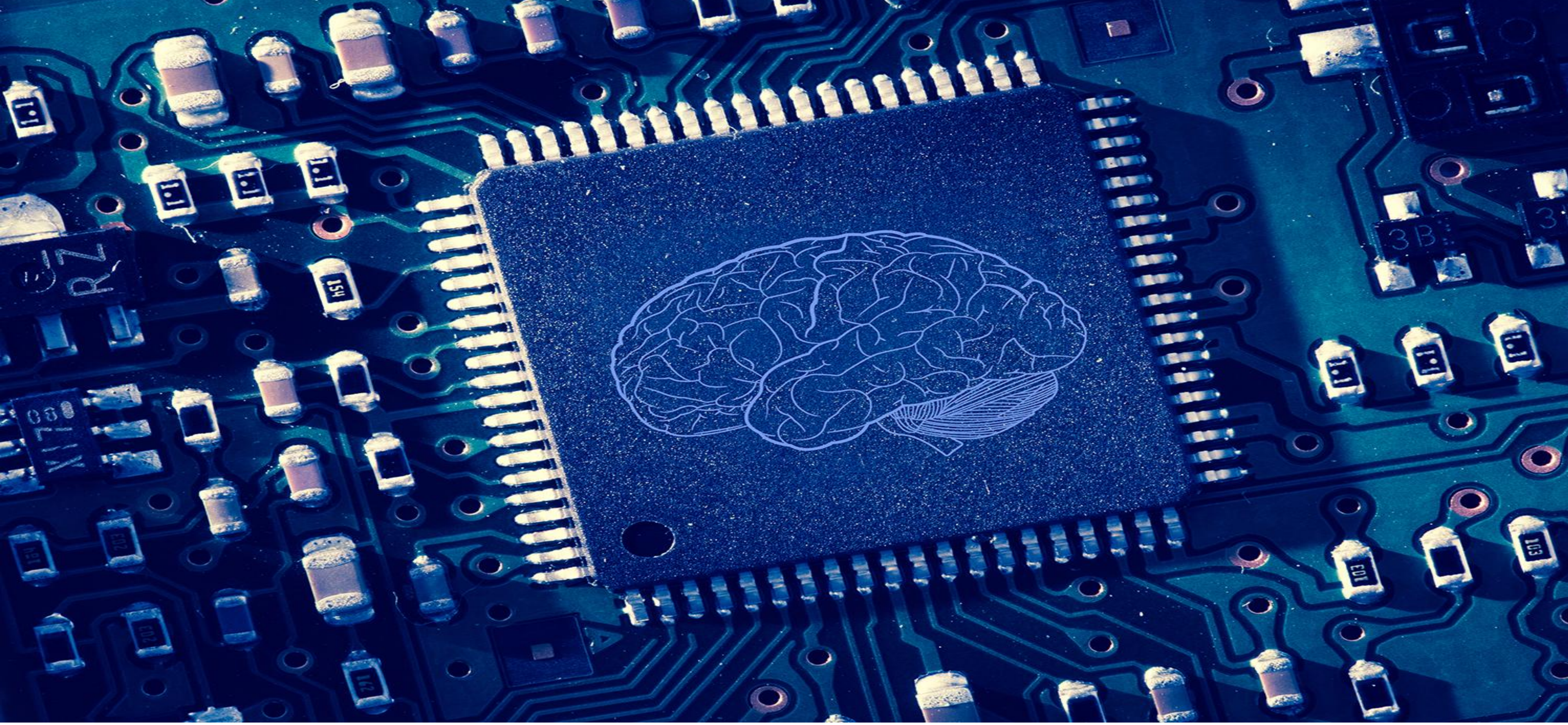

Intelligent System for AI

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2018/5/19 @ AII Workshop

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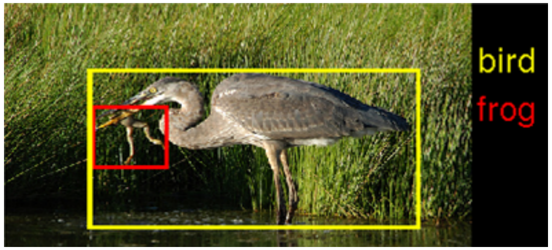
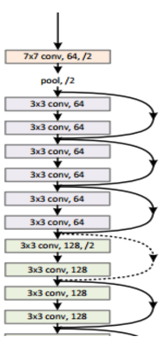
國立清華大學
NATIONAL TSING HUA UNIVERSITY

