Scheduling of Time-Varying Workloads Using Reinforcement Learning

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Abstract

Resource usage of production workloads running on shared compute clusters often fluctuate significantly across time. While simultaneous spike in the resource usage between two workloads running on the same machine can create performance degradation, unused resources in a machine results in wastage and undesirable operational characteristics for a compute cluster. Prior works did not consider such temporal resource fluctuations or their alignment for scheduling decisions. Due to the variety of time-varying workloads and their complex resource usage characteristics, it is challenging to design well-defined heuristics for scheduling them optimally across different machines in a cluster. In this paper, we propose a Deep Reinforcement Learning (DRL) based approach to exploit various temporal resource usage patterns of time-varying workloads as well as a technique for creating equivalence classes among a large number of production workloads to improve scalability of our method. Validations with real production traces from Google and Alibaba show that our technique can significantly improve metrics for operational excellence (e.g. utilization, fragmentation, resource exhaustion etc.) for a cluster compared to the baselines.

Introduction

In large production clusters, multiple workloads are co-located on the same machine to achieve operational efficiency at scale. They share the underlying physical resources of the machine such as CPU, cache, memory, disk, network-bandwidth. Today, the standard practice is to deploy these workloads as microservices inside containers that are managed by various orchestration-engines (COEs) such as Mesos (Hindman et al. 2011) and Kubernetes (Burns et al. 2016). These engines either use standard bin-packing algorithms or custom heuristics (Ghodsi et al. 2011; Garefalakis et al. 2018; Verma et al. 2015) to place these workloads on the available machines in a multi-tenant cluster. However, a very significant fraction, if not all, of these services or applications show time-varying-workload (TVW) characteristics, i.e. their resource usage vary significantly over time (Tian, Zheng, and Wang 2019; Reiss et al. 2012; Mishra et al. 2010). This can happen because of algorithmic phases (Amvrosiadis et al. 2018; Reiss et al. 2012; Mitra et al. 2017; Zhang et al. 2007), variations in load or the number of users interacting with the workload. For user-facing services, such temporal resource usages can have daily and seasonal patterns due to fluctuations in user-demands (Amvrosiadis et al. 2018; Mishra et al. 2010) (e.g. some services are mostly used during working hours while some are used during holiday seasons).

In a multi-tenant cluster, services are developed and deployed by different engineering groups, where none, including the cluster manager, usually have a detailed understanding of the temporal resource-usage characteristics of each of these services. (Garefalakis et al. 2018) reported that today a substantial fraction of common clusters as well as dedicated cluster in production are devoted to only long-running workloads. When placing long-running workload containers, the cluster scheduler must also target operational excellence, such as improving overall cluster utilization, minimizing performance degradation due to resource contention (e.g. memory usage of two workloads on the same machine spikes at the same time), service level objective (SLO) violations due to resource over utilization or exhaustion, resource fragmentation and the number of machines used. Finding optimum initial placement for these workloads are crucial as later migration has a high overhead and causes degraded user-experience (Garefalakis et al. 2018).

Problem Statement: In this paper we explore how we can build a self-learning scheduler that can take historical resource-usage characteristics for each service[1] as a time-series: $r_d(t)$ and attempt to optimize various components of operational excellence in a cluster. Here $r_d(t)$ is the resource usage along the measurable resource dimension d (CPU, Memory etc.) and t is a timestamp.

The absence of optimal co-location labels makes this an unsupervised problem. Since the impacts of placement decisions are not immediately observable, a cost-based heuristic would be sub-optimal. While Reinforcement Learning is a feasible solution, the large number of ways a variety of services can be co-located over different machines in the cluster, makes state-transition probability modeling infeasible.

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[1]We use the terms TVWs, services, jobs, tasks or applications interchangeably, to generally mean containerized microservices.

Our proposed TVW-RL is a Deep Reinforcement Learning (DRL) based approach to make the cluster scheduler automatically learn temporal resource usage patterns for each service and dependencies across different services using deep neural network as function approximators. This learning helps the scheduler place the services in a shared cluster without requiring any manually provided placement heuristics in order to achieve operational excellence.

