Optimus: An Efficient Dynamic Resource Scheduler for Deep Learning Clusters

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Presenter: Silvery Fu

What is the problem?

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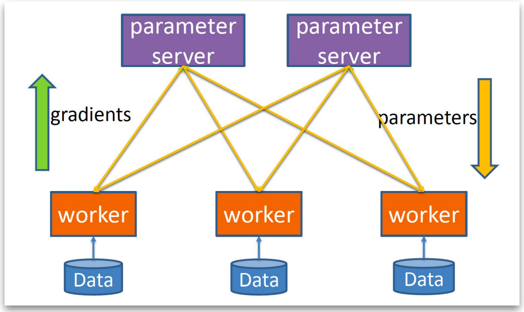
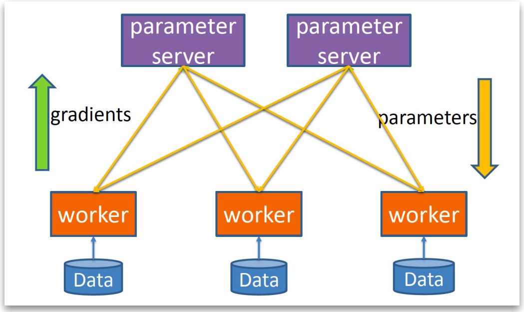
- How? Leverage more application-level semantics.

Application semantics: DL

- What semantics?
  - DL's job-task model: parameter server tasks and worker tasks
  - JCT correlates w/ convergence, iterative, ...



Application semantics: DL



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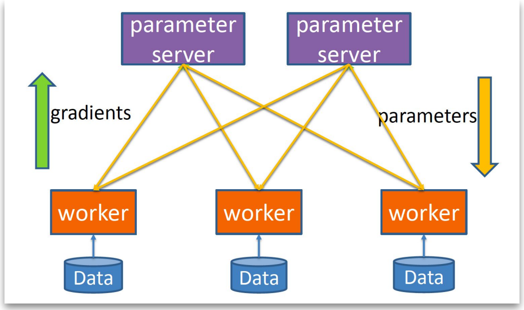

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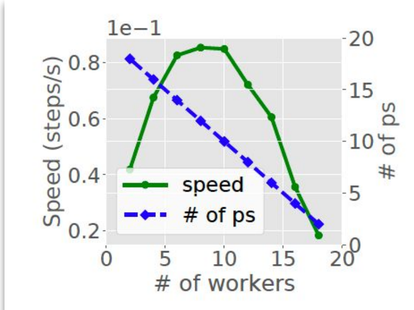

(a) 20 ps and workers

- How to use these semantics?
  - Tune knobs: `num_worker and num_parameter_server`
  - ..minimize makespan and average job completion time

Performance modeling

- Goal: predict the JCT for each DL training job
  - ..given the knobs: `num_worker` and `num_parameter_server`
  - JCT = **F**(`num_worker, num_parameter_server`)

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  - JCT is the sum of the time to complete each training step (process one minibatch)
  - How many training steps remaining? Estimate how far away from convergence.
  - The duration of each training step breaks down to:
    - forward/back propagation time
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graybox vs.
blackbox?

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Performance modeling

- Curve 1: convergence curve
  - loss-based training convergence
  - f: completed epochs → training loss