AI



ResNet-50

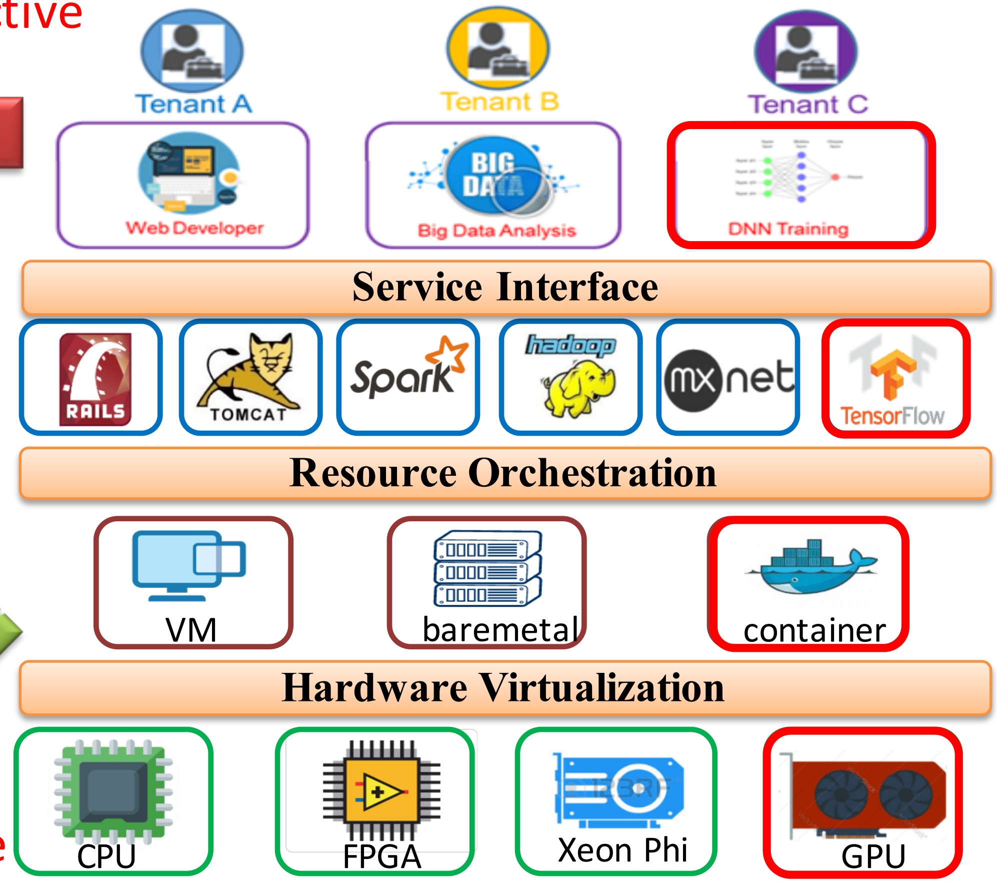


256 GPUs in one hour
[facebook2017]

High throughput
& cost effective

Intelligent resource
management &
system administration

System



150,000 USD

DGX-1

Systems for AI

amazon web services™

Google Cloud Platform

Azure

Public cloud

Managed service
Pay-as-you-used
Availability, Reliability

Cost: 10K TWD for 256GPU-hour
Data privacy and transfer

Systems for AI

Public cloud

Managed service
Pay-as-you-used
Availability, Reliability

Cost: 10K TWD for 256GPU-hour
Data privacy and transfer

Private cloud

Control & efficiency
Security & privacy
Customization

Complex & virtualized HW infra.
Diverse SW deployment
Resource management

Systems for AI

Google Cloud Platform

amazon web services

【財訊快報／王宜弘報導】搶攻AI商機，台廠大團結！華碩(2357)、廣達(2382)以及台灣大(3045)結盟組成「台灣人工智慧A Team」，成軍後首戰告捷！週一(30日)三方共同宣布取得國家實驗研究院國家高速網路與計算中心「雲端服務及大數據運算設施暨整合式階層儲存系統建置案」，將協助建置新一代的AI計算主機，並建立產官學研共用具延展性的AI雲端大資料計算平台，建置總金額近11億新台幣，預計今年第四季建置完成。

Availability, Reliability

Security & privacy
Customization

Cost: 10K TWD for 256GPU-hour
Data privacy and transfer

Complex & virtualized HW infra.
Diverse SW deployment
Resource management

Key Challenges of AI Systems

- System Infrastructure:
  - VM + CPU

    ➔ Container + GPU

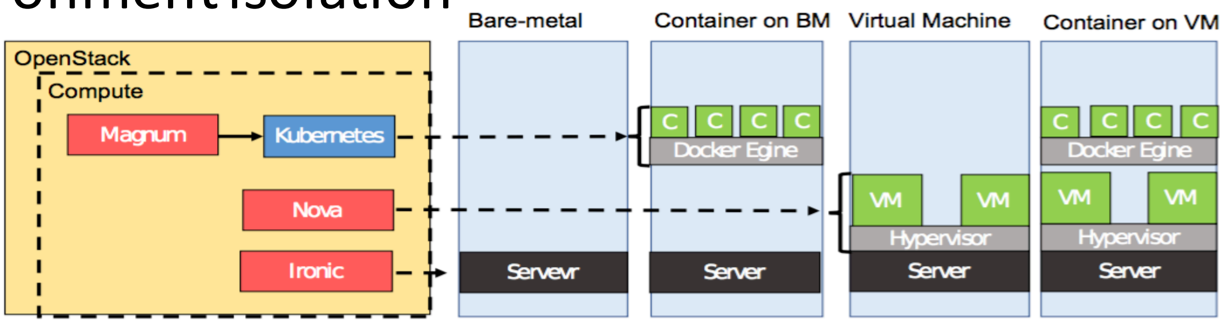
- Training job execution:
  - Static Single instance execution

    ➔ Elastic distributed execution

Container-based GPU Cloud

- Why Container?
  - Lightweight, low performance overhead
  - High deployment density
  - Execution environment isolation

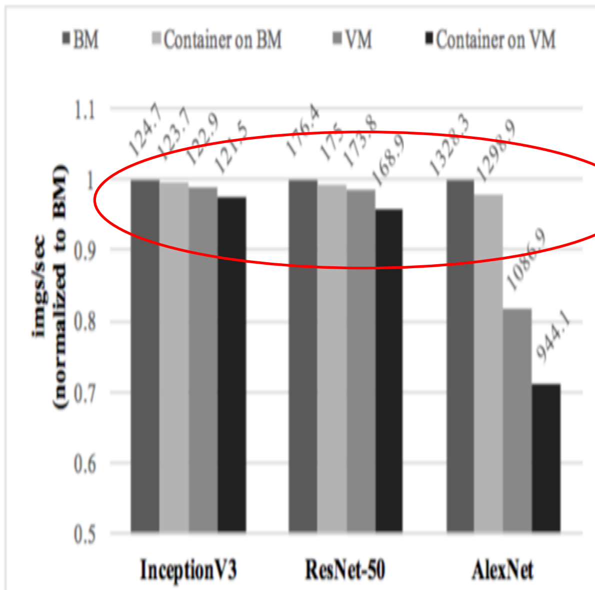
Benchmark TensorFlow on varied resource orchestration (baremetal, container, VM) and execution environment (single, distributed, multi-tenant)



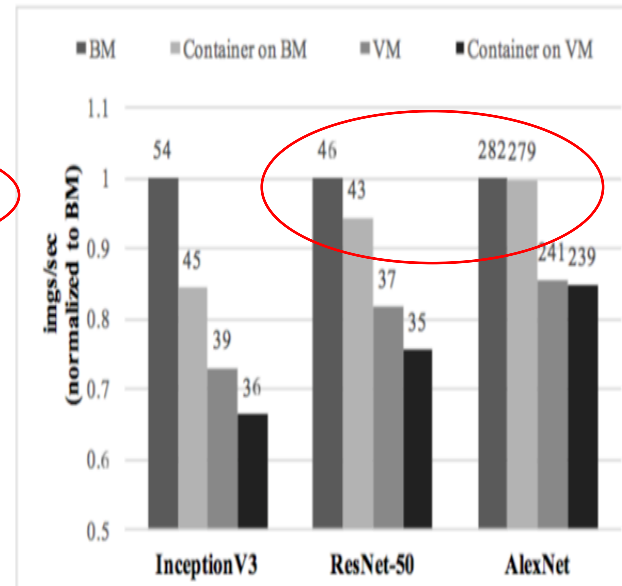
Container-based GPU Cloud

- Why Container?
  - Lightweight, low performance overhead
  - High deployment density
  - Execution environment isolation

Container can deliver close to the bare-metal performance in dedicated resource environment