We make the following key contributions:

- We novelly use DRL approach to provide better placement for time-varying-workloads (TVWs).
- We propose novel reward designs to improve operational excellence for a cluster handling long-running TVWs.
- We present resource-usage based equivalence mapping of workloads for robust learning and scalability.
- We present extensive evaluation using real workload traces from Google and Alibaba production clusters and show that our technique can improve resource utilization by 30-100%, reduce resource fragmentation by 5-13% and reduce the number of machines needed by 8-50% under variable load conditions.

Background and Related Work

A cluster administrator targets to improve the *Operational Excellence* on the following aspects.

Maximize Workload Performance: A scheduler should attempt to minimize the probability of performance degradation through contention in poorly isolated resources (last-level cache, memory bandwidth etc.). If the surge in the resource demand in two co-located services do not happen at the same time, it is unlikely that they would contend each other and hence their performance will be maximized.

Maximize Overall Cluster Utilization: Maximizing overall cluster utilization by efficient packing of workloads is important to reduce computing cost for any organization.

Minimize Resource Overshoot: When the number of workloads is large and/or load for the workloads is high, some machines might experience periods of resource overshoot and exhaustion (sum of resource requests from co-located applications shoots beyond the machine's capacity). Placement algorithms should avoid such situations.

Minimize Resource Fragmentation: If amounts of unutilized resources remain spread across a large number of machines, those fragmented resources cannot be used to host new workloads leading to undesirable resource wastage.

Minimize Number of Machines used: If same workloads can effectively be run on a smaller number of machines, it can significantly reduce operating cost as idle machines can be stopped/hibernated. It is challenging to efficiently explore this trade-off space for a mix of TVWs as several of these aspects are naturally conflicting to each other.

Reinforcement Learning. In RL, at a high-level, an agent interacts with a system and tries to learn an optimized policy. At each timestep t, the agent observes the *state* of the system s_t, and chooses to take an *action* a_t that changes the state to s_{t+1} at timestep $t+1$, and the agent receives a reward r_t. The goal of the agent is to learn the best policy to maximize its expected cumulative discounted reward: $E[\sum_{t=0}^{\infty} \gamma^t r_t]$ where $\gamma \in (0,1)$ determines how much the future rewards contribute to the total reward (Sutton, Barto et al. 1998). In DRL, neural networks are used as agents to handle large state and action spaces (Lillicrap et al. 2015; Mnih et al. 2015). We used policy-gradient method with REINFORCE algorithm (Sutton et al. 2000) with the neural network as a function approximator.

Related works. Prior work related to scheduling and job packing in multi-tenant clusters looked at multi-dimension resource packing (Parkes et al. 2015; Joe-Wong et al. 2013; Ghodsi et al. 2011; Grandl et al. 2014), opportunistic scheduling for improving cluster utilization (Boutin et al. 2014; Verma et al. 2015; Schwarzkopf et al. 2013), performance-aware placement (Nathuji et al. 2010; Delimitrou and Kozyrakis 2013, 2014; Gog et al. 2016; Isard et al. 2009) or cost-models for template workloads (Marcus and Papaemmanouil 2016). None, handles time-varying resource usage aspects of the workloads. DeepRM (Mao et al. 2016) used DRL to schedule jobs that use *constant amount of resources*, on a *single monolithic machine*. It neither considers temporal variations in resource usage nor individual machine-specific views that is necessary to understand and optimize for job alignment to minimize resource interference and resource fragmentation. (Mitra et al. 2019) cannot handle real production workloads because of scalability challenges. Other works applied DRL in video streaming (Mao et al. 2017), routing (Mestres et al. 2017) and device-placement (Mirhoseini et al. 2017). Tetris (Grandl et al. 2014) uses heuristics to account multiple resource dimensions but does not consider the temporal resource usage changes during runtime. Tetris assumes complete knowledge of the resource requirements of tasks and resource availability at machines. Recently proposed Decima (Mao et al. 2019) used RL to learn optimized scheduling for DAG-structured analytic jobs and is complementary to our work as it does not handle TVWs.

