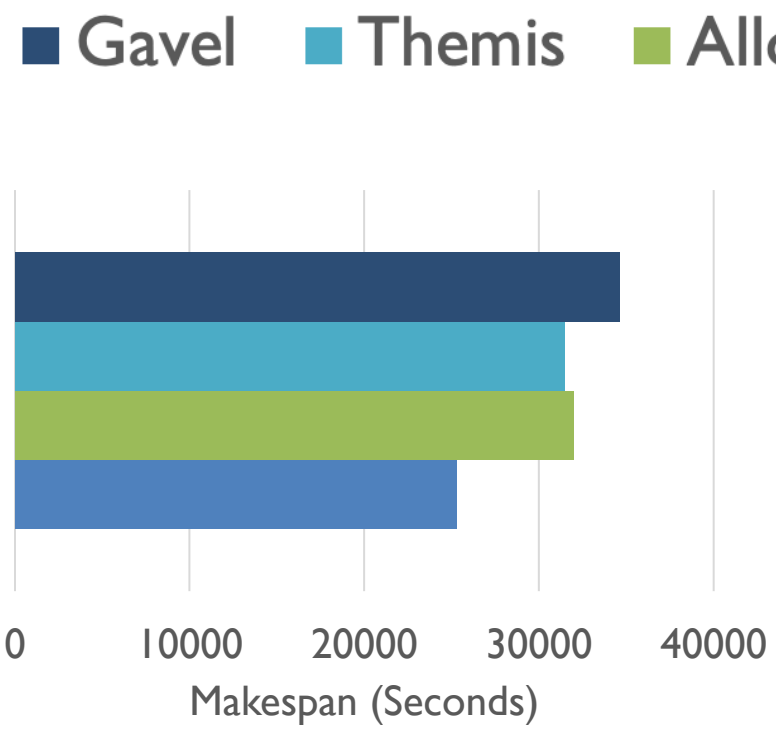
- **Workloads**
  - Gavel Workload Generator (OSDI'20)
  - Microsoft's Philly trace (ATC'19)
  - Mix of GNS and Accordion jobs (50%-50%)

Model	Task	Dataset	Batch Size(s)
ResNet-50	Image Classification	ImageNet	16 - 128
ResNet-18	Image Classification	CIFAR-10	16 - 256
LSTM	Language Modeling	Wikitext-2	5 - 80
Transformer	Language Translation	Multi30k (DE-EN)	16 - 256
Recoder Autoencoder	Recommen-dation	ML-20M	512 - 8192