Single instance

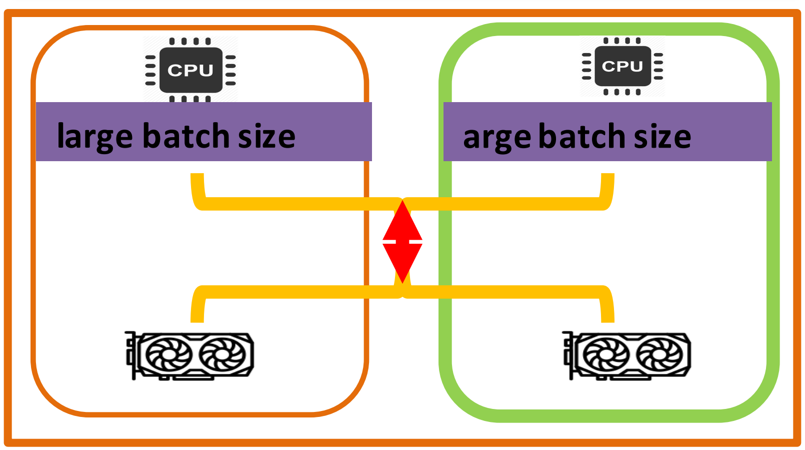


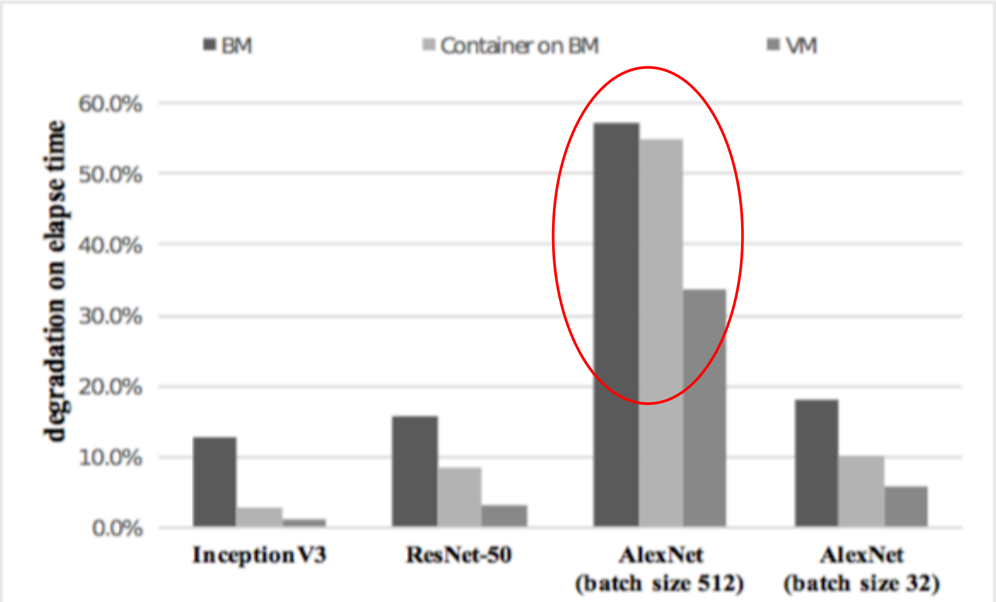
Distributed

Container-based GPU Cloud

- Why Container?
  - Lightweight, low performance overhead
  - High deployment density
  - Execution environment isolation

- Continer lacks of QoS control for PCIE and GPU
- GPU may not be fully utilized by a single job





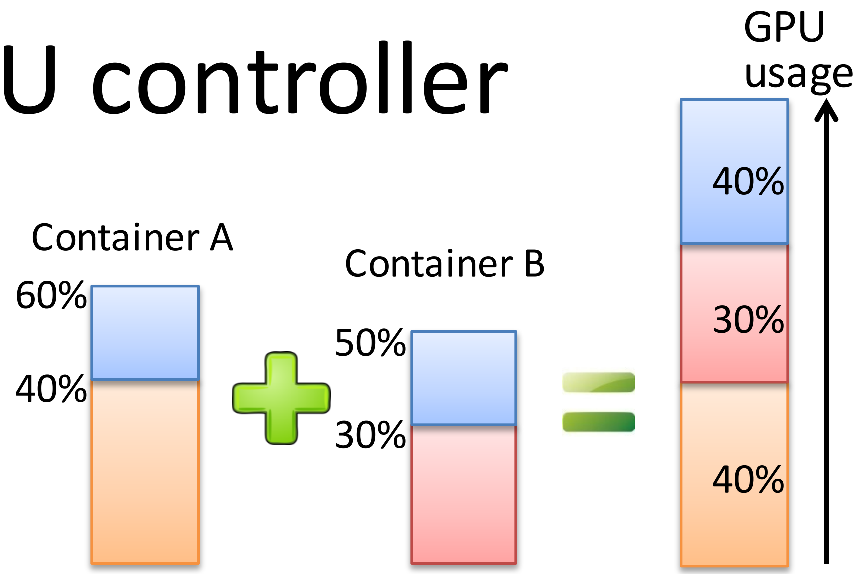
Multi-tenant

Container-based GPU Cloud

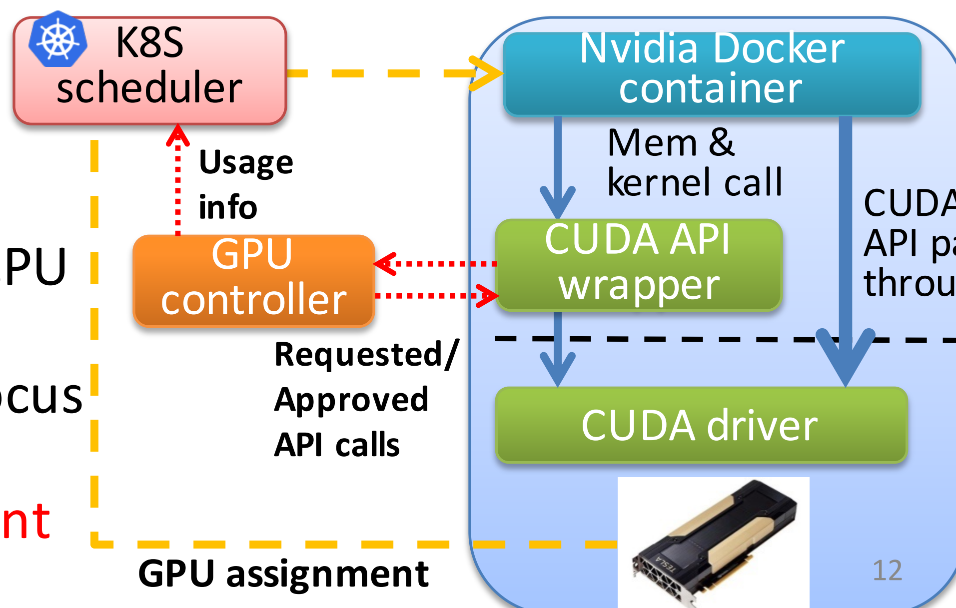
- Why Kubernetes (container orchestrator)?
  - Automating deployment, scaling, and (lifecycle & resource) management of containerized applications
- Current solutions & limitations
  - NVidia-Docker: expose GPU devices to containers
    - Dedicate GPU allocation to container
  - K8S resource limit: control memory and CPU usage
    - GPU is not manageable resource yet
  - KubeFlow: A TF-operator to deploy containerized TF job as a set of K8S applications
    - Naïve round-robin scheduling without scaling and management

Proposed Solutions: Multi-tenant GPU controller

- Objective
  - Treat GPU as the **first class** resource like CPU
  - Allow users to specify the **max** and **min** requirements for GPU utilization and memory usage