Design of TVW-RL

TVW-RL represents the workload scheduler as an agent where the scheduling policy is encoded in a neural network. For an incoming scheduling request of a TVW, a trained policy network takes *actions*: where that service should be placed to optimize for the operational excellence.

We model the cluster environment as composed of N machines on which the TVWs are to be scheduled. Each machine has C_d amount of total physical resource capacity for resource dimension d (e.g., CPU, memory). For a service j, the agent observes the resource usages' time-series denoted as $r_{d_j}(t)$, where r_d is the resource usage along the resource dimension d and t is a timestamp. Along with the current placement map of which services are running on which machines, the agent keeps track of the incoming scheduling requests in the queue. The complete workflow of the TVW-RL technique is shown in Fig. 1 and Algorithm 1 describes the high-level online learning and placement logic.

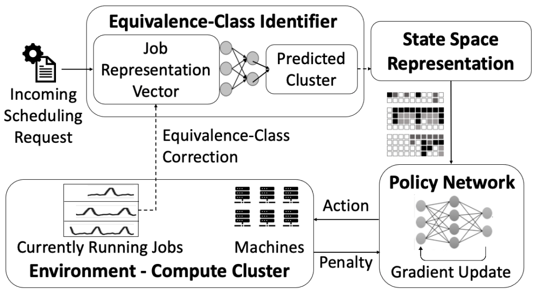


Figure 1: Workflow of TVW-RL

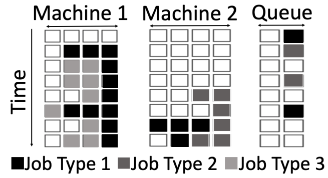


Figure 2: State representation (For 2 machines with 4 resource units, 2-slot waiting queue, and 3 types of jobs with resource variation over last 8 timesteps.)

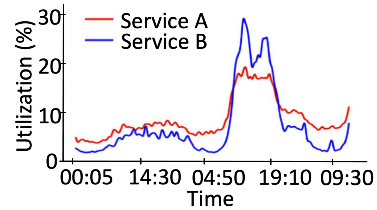


Figure 3: Services showing simultaneous spikes in resource usages

State Space Representation for RL

We design the state-space such that it can capture the temporal variations of resource usages as well as the degree of competition among co-located services sharing the same underlying resources within a machine.

Fig. 2 illustrates our input-space representation. State of each machine in the cluster is represented as a 2D matrix with h x C_d pixels for each of the resource dimension d, where h is the number of previous logical timesteps. Within each machine, one dimension of the matrix represents the time axis and captures the utilization of TVWs for up to h previous logical timesteps. Length of the history, i.e. h helps the agent to learn the temporal characteristics of each TVW. The value of h should be reasonably large enough w.r.t. the scheduling time-scale so that it helps the agent to capture a significant overlap among services. h can be configured for different cluster deployments, depending on the typical periodicity of their corresponding workloads.

For each machine, the number of pixels in the horizontal direction (C_d) represents the quantized resource capacity of that machine for resource dimension d. We use quantization to map both - resource usage by TVWs and machine capacities to integer units of resources to aid fixed state-space representation for DNN. C_d can be calibrated to adjust trade-off between reducing resource wastage by reducing quantization error vs. increase in of state-space size.

The pixels in this matrix representing machine-states are labeled differently to denote different workloads. Empty label denotes unused resources as shown with different colored pixel labels in Fig. 2. Our state-space representation supports up to G labels. To make TVW-RL scalable, we can map a large number of workloads to this G set of equivalence-classes (EC).

Labels help TVW-RL to distinguish and learn resource usage characteristics between different equivalence-class of services. A waiting-queue captures the workloads waiting to be scheduled. TVW-RL combines the state of individual machines and the waiting-queue into a cluster-level state representation that is given as input to the policy-network.