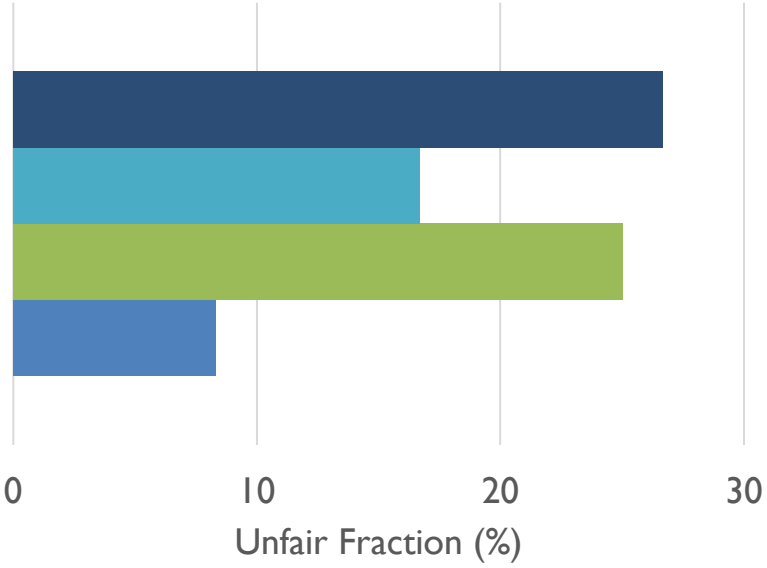
END-TO-END COMPARISONS

32-GPU Cluster in TACC, Gavel trace

END-TO-END COMPARISONS



32-GPU Cluster in TACC, Gavel trace



Reduces Makespan by ~1.3x, Unfair fraction by ~2x

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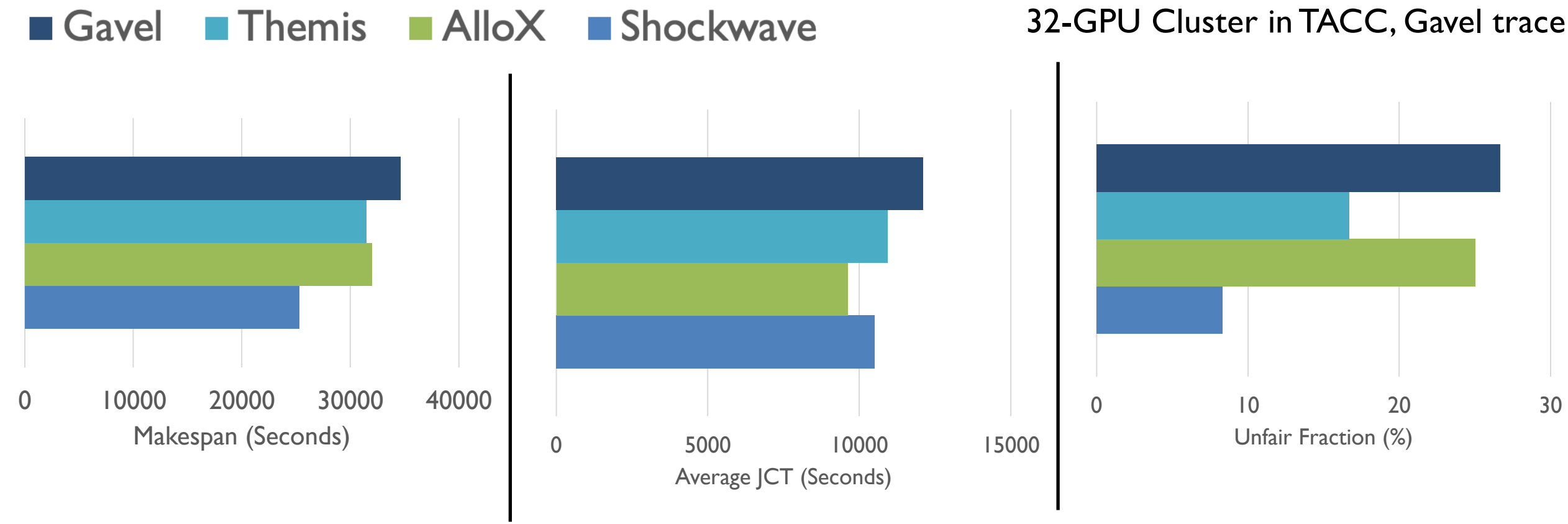
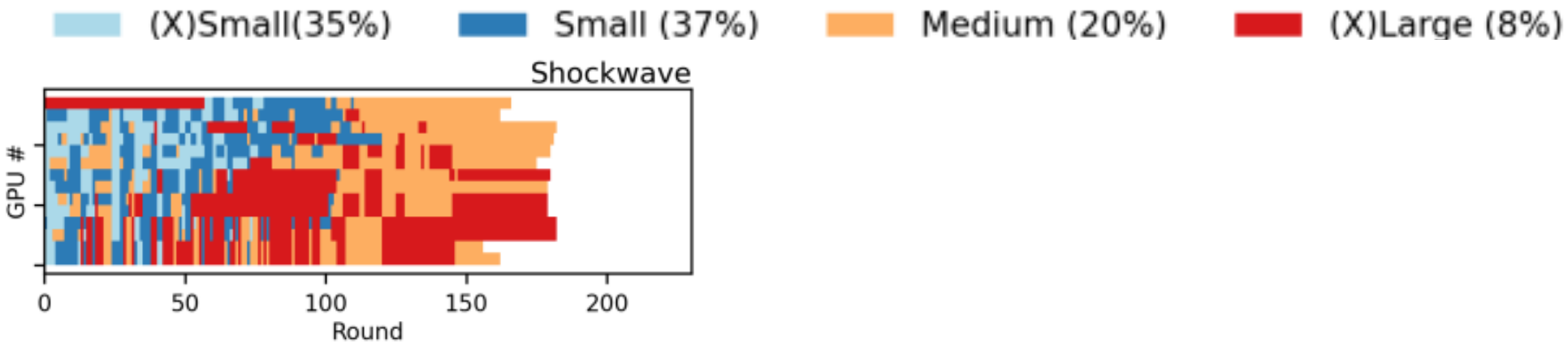