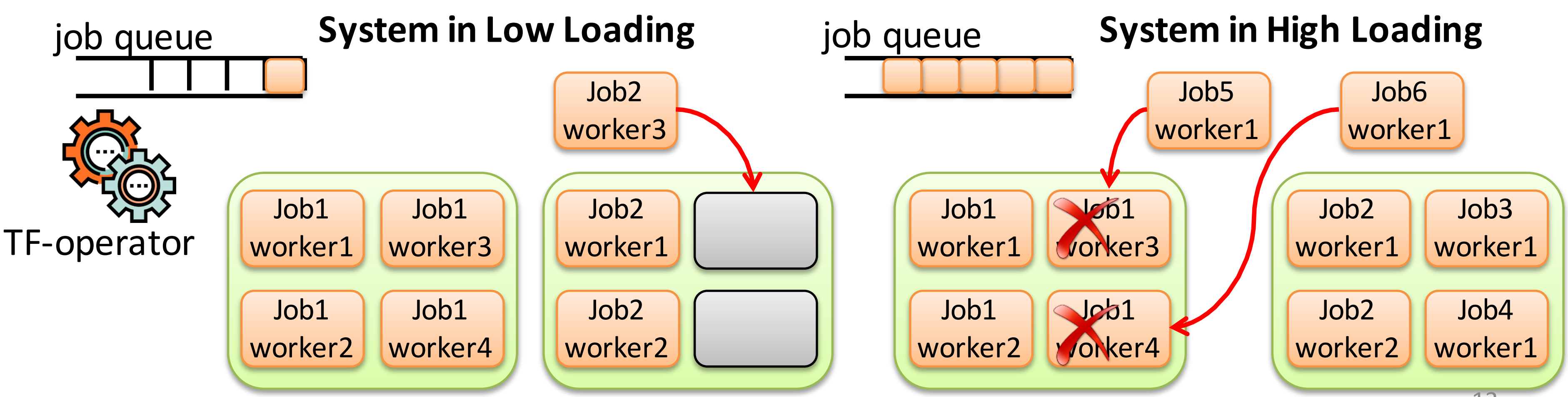
- Approach
  - Intercept CUDA driver & runtime API
  - Forward requests to a centralized scheduler for CPU and memory control
  - Similar to conVGPU, but focus more on GPU utilization control and GPU assignment



Proposed Solutions: Elastic-KubeFlow

- An enhanced K8S TF-operator over KubeFlow

	Auto-Deployment	Scheduling	Scaling
KubeFlow	✓	Round-Robin	✗
Elastic-KubeFlow	✓	Perf. Aware Placement	Scale-up when util. is low Scale-down when wait time is high



Proposed Solutions: Elastic-KubeFlow

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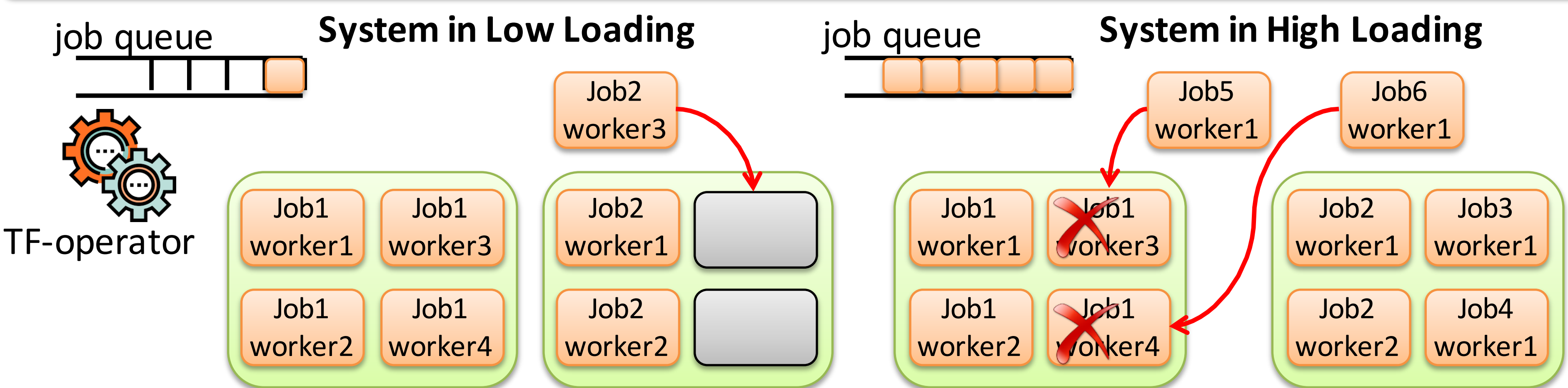
Total job run time: 4:11:44 → 3:16:54 (22% ↓) Total job wait time: 4:45:02 → 2:57:37 (38% ↓)

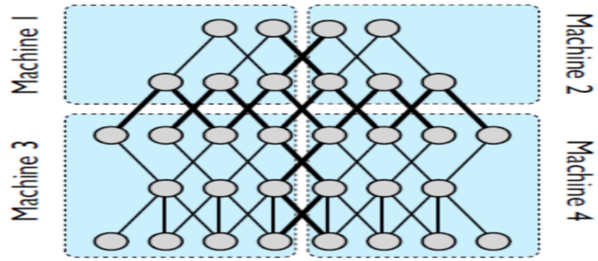


Distributed Deep Learning

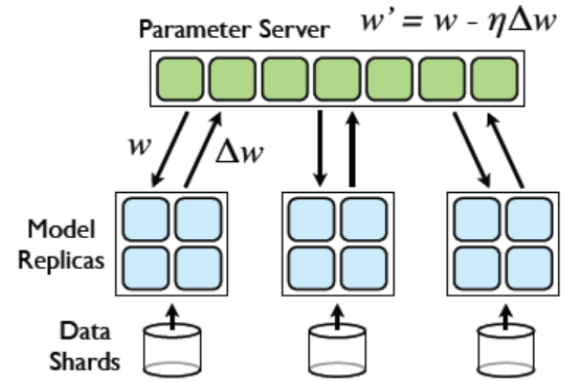
- Model Parallelism
  - Within a node: shared memory, auto-managed by **framework**
  - Across nodes: message passing, model rewritten by **developers**
- Data Parallelism
  - Parameter server:
    - Asynchronous centralized comm.

      ➔ Faster converge time, but higher network BW requirement
    - Main strategy in TF
  - All reduce:
    - Synchronous P2P comm.

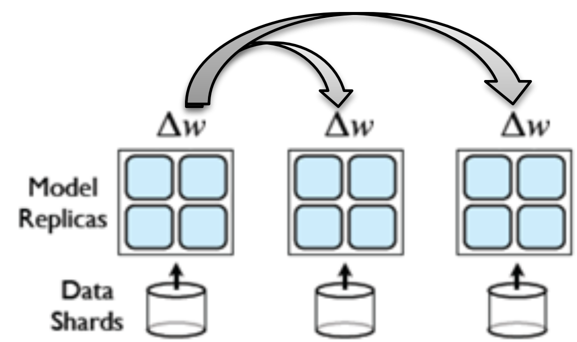
      ➔ Higher latency delay, but more balanced network traffic (avoid hotspot)
    - Recent optimized imp. by **Horovod**



Model parallelism



Data parallelism (PS)