Rewards Design for RL

We use negative rewards or penalty to teach the RL-agent with the following components:

Resource contention penalty. To help the agent learn a policy that avoids placement of TVWs whose resource usages are likely to spike at the same time, we use a penalty proportional to the *contention-score*, which is a timeseries inner product between two TVWs running on the same machine.

$$P_C = -\sum_{d} \sum_{m \in M} K_c * Cr(m, d)$$

Contention-score (Cr) for a machine m, along resource dimension d is calculated as:

$$Cr(m, d) = \sum_{W_i \in m_W} \sum_{W_j \in m_W, j>i} \langle R(W_i, d), R(W_j, d) \rangle$$

where m_W is the set of TVWs running in the machine m in the increasing order of their starting time and $R(W_i, d)$ is a vector denoting the resource usage timeseries of workload W_i along resource dimension d, throughout its life time on the machine. While taking the inner product of two resource usage vectors relative time shifting and appropriate padding with zeros are done to ensure each vector is of the same length and the overlap time is taken into account. M is the total number of machines in the cluster. K_c is a constant that determines the weight of resource contention penalty. The contention-score formula amplifies the effect of *simultaneous spike* (see Fig. 3) in resource usage among TVWs and thus would avoid resource contentions among co-located services. We observed that such penalty also helps the agent to learn better alignment w.r.t. resource usage (or rather complementary of resource usage) among different TVWs during placement – one of our target goals.

Under-utilization penalty. Since our goal is to improve overall utilization of the cluster by helping the scheduler learn how to achieve tighter packing and pack on less number of machines whenever possible, we add a penalty proportional to the sum of unused resources in the *used machines*. A *used machine* is one with at least one workload running. Empty pixels in our state-representation denote the number of unused resources at any given time.

$$P_U = -\sum_{d} \sum_{m \in M_u} |U_m(t, d)|^{K_u}$$

$U_m(t, d)$ denotes the unused resource for machine m at time t across resource dimension d. The constant term K_u which also acts as a weighting factor, is an exponent here so that the error gradient term has a direct component denoting amount of unused resources. M_u denotes the set of *used machines*.

Algorithm 1: Online Learning and Placement

```
Input: State-space parameters: M, h, d, C_cpu ,C_mem
Output: Machine to schedule Incoming Workloads
1  Initialize: Pretrained Policy Network with parameter θ;
2  for iteration i= 1 to MaxIteration do
3      Initialize: State Representation S;
4      for episode e=1 to MaxEpisode do
5          J ← Incoming Workload;
6          Z ← meta-information(J);
7          ec ← ClassifyToEC(Z, resource_usage = null);
8          UpdateECLabels();
9          S ← GetStateRepresentation();
10         m ← PolicyNetwork.action(ec,S);
11         PlaceWorkload(J,m);
12         S ← GetStateRepresentation();
13         r ← CalculatePenalty(S);
14     end
15     UpdatePolicyNetwork(θ, r);
16 end
```

Overshoot penalty. We teach the agent to prevent scheduling of more tasks than that can be handled by a single machine, as this would lead to TVWs not getting enough CPU time-slices, memory thrashing etc. leading to undesirable performance or even SLA violations. We design high penalty to the cases where any of the machines were not able to meet the aggregate resource requirement of TVWs scheduled in that machine, during any period of time. It is calculated by adding a high value (K_o) each time a machine is unable to provide appropriate resources to the running services for the first time. An indicator function ($\mathbb{I}$) keeps track of whether a TVW running in machine m, overshooted.

$$P_O = -\sum_{d}\sum_{m \in M} K_o * \mathbb{I}_{m,d}[\text{First overshoot for the TVW}]$$

Wait-time penalty. To prevent the scheduler from holding scheduling requests for a long time in search of a better placement, in each timestep we add a penalty that is equal to the number of waiting requests in the queue ($|Q_t|$) multiplied by a constant (K_w).

$$P_W = -K_w * |Q_t|$$

The calibration of weight K_w in the penalty function also helps in teaching the scheduler to switch between highly optimum placement mode (when less incoming TVW scheduling requests are expected) to a less optimum placement mode (when burst of scheduling requests are expected to hit the cluster). TVW-RL can have different penalty coefficients for different resource dimensions.