Reduces Makespan by ~1.3x, Unfair fraction by ~2x, maintains JCT

COMPARING SCHEDULERS: EFFICIENCY



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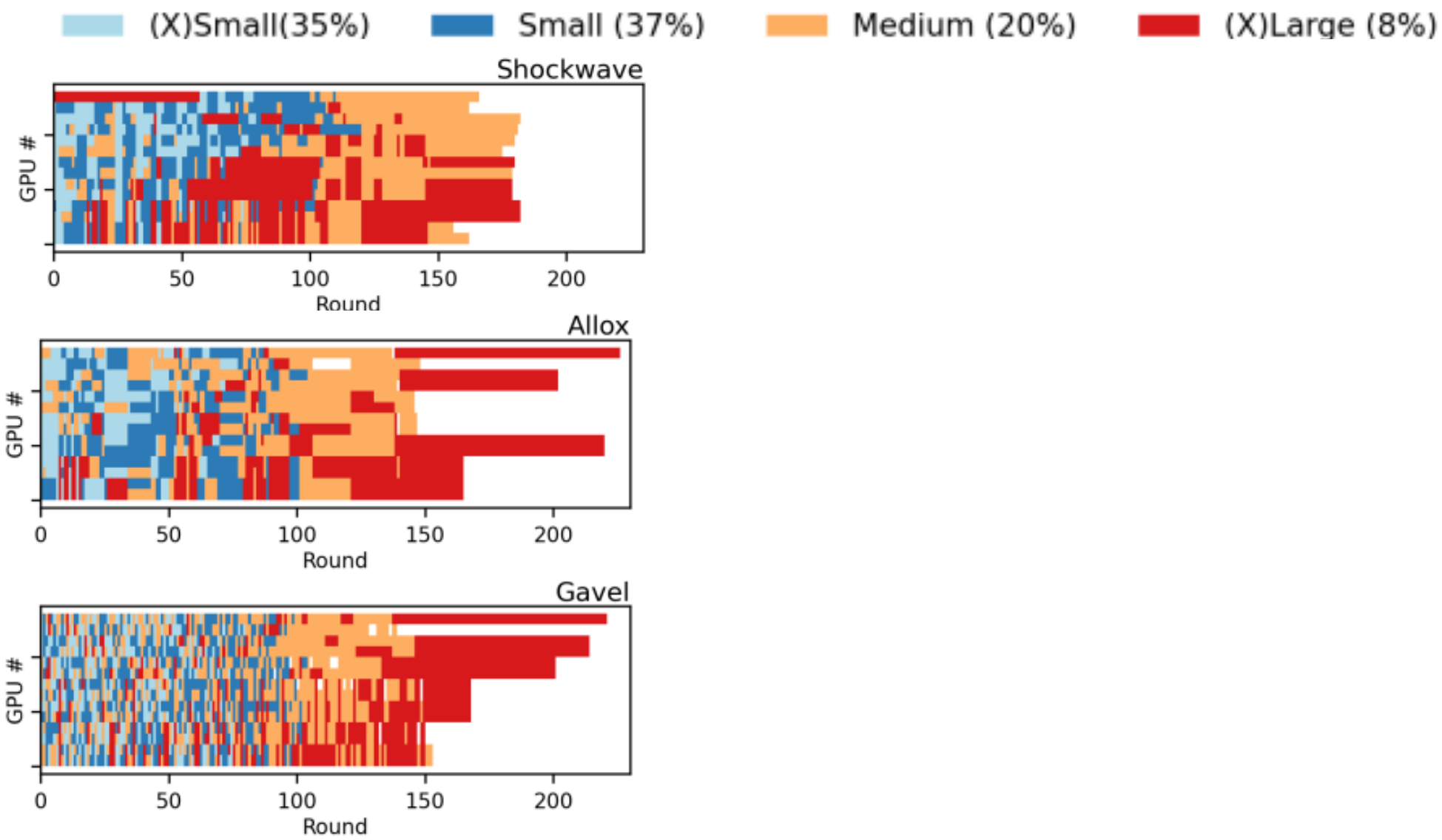