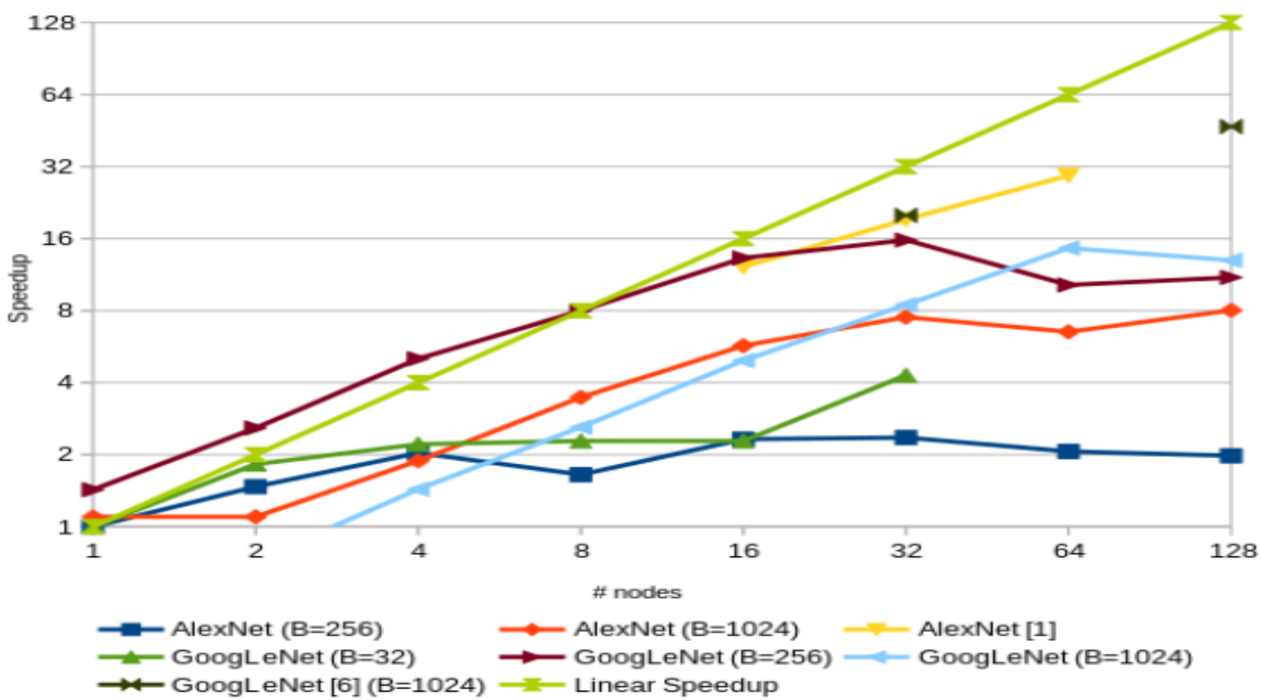


Data parallelism (P2P)

Distributed Model Training

- Why distributed model training?
  – Shorter training time
  – Fully utilize computing resources

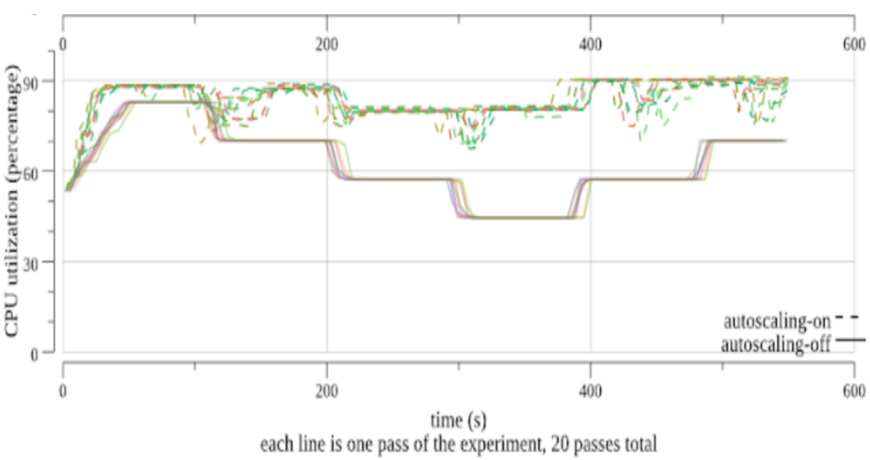
- Non-negligible overhead
- More tuning nobs: batch size, learning rate, #PS



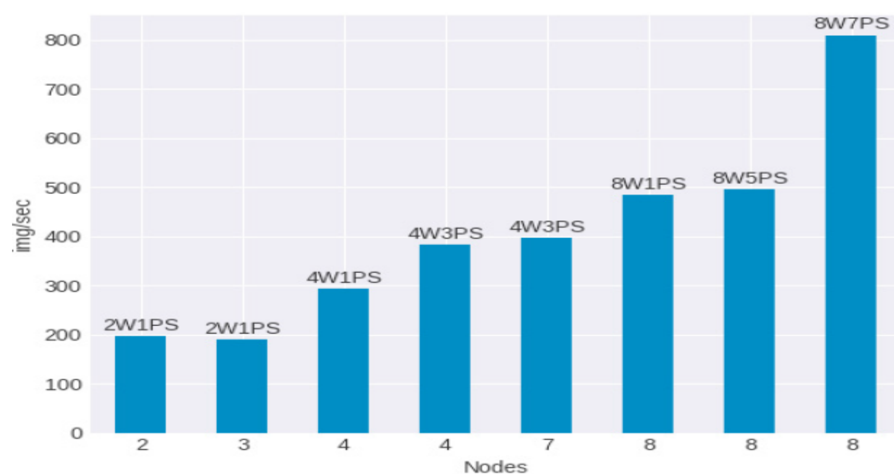
Distributed Training of Deep Neural Networks: Theoretical and Practical Limits of Parallel Scalability.

Proposed Solutions: Elastic-TensorFlow

- Why we want to dynamically add/remove workers from a training job without checkpoint-restart?
  - Auto-tuning PS/Worker ratio at runtime
  - Reach desired performance with minimum cost
  - Maximize system utilization & throughput (Combine with our elastic-kubeflow controller)



http://blog.kubernetes.io/2017/12/paddle-paddle-fluid-elastic-learning.html



Distributed training strategies for a computer vision deep learning algorithm on GPU cluster

