Deep Domain Adaptation for Runtime Prediction in Dynamic Workload Scheduler

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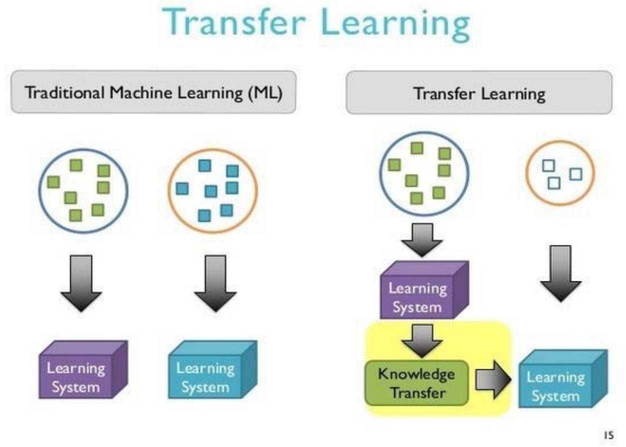
Introduction

HPC schedulers are prone to delaying job execution due to overestimation of the running time for submitted jobs. This not only wastes hardware resources, but it also extends the time some users must wait for their jobs to execute. This work focuses on minimizing mis-predictions of job running times from different workloads.

Traditional methods are trained on a single workload to make predictions. Domain Adaptation methods are employed to minimize domain shift for better generalization of runtime predictions across workloads.



Methods

Domain Adaptation with Correlation Alignment (DCORAL)

- Integrate correlation distribution alignment (CORAL) (*Sun et al.,2016*) with source domain cross-entropy loss for domain adaptation

Labeled Source Data

$$\{x_i^s, y_i^s\} \in \{X^S, Y^S\} \equiv D_s, i \in (0, n_s)$$

Unlabeled Target Data

$$\{x_j^t\} \in \{X^T\} \equiv D_T, j \in (0, n_t)$$

1. Cross-entropy Loss (Source Loss)

$$\mathcal{L}_s = \frac{1}{n_s}\sum_{i=1}^{n_s} c(\theta|x_i^s, y_i^s)$$

c(.): cross-entropy loss function

2. Correlation Alignment Loss (CORAL)

$$\mathcal{L}_d = CORAL(H_s, H_t) = \frac{1}{4L^2}(Cov(H_s) - Cov(H_t))$$

$H_s, H_t \in \mathcal{R}^{bxL}$: *learned deep features from bottleneck layers*

L: *length of learned deep features*

b: *batch size*

$Cov(.)$: *covariance matrix*

→ **Overall Loss Function:**

$$\mathcal{L}(\theta|X_s, Y_s, X_t) = \mathcal{L}_s + \mathcal{L}_d$$

Architecture & Results

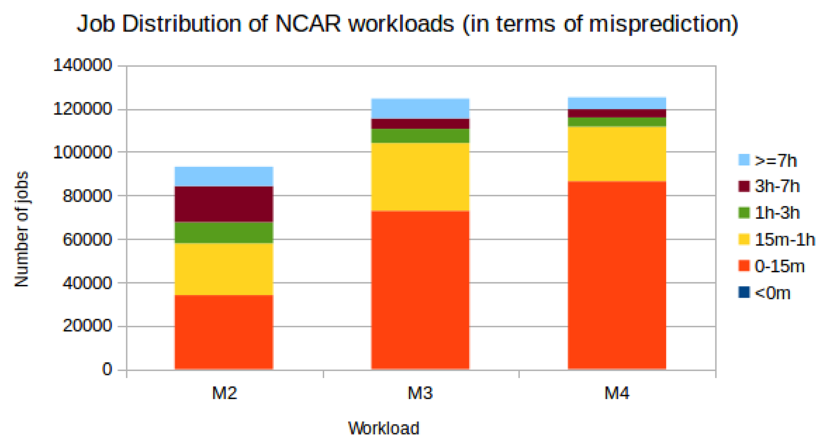
DATA PREPROCESSING

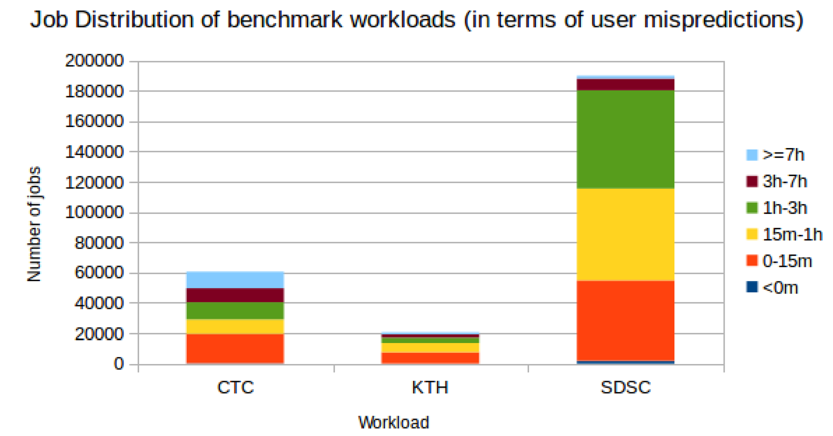
- Divide users' mispredictions into 6 time ranges
- Classify users' mispredictions based on request resources and historical data