$$l = \frac{1}{\beta_0 \cdot k + \beta_1} + \beta_2$$

learned
online

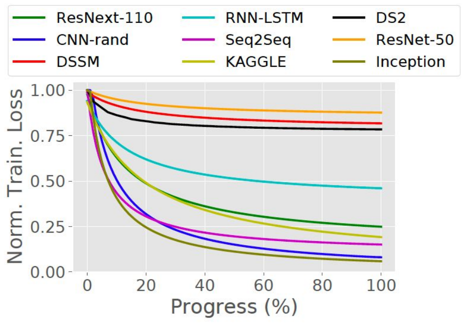

Figure 5: Training loss curves for different DL jobs

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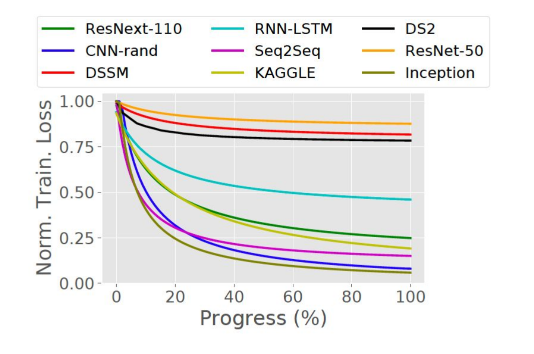
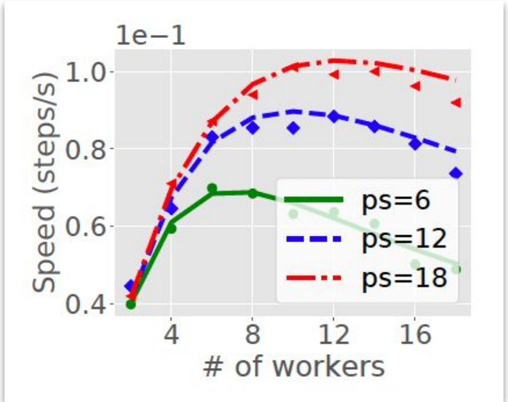


Figure 5: Training loss curves for different DL jobs

- Curve 2: resource-learning speed curve
  - f: resource configuration → learning speed

$$f(p, w) = \left(\theta_0 \cdot \frac{M}{w} + \theta_1 + \theta_2 \cdot \frac{w}{p} + \theta_3 \cdot w + \theta_4 \cdot p\right)^{-1}$$

learned "offline", adapted online



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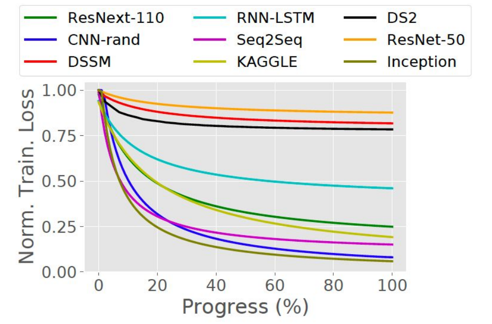

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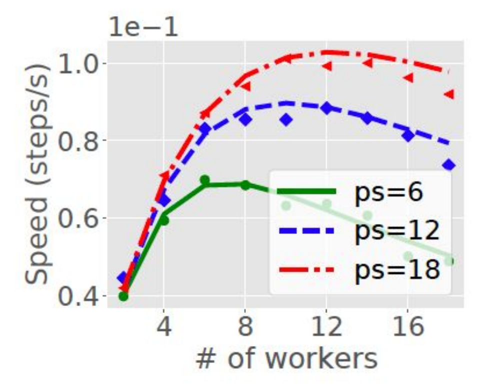
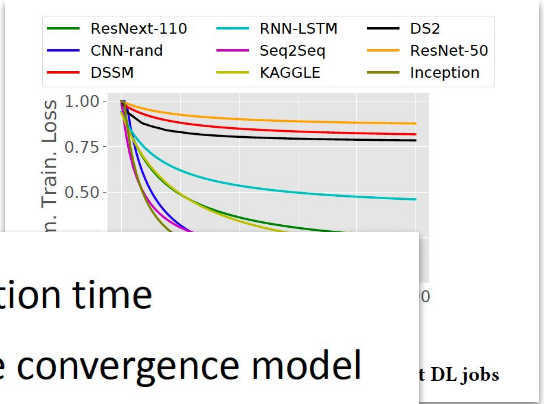


- Given the two curves:
  - Optimus decides the numbers of parameter servers and workers for *each* job

Performance modeling

- Curve 1: convergence curve

learned



t DL jobs

minimize $\sum_{j \in J} t_j$ → Minimize job completion time

remaining steps predicted by the convergence model

subject to: $t_j = \frac{\boxed{Q_j}}{\boxed{f(p_j, w_j)}} \quad \forall j \in J$ → job remaining time

training speed estimated by the speed function

$\sum_{j \in J} (w_j \cdot O_j^r + p_j \cdot N_j^r) \le C_r \quad \forall r \in R$ → capacity constraint