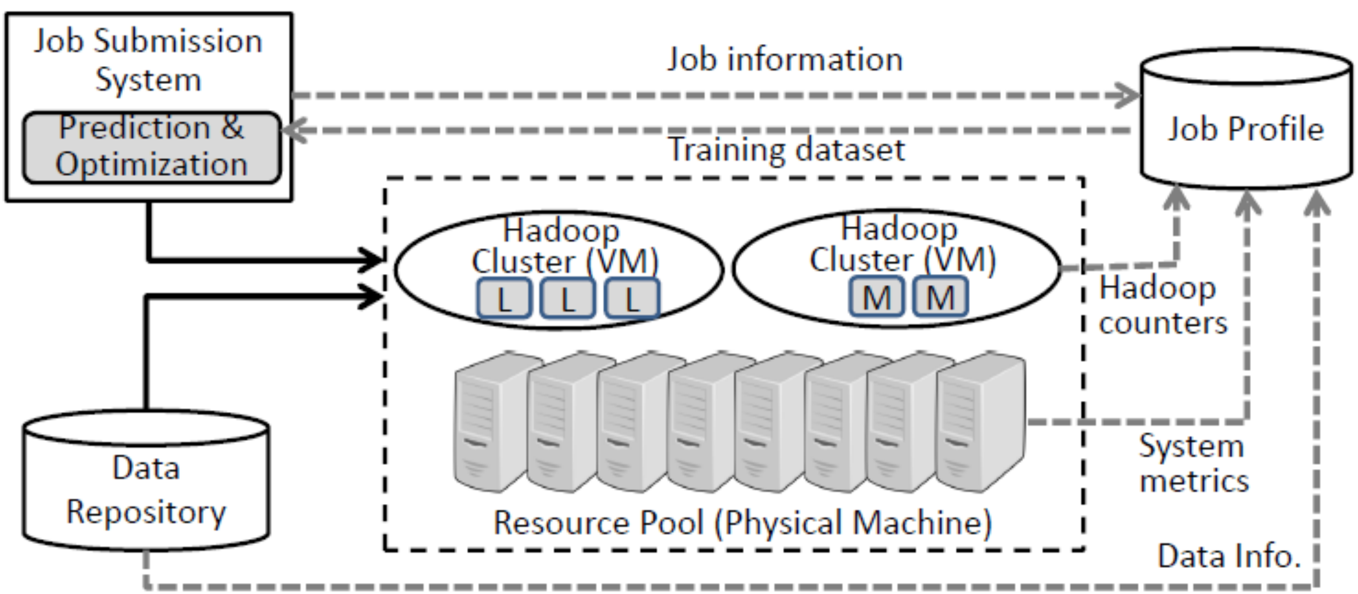
AI for Systems

- Time prediction for optimizing job execution
  - Apply FCN、RNN for complex parallel DAG
- Anomaly & failure prediction for minimizing cost
  - DNN along might not be enough…
    - Using SVM for rare class classification
    - Using bayesian network or decision tree for root cause diagnosis
    - Using probability distribution for system metrics prediction
- Auto-scaling & Scheduling for maximizing system performance
  - Apply reinforcement learning: A3S, Deep Q-learning

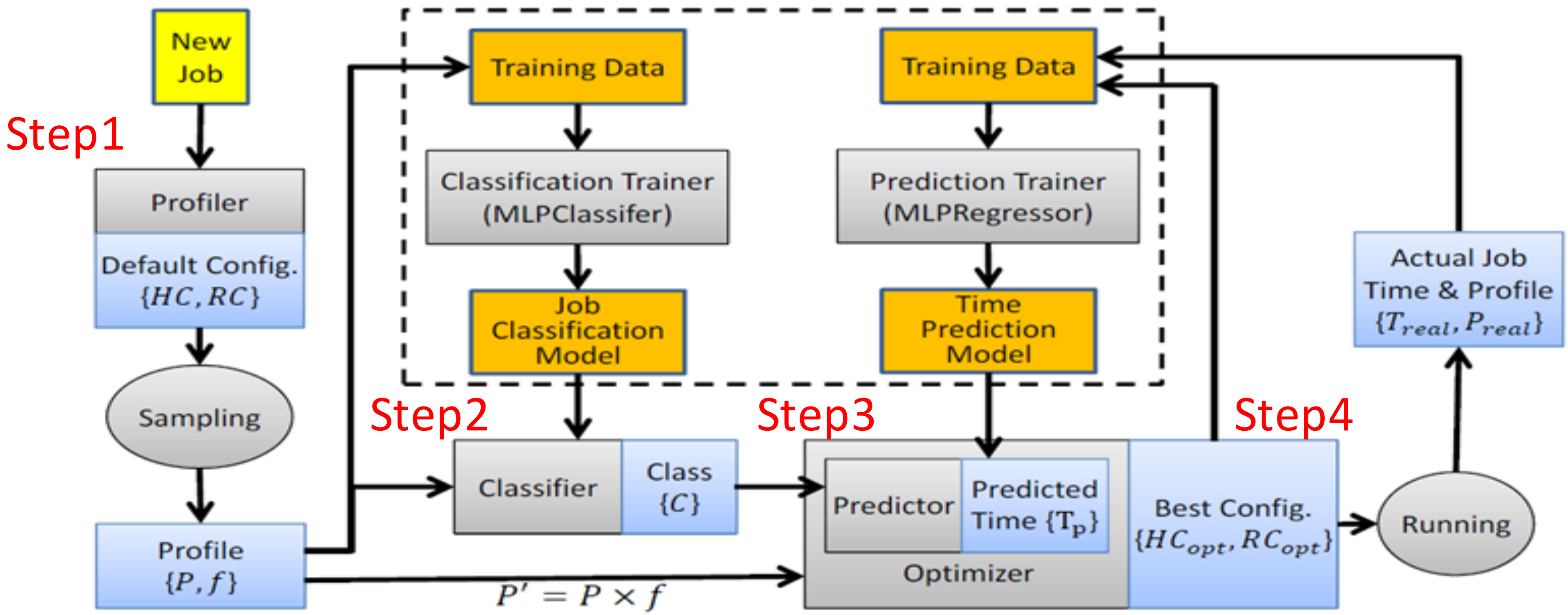
Time Prediction of Hadoop Execution

$$\boldsymbol{f}(job\ profile, resource\ spec, exe\ config) = job\ execution\ time$$

- A parallel execution job
- Over 100 execution configurations
- Cloud platform provides varied compute instance types
- Inexperienced users for performance optimization