The agent receives the *Wait-time* and *Under-utilization* instantly. But the *Resource contention* and *Overshoot* penalties are delayed because resource contention can only be detected at a later time, and hence the actions that caused it should be penalized in future, but scheduling delay (Wait-time) can be detected immediately.

Workload Equivalence-Class (EC) Mapping

Real production clusters need to handle a large number of different workloads. It is not scalable to treat each TVW differently. Too many distinct TVW-labels would make the agent's policy learning difficult, and less generalizable. We explore how these numerous real production traces of TVWs can be mapped to a much smaller number of equivalence-classes (**EC**). Then we can assign a unique type-label to each EC (rather to each individual TVW) helping the agent in its policy learning. Note, the TVWs belonging to the same EC will have *similar shape* in terms of temporal resource usage characteristics and thus can create higher contention (if placed together), as compared to TVWs in different ECs. We consider two different *distance-metrics* to capture the temporal aspects described as follows. **Temporal Features.** We extract temporal features such as auto-correlation, linear trend, agg. linear trend as well as aggregate features like mean, mean absolute change and std. of the input time-series. These features capture the aspects of shape, trend and diurnal patterns. We normalize the obtained values of each feature to [0,1] allowing for comparability between different features. On the obtained feature vector, we define euclidean as the distance metric.

Dynamic Time Warping (DTW). DTW (Ding et al. 2008) gives a shape specific distance measure between two time-series adjusting for any time shifts. We compute the distance metric by averaging the normalized DTW distances along different resource dimensions. We use K-Means (K-Medoids for DTW) clustering (MacQueen 1967) on the obtained distance metrics. We perform selection of suitable value of k, by plotting the *Silhouette Score* (Rousseeuw 1987) for different values of k and selecting k corresponding to the maximum silhouette score. Characteristics of production cluster workloads vary across different organizations (Amvrosiadis et al. 2018). Potentially the optimum distance-metric and associated number of ECs can be different for different organizations. Training a policy-network using RL is a computationally expensive task. Hence, it is not practical to evaluate the goodness of the EC mapping by training the RL agent for all different choices. We propose a lower overhead proxy for evaluating the *distance-metric* and *goodness* of EC creation by training a resource usage prediction model (a multi-variate time-series prediction model (Lai et al. 2018)) per EC. We choose most suitable combination of distance-metric and EC numbers by comparing the prediction accuracy of this model. A reasonably good time-series prediction model would also get similar benefit during RL training from the chosen best combination.

Run-time Logic. Line #5-8 in Algorithm 1 describes the steps for deciding the placement for an incoming workload. Before probing the policy-network for the optimum machine (line #10), the state-representation is updated by re-predicting the EC-labels for the already running workloads (line #8). EC prediction is a multi-class classification problem. TVW-RL uses a fully connected network to classify it to one of the ECs. It takes two inputs (1) featurized representation of meta-information (requested CPU/memory limits, scheduling priority, etc.) and (2) a vectorized representation of the partial resource usage.

Evaluations

Real Production Workload Traces

Google traces (Wilkes 2011) contain production workload scheduling requests for a period of 29 days. Alibaba traces (Alibaba 2018) contain production traces from 4k machines over 8 days. Both contains CPU/memory numbers used by each workload at a granularity of 5 minutes, along with scheduling details, e.g., priority, class and original resource request. We filtered the workload traces by discarding the ones that were evicted, killed or failed. We also removed the partially recorded traces. Since our focus is on optimal placement of long running jobs, we filtered-in long-running jobs that had at least 6000 continuous timestamped resource usage records for Google traces and, at least 2000 timestamped resource usage records for Alibaba traces.

Implementation

EC Creation. For temporal features, we used `tsfresh` (Christ et al. 2016) for feature extraction and K-Means clustering algorithm (Pedregosa et al. 2011) with 'k-means++' initialization for EC creation. For DTW, we used K-Medoid algorithm (Kaufmann et al. 1987) with random medoid initialization. The value of k ranged from 3 to 15 and k corresponding to maximum average silhouette over 50 different initializations was selected.

EC Prediction. This model has two dense layers with ReLU activation and output softmax layer. It was trained with Adam optimizer and a categorical cross-entropy loss.