$p_j \in Z^+, w_j \in Z^+ \quad \forall j \in J$

p_j: number of parameter servers of job j w_j: number of workers of job j

- C

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- G
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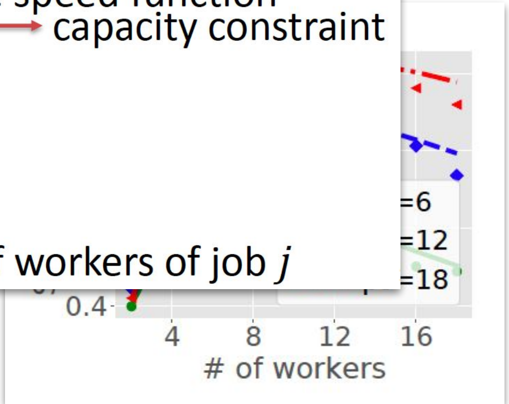

Task placement

- Given the number of workers and the number parameter servers, decide where to place them at each scheduling iteration.

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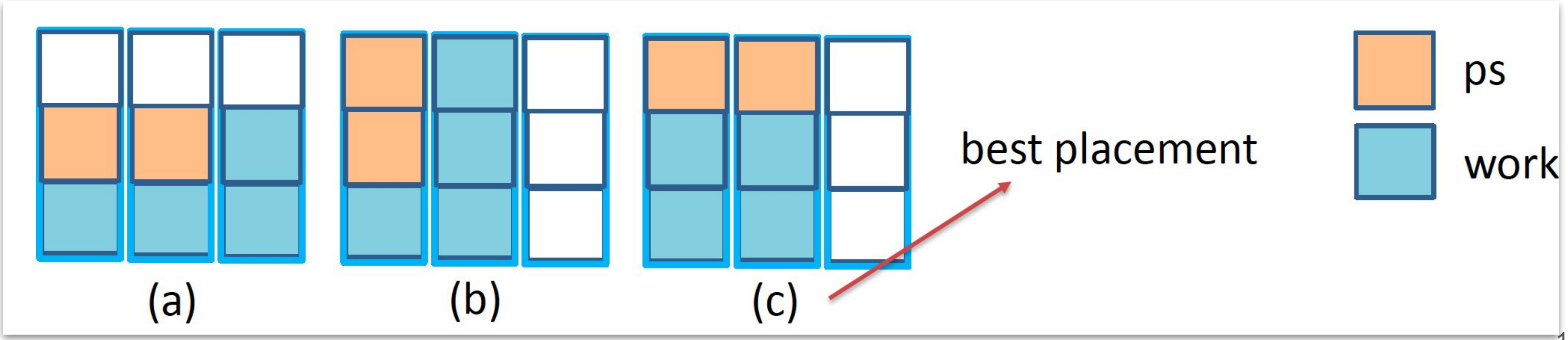
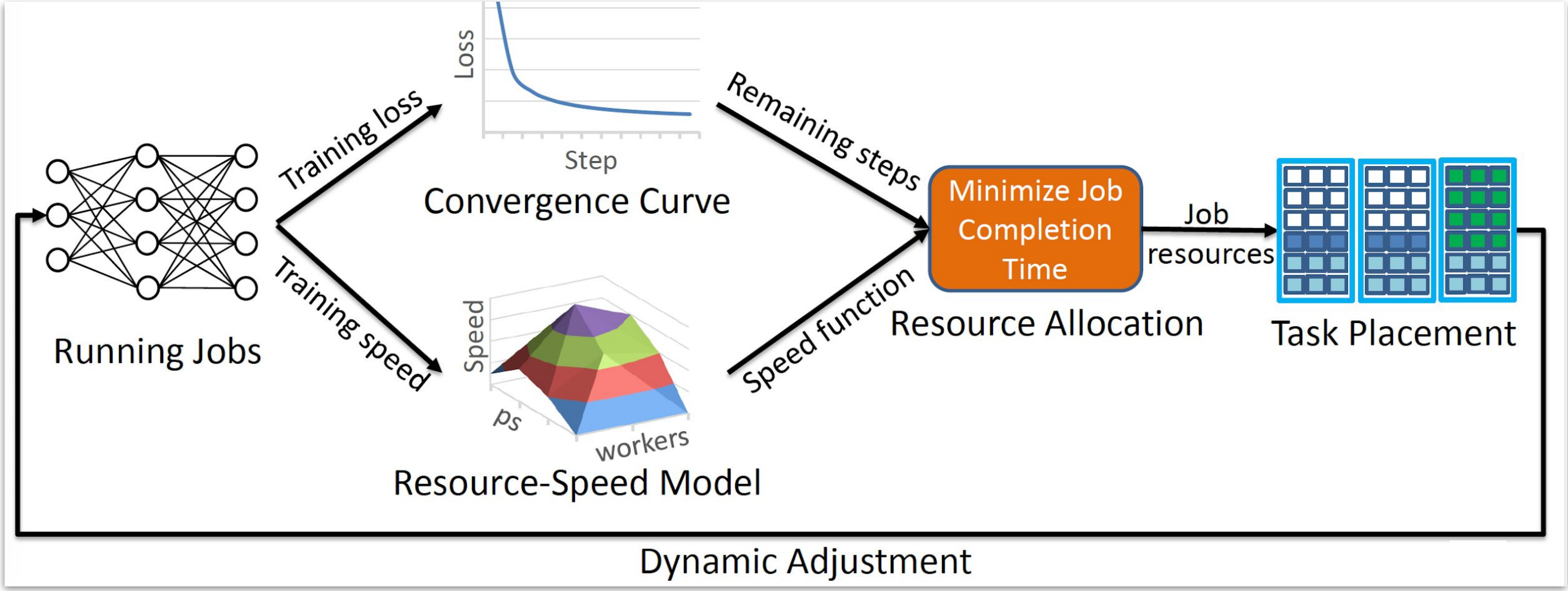
- Optimal placement should minimize the data transfer