NCAR Workload	Benchmark Workload
April 2019 Week 2 (M2)	Cornell Theory Center IBM SP2 (CTC) [1]
April 2019 Week 3 (M3)	Swedish Royal Institute of Technology IBM SP2 (KTH) [2]
April 2019 Week 4 (M4)	San Diego Supercomputer CenterBlue Horizon (SDSC) [3]

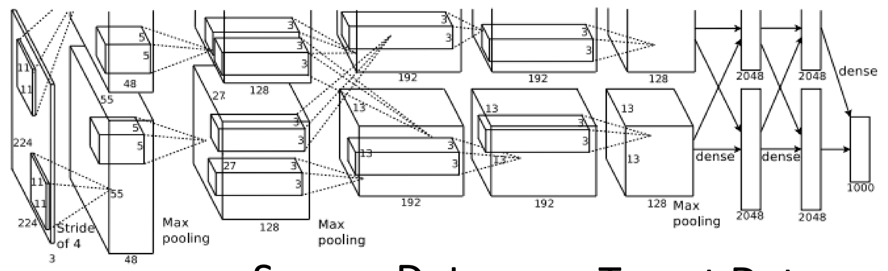
NCAR Workload Features	Benchmark Workload Features
PBS features recorded from accounting log	Standard Workload Format (SWF)
Additional historical features suggested from *Gaussier et al., 2015*	
79 features	34 features

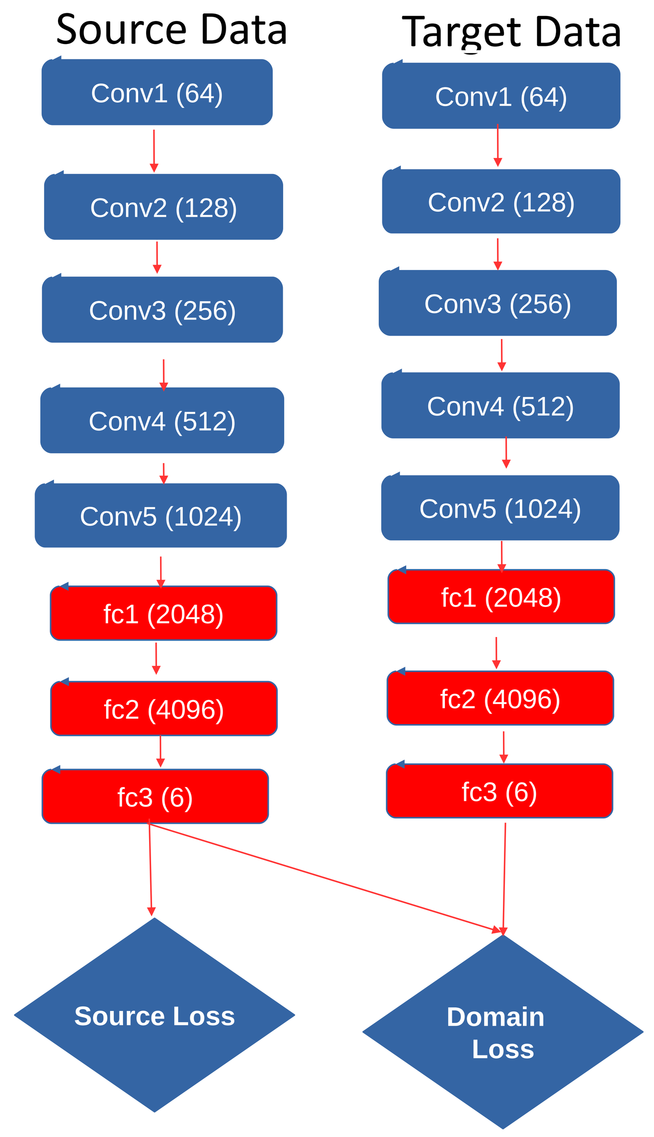
DATA DISTRIBUTION





BACKBONE ARCHITECTURE (AlexNet) (*Krizhevsky et al., 2012*)





Learning Rate Schedule

- Adapt learning rate with adaptation factor λ

$$\lambda = \frac{2}{1 + \exp(-\mu p)} - 1$$

$$p = \frac{current\ epoch}{num\ epoch}\ (training\ progress)$$

$\mu = 10$ (fixed)

EVALUATION METRIC:

- Accuracy:
  - Direct measure of correct predictions generated by model on target domain