Policy Network. The policy network is implemented using Theano. It consists of a single hidden layer of 20 neurons followed by output neurons equal to the number of actions (= number of machines in the cluster) and ReLU activation function for the hidden-layer. For the output layer we use softmax activation. We use Adam optimizer and a learning rate (η) of 0.001. We train using REINFORCE algorithm (Sutton et al. 2000) with the number of trajectories (N) set to 20 and in an episodic manner (Mnih et al. 2013) for a total of 2000 iterations, with maximum episode length (L) 200. In a given episode, a fixed number of jobs arrive and are scheduled by the agent. The parameters for the state-space are $M = 10$, $h = 20$, $d = 2$, $C_1 = C_2 = 8$. The weights of the penalty parameters are chosen as $K_c = 0.1$, $K_u = 3$, $K_o = 30000$, $K_w = 50$. Training and testing used a batch size of 20 examples run in parallel on a 32 core Intel Xeon CPU E5-2686 v4.

Distance	Google Traces			Alibaba Traces		
	k	f	Eff. % gain	k	f	Eff. % gain
Aggregate	5	0.65	6.82	4	0.68	5.13
Temporal	6	0.58	**9.83**	4	0.54	**8.14**
DTW	3	0.55	9.3	3	0.25	5.73

Table 1: Different distance methods for Usage Prediction

Equivalence-class (EC) Analysis

For EC analysis, we compare the proposed **Temporal Features** and **DTW** against an aggregate-features based baseline inspired by (Zhang et al. 2011). The baseline is defined as the euclidean distance on the job characteristic vector of total and avg. CPU, total and avg. memory, job duration and avg., std. and normalized std. of the memory-CPU ratio. Table 1 shows the optimum k that maximizes the Silhouette score for the distance-metric chosen. Optimum k can be different for other production environment traces.

Further, we evaluate the effect of different distance-metrics and k on the goodness of EC mapping by training and evaluating a resource-usage prediction model *for each EC*. We compute a measure called *effective prediction gain* (EG):

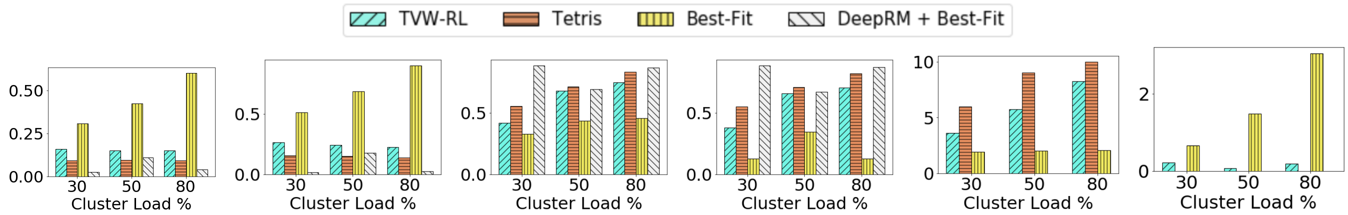
$$EG = \frac{1}{n} \sum_{e \in EC} max(0, G(e)) * |e|$$

where n is the total number of jobs, e is an equivalence class from the set of equivalence classes (ECs) and $G(e)$ is the percentage gain in the *correlation between the predicted and actual resource usages* of a model trained on EC e with respect to an EC-agnostic model that takes all the examples into account irrespective of the EC. Table 1 shows the fraction of the data (f) and the effective prediction gain for both Google and Alibaba data. We see that distance-metrics incorporating time-varying features (Temporal Features and DTW) perform better than the aggregate features baseline. Thus, the temporal features based method efficiently captures the temporal aspects of resource usage making it the suitable choice for EC mapping for our RL-agent.