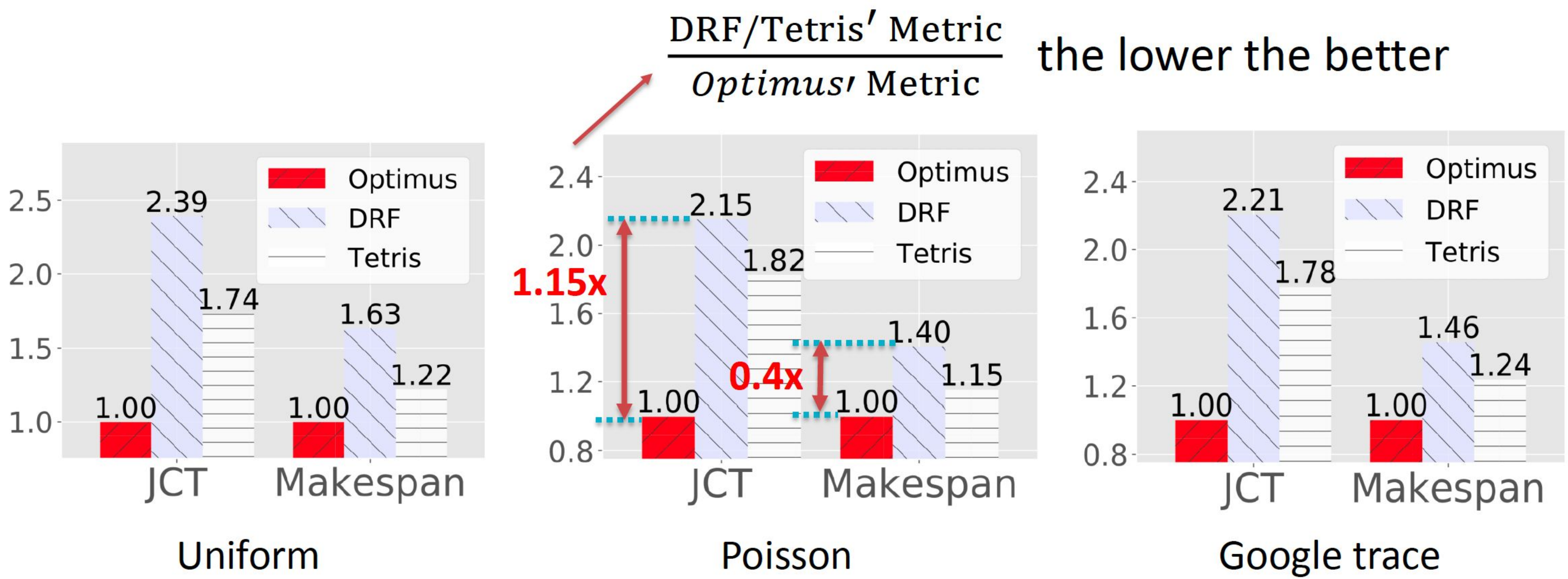
The paper has a proof for this