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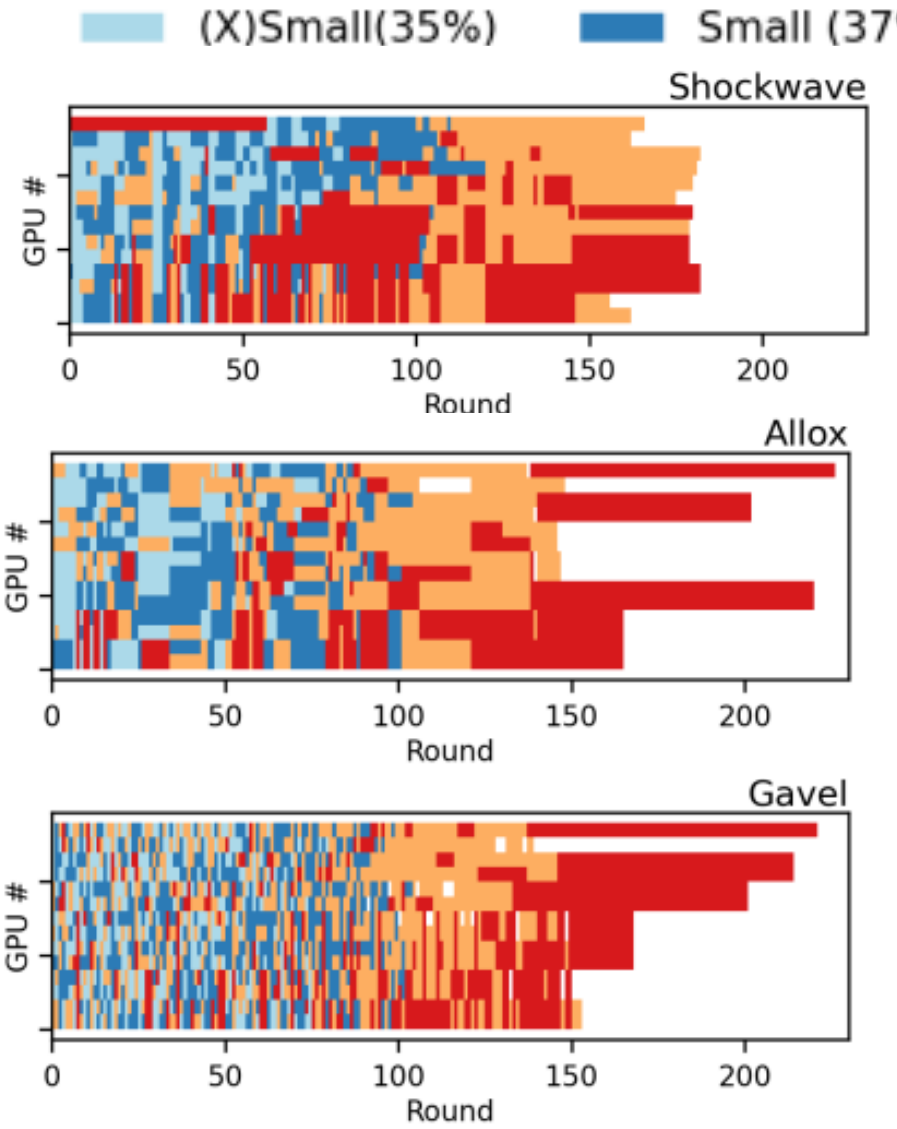
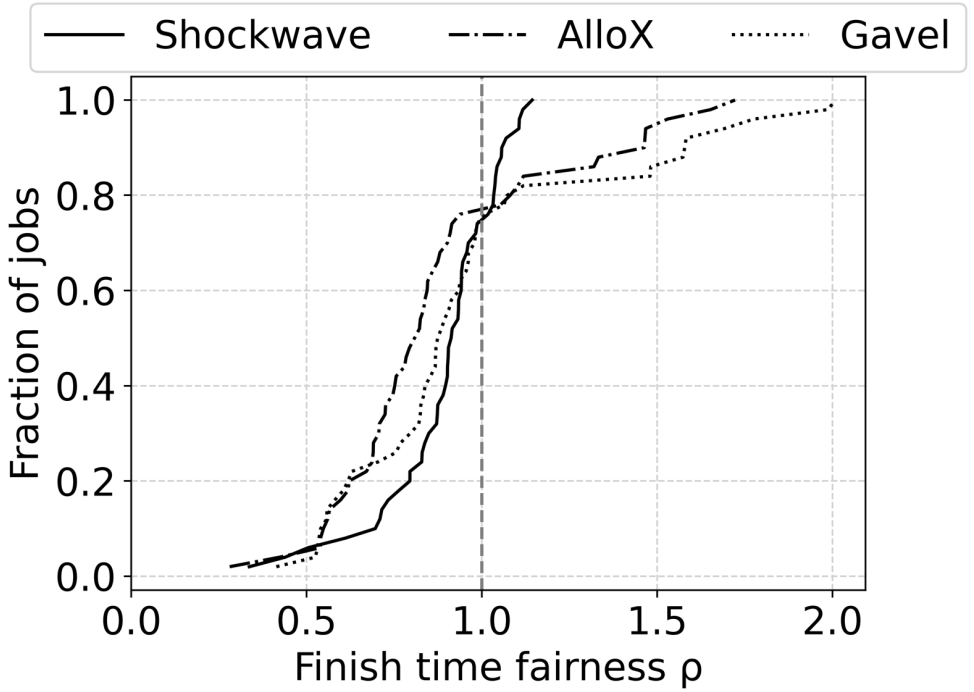


Shockwave minimizes Makespan
while lowering the number of jobs with unfair allocations



CONCLUSION

Dynamic Adaptation introduces challenges for fairness and efficiency

Shockwave: New predictive scheduler that uses a Market-based formulation

- Bayesian model for predicting dynamic adaptation
- Time-varying utility and provable guarantees on fairness and efficiency

Open source: https://github.com/uw-mad-dash/shockwave

Questions?