Time Prediction of Hadoop Execution

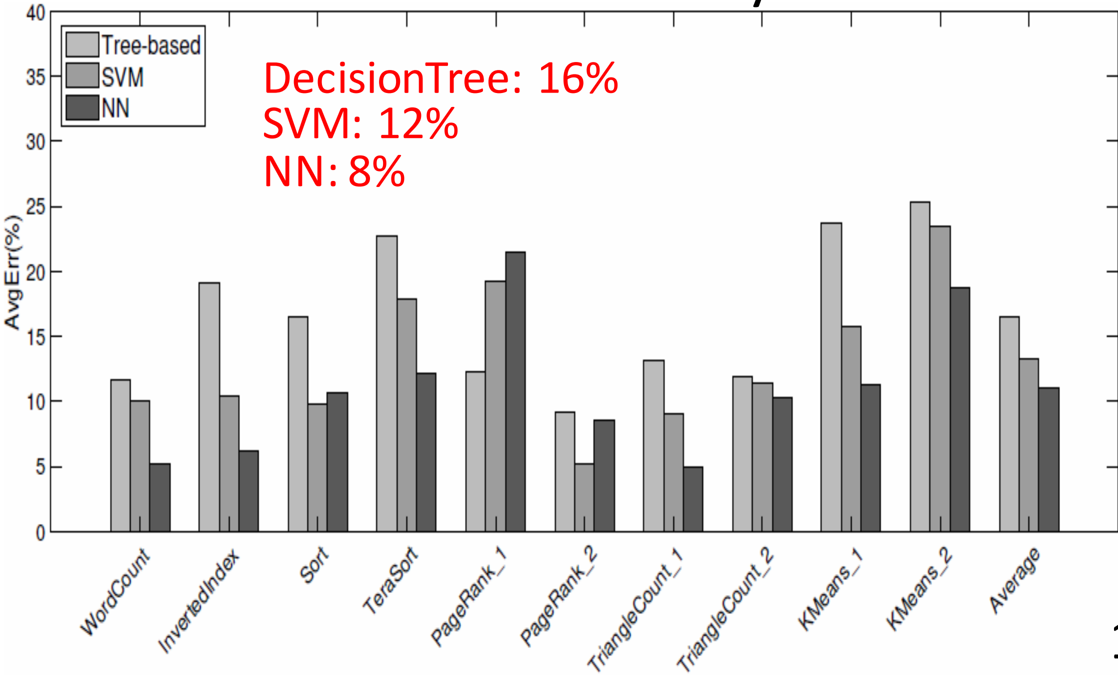


- Step1: Job Profiling
  - Collect job features
- Step2: Job classification
  - Improve prediction accuracy
- Step3: Model prediction
  - Fully-Connected NN
- Step4: Optimization
  - Search optimal configurations

Evaluation Results

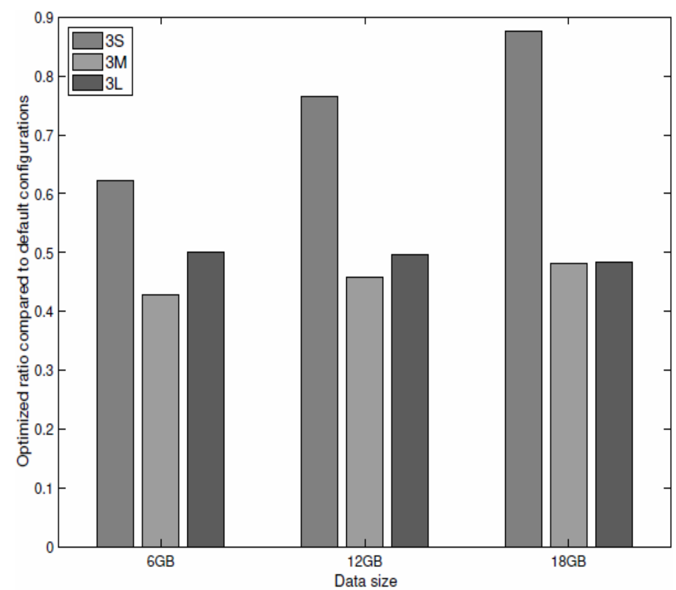
- Workload from HiBench, a Hadoop benchmark suite

Prediction Accuracy



More accurate time prediction than traditional ML methods

Performance Improvement



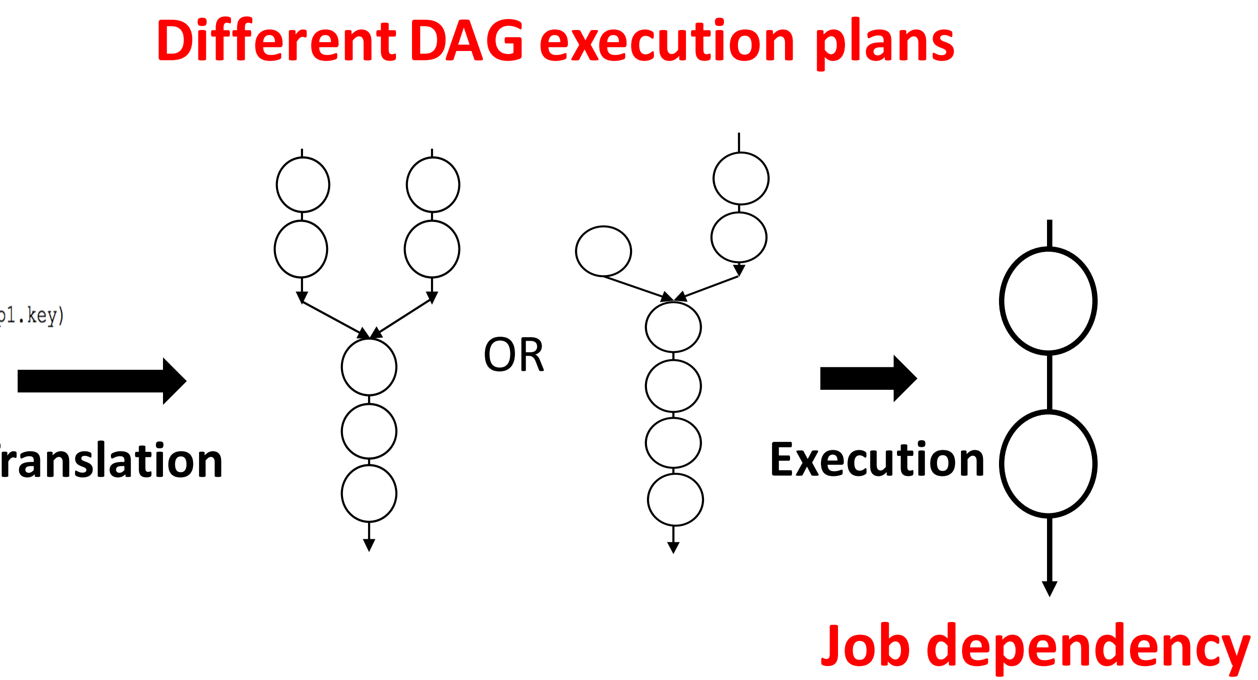
10~50% performance improvement by choosing the proper execution configurations

Time Prediction of Hive Query

- Hive: A query engine on Hadoop
  - Complex workflow represented by DAG

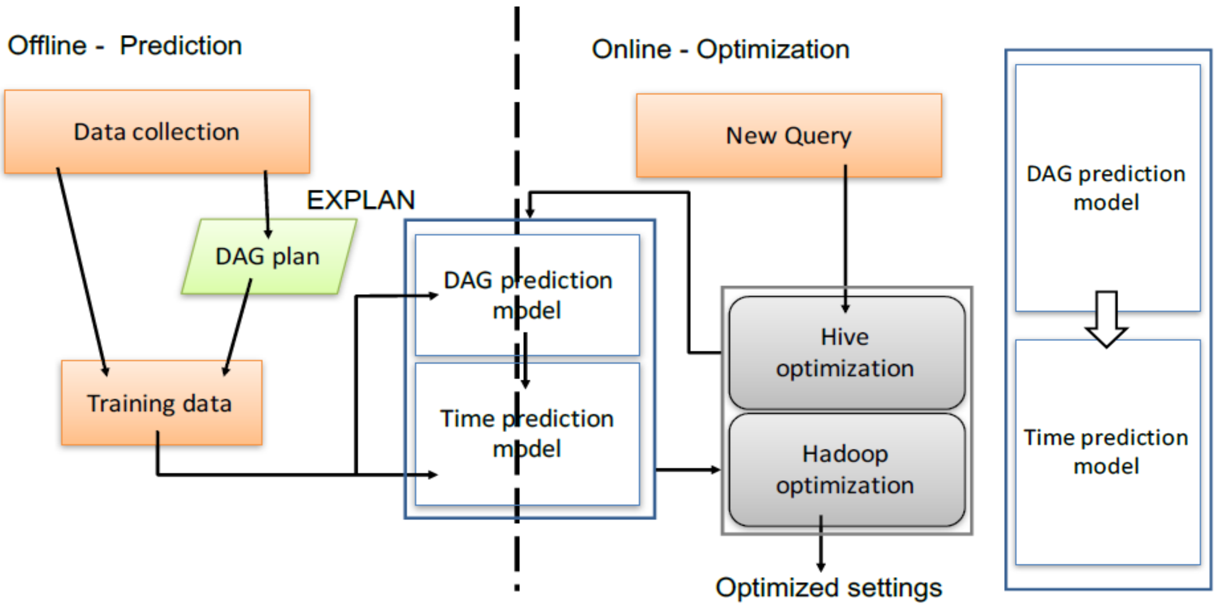
```
SELECT tmp1.key, count(*)
FROM t1
JOIN /*JOIN1*/ (SELECT key, avg(value) AS avg
               FROM t1
               GROUP BY /*AGG1*/ key) tmp1 ON (t1.key = tmp1.key)
JOIN /*JOIN1*/ t2 ON (tmp1.key = t2.key)
WHERE t2.value > tmp1.avg
GROUP BY /*AGG2*/ t1.key;
```