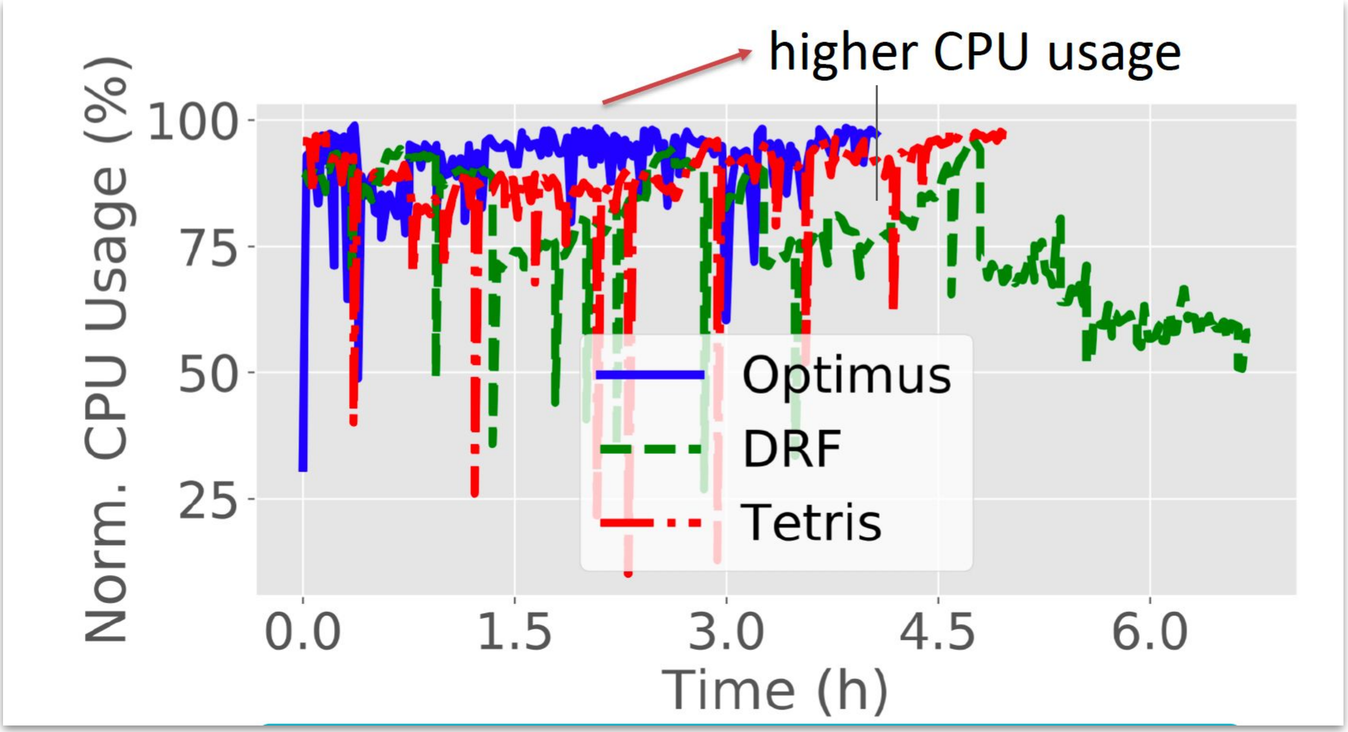
Put together:



Key results: avg. JCT and Makespan



Key results: cpu utilization



Prediction Accuracy vs. Performance

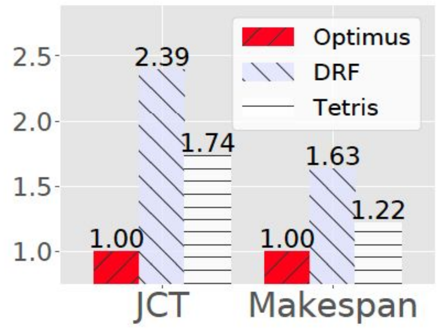
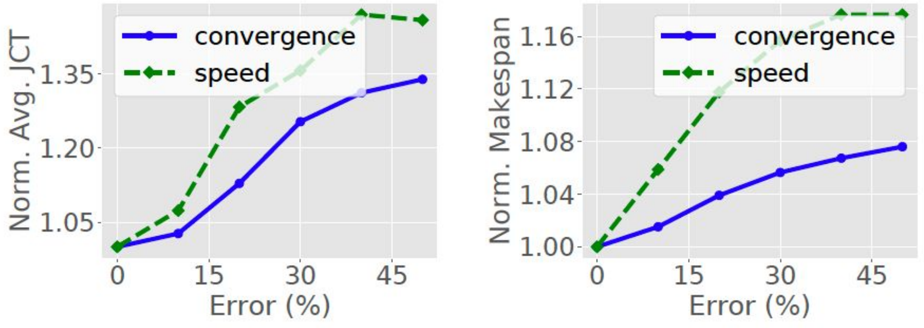


Figure 11: Performance comparison

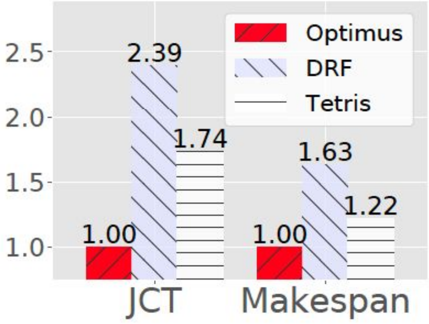


(a) Average completion time **(b) Makespan**

Figure 15: Sensitivity to prediction errors

Prediction Accuracy vs. Performance

how much accuracy do we need?



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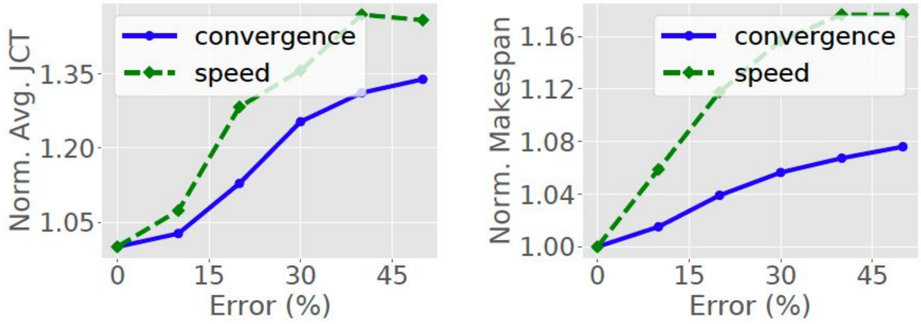