BASELINE METHODS:

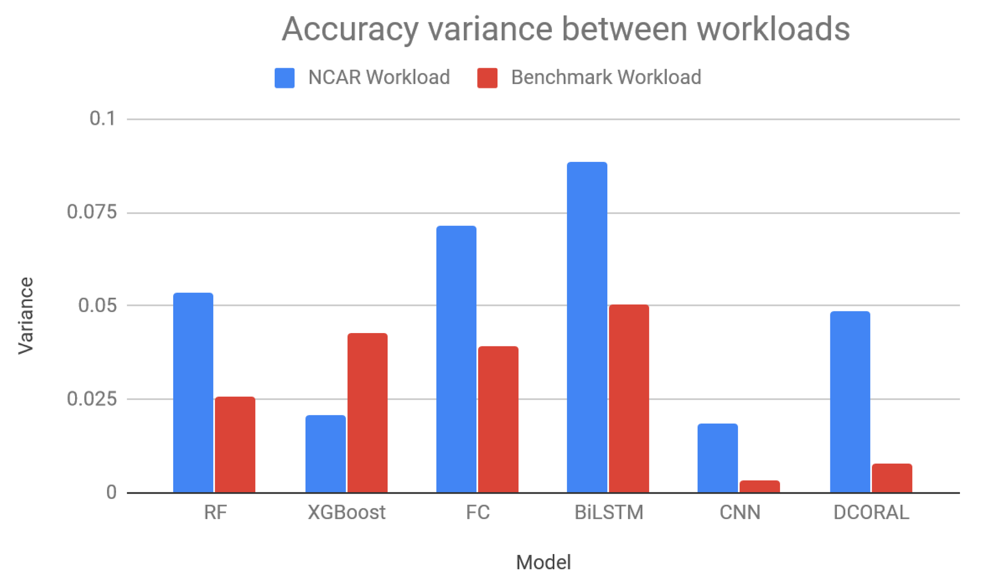
- Random Forest (RF) (*Guo et al.,2018*)
- XGBoost (Gradient Boosting Classifier) (*Guo et al., 2018*)
- Feed Forward Neural Network (FF)
- Convolutional Neural Network (CNN)
- Bi-directional Long short-term memory Network (Bi-LSTM)

Table 1: NCAR Workload Accuracy Summary

Methods	RF	XGB	FF	Bi-LSTM	CNN	DCORAL
M2->M3	0.467	0.054	0.389	0.357	0.412	**0.875**
M3->M2	0.396	0.295	0.591	**0.61**	0.211	0.365
M2->M4	0.258	0.041	0.105	0.129	0.295	**0.398**
M4->M2	0.372	0.326	**0.498**	0.456	0.349	0.383
M3->M4	0.849	0.377	0.772	**0.882**	0.129	0.698
M4->M3	0.747	0.277	0.835	**0.873**	0.505	0.735
Average	0.515	0.228	0.532	0.551	0.317	**0.576**

Table 2: Benchmark Workload Accuracy Summary

Methods	RF	XGB	FF	Bi-LSTM	CNN	DCORAL
CTC->KTH	0.254	0.089	0.191	0.245	0.193	**0.385**
KTH->CTC	0.462	0.118	**0.528**	0.303	0.276	0.426
CTC->SDSC	**0.292**	0.058	0.092	0.161	0.143	0.241
SDSC->CTC	0.256	**0.611**	0.204	0.21	0.285	0.395
KTH->SDSC	0.563	0.273	0.695	**0.886**	0.287	0.384
SDSC->KTH	0.614	0.159	0.749	**0.799**	0.212	0.511
Average	0.407	0.218	0.410	**0.434**	0.233	0.390



Discussion & Future Work

- Pre-train backbone architecture with large workload datasets (similar to MNIST in Computer Vision) prior to domain adaptation
- Integrate Domain Alignment approach with Discriminative Feature Learning (*Chen et al., 2018*) from source domain for improved accuracy
- Run simulator to estimate performance improvements for HPC scheduler in more diverse workloads

[1] http://www.cs.huji.ac.il/labs/parallel/workload/l_ctc_sp2/index.html

[2] http://www.cs.huji.ac.il/labs/parallel/workload/l_kth_sp2/index.html

[3] http://www.cs.huji.ac.il/labs/parallel/workload/l_sdsc_blue/index.html

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Conclusions

- DCORAL outperforms CNN with similar backbone architecture (AlexNet) (average accuracy improvement of **15.7%** on **Benchmark dataset**, **25.9%** on **NCAR dataset**)
- DCORAL and CNN provide more stable models for knowledge transfer between different workloads (low accuracy variance)
- Bi-LSTM is the best backbone architecture
- DCORAL outperforms traditional methods on NCAR dataset (**2.5%** above average accuracy of the second best model (Bi-LSTM))

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