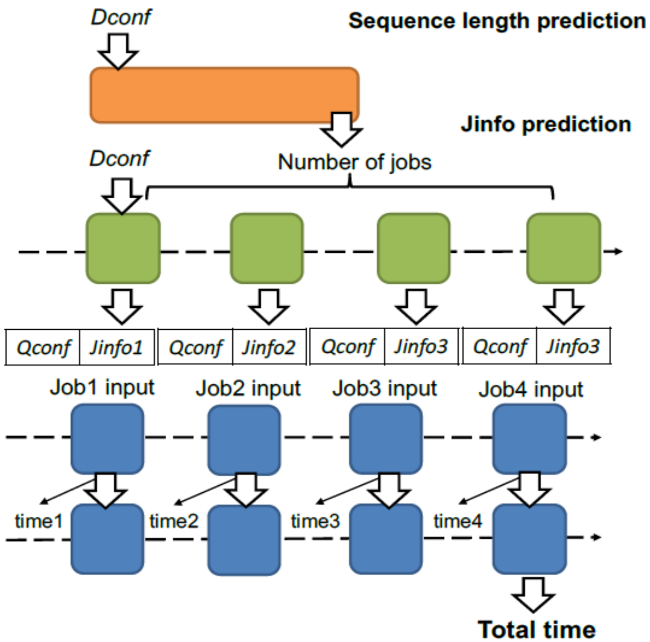
Query Statement



Time Prediction of Hive Query

- RNN model
  - Serialized DAG workflow with arbitrary job sequence length
  - Stored state for capturing job dependency effects
- Two level prediction & optimization
  - Query level (Hive) and job level (Hadoop)

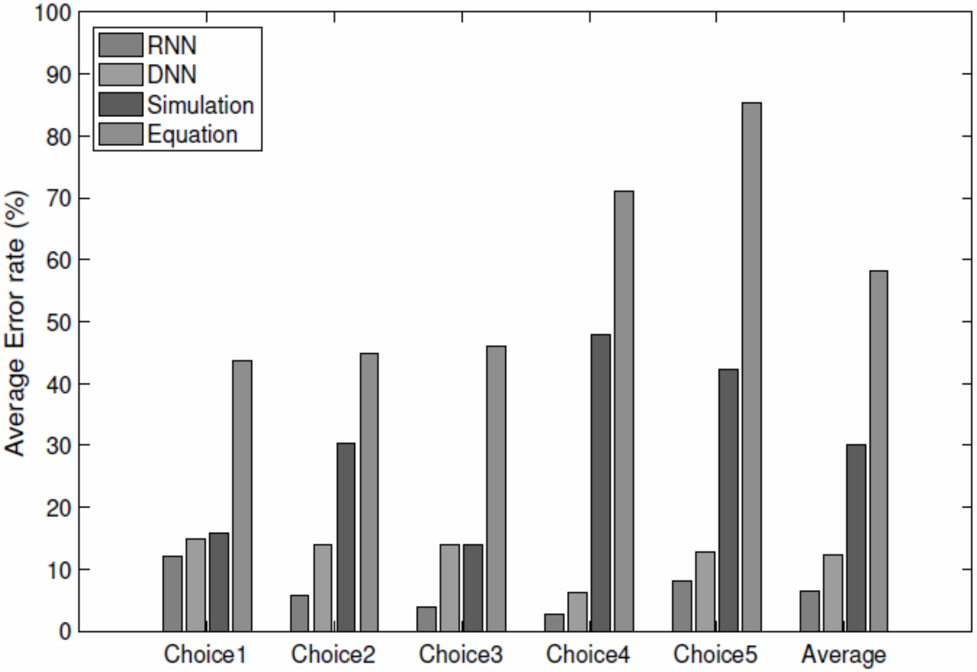




Evaluation Results

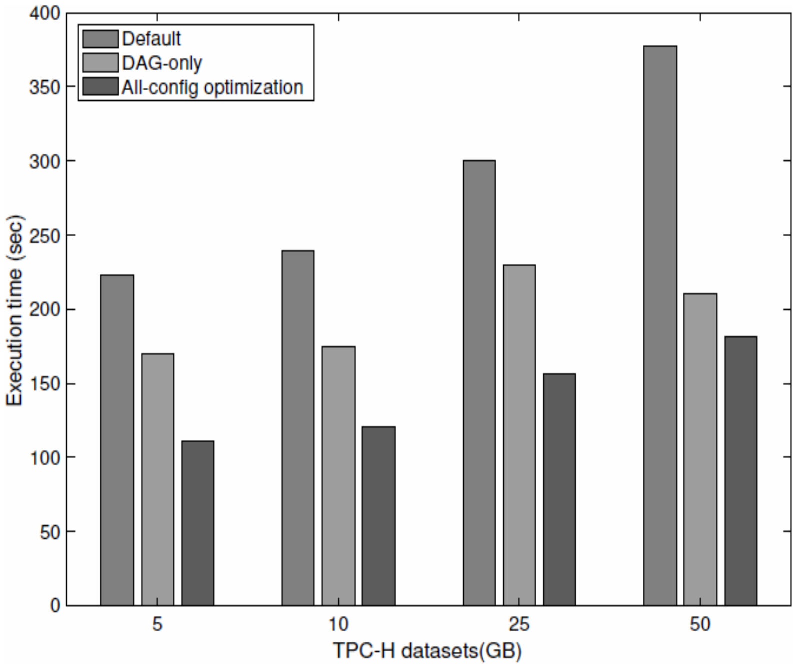
- Workload from TPC-H benchmarks

Prediction Accuracy



RNN has the lowest error rate comparing to DNN and other methods

Performance Improvement



Improve performance by over 50% when both Hadoop and Hive configurations are optimized

Thanks