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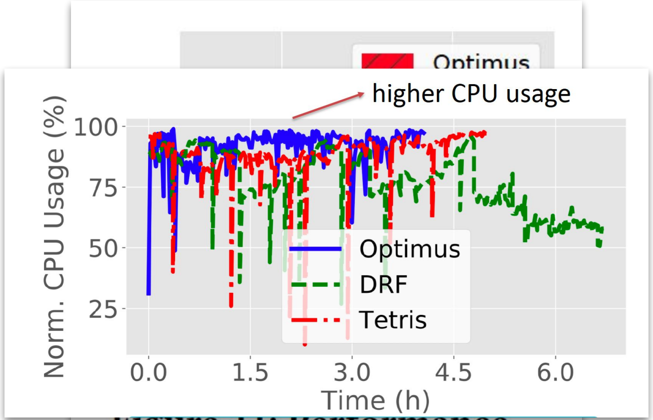

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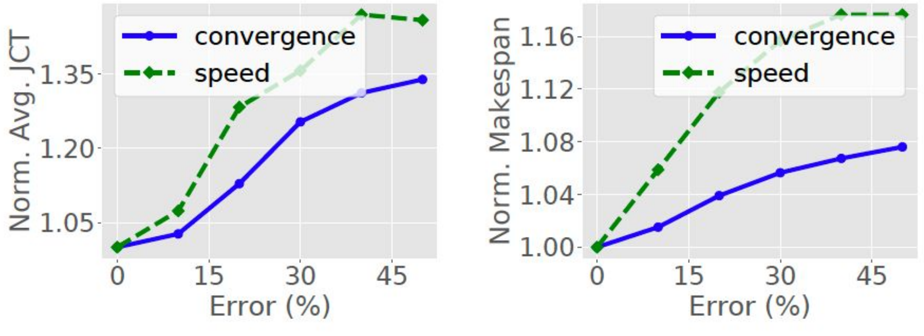

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Prediction Accuracy vs. Performance

how "cheap" is accuracy?

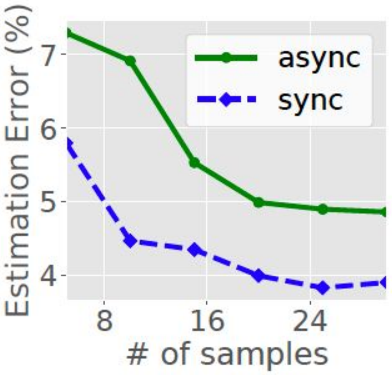

Figure 8: Estimation errors of training speeds

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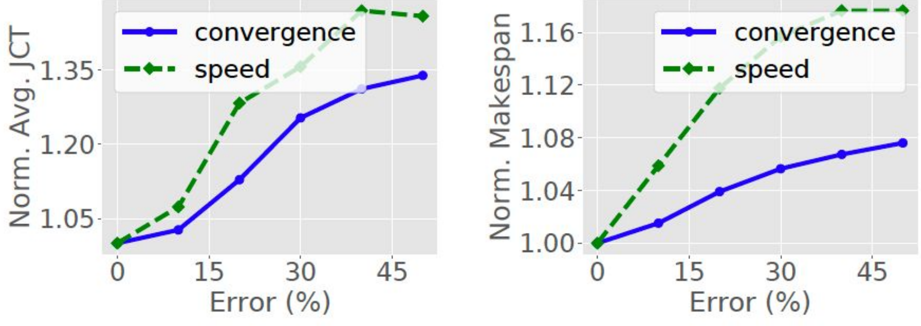

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What are the metrics of success?

- Resource efficiency
  - makespan
- Training time
  - average job completion time

- Others:
  - scalability: scheduling overhead, scaling overhead
  - easy adoption

Long-term impact

System ⇄ ML

Deep Learning

- Increasing deep learning workloads in production clusters
  - Speech recognition
  - Object classification
  - Machine translation

Google Translate

- Many machine learning frameworks
  - TensorFlow
  - MXNet
  - PaddlePaddle

TensorFlow mxnet PaddlePaddle

Discussion

- "..Optimus has a relatively **small configuration space** (i.e., the number of tasks) and **5-10 sample** runs are enough for fitting the performance model quite accurately."
  - is this a useful assumption in practice? (each container fixed resources, horizontal scaling)

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- Who will use this? Who will run this?
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- Graybox vs. blackbox
  - can we extract the "formula" from offline profiling for a given type of application?

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