End-to-End Evaluation

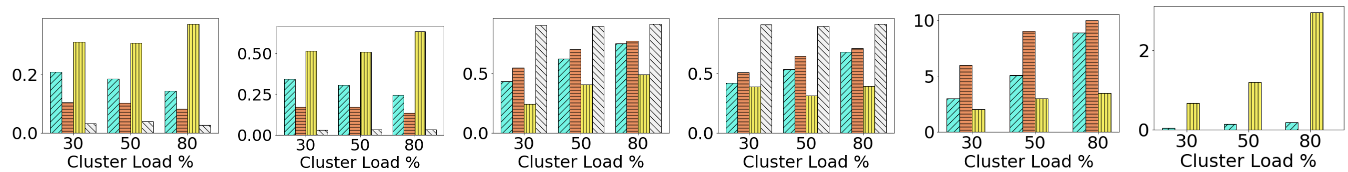
Methodology. We simulate incoming workload placement requests to the cluster as a Poisson process. The interarrival-rate is calibrated to create three average cluster load scenarios: 30%, 50% and 80%. Our evaluation runs with a cluster setting of 10 machines. Each workload has 2 resource dimensions: CPU and memory. From both Google and Alibaba traces, we select a mix of production workloads with 50% of as long-running (>30 hrs), with approximately equal number of them being CPU intensive and memory intensive. For each trace, the training and test set consists of 100 and 30 such distinct job sequences, respectively. The resource utilization values from the traces were mapped to our state-space dimensions. The offline training time ranged from approximately 28-108 hrs depending on the load, state space dimensions and the number of iterations.

Baselines. We compare TVW-RL with Tetris (Grandl et al. 2014), DeepRM (Mao et al. 2016), and Best-Fit heuristic (Berkey and Wang 1987). Tetris has a setting for controlling fairness in scheduling. Since our solution does not use a notion of fairness, we turn off the fairness knob which improves job performance in Tetris. To have a fair comparison, we made the following modifications to DeepRM: (1) *Inputs:* As DeepRM does not support temporal variations in resource usage, we provide the peak resource used by the job along CPU and memory resource dimensions as the resource-limit. (2) *State Space:* As required by DeepRM, we calculate the capacity of the compute cluster as monolithic resource capacity by multiplying the capacity of each machine by the number of machines. (3) *Rewards:* To help optimize for cluster utilization, we added an additional penalty



(a) Avg. CPU Util. (b) Avg. MEM Util. (c) Avg. CPU Frag. (d) Avg. MEM Frag. (e) Machines Used (f) Avg. Overshoot

Figure 4: Google Cluster Data



(a) Avg. CPU Util. (b) Avg. MEM Util. (c) Avg. CPU Frag. (d) Avg. MEM Frag. (e) Machines Used (f) Avg. Overshoot

Figure 5: Alibaba Data

proportional to the number of total unused resources. We feed DeepRM's action ("which job to schedule") at a particular timestamp, through a *Best-Fit* heuristic to identify a machine for placement. Among the machines that have enough resources to host the job, the Best-Fit heuristic chooses the machine having the least units of the dominant resource of the job available. We also compare against vanilla *Best Fit* heuristic that selects the jobs in a FIFO (first-in-first-out) manner and places in the machine with the least units of the dominant resource of the job available at the current-time. We use **DeepRM** to denote {DeepRM+Best-Fit} combination and **Best-Fit** to denote vanilla Best-Fit.

Metrics for Operational Excellence. We use the following metrics (Garefalakis et al. 2018; Grandl et al. 2014) to capture improvements in operational excellence of the cluster. T denotes the length of the observation period until all jobs have finished running.

[Resource Utilization] Average utilization of the cluster along each resource type:

$$\text{Avg Util}(d) = \frac{\sum_{t=0}^{T} \sum_{m} R(m,t,d)}{T \times \max_t A(t) \times C_d}$$

Since the number of machines that are actively used varies over time ($A(t)$), maximum # of machines used at any point, shows up in the denominator as a normalizer. $R(m,t,d)$ denotes the resource usage of machine m at time t across dimension d. Higher utilization is better.

[Resource Fragmentation] It measures what fraction of all the unused resources in a cluster are concentrated.

$$\text{Avg Frag}(d) = 1 - \sum_{t=0}^{T} \frac{\max_{m \in A(t)} U_m(t,d)}{T \times \sum_{m \in A(t)} U_m(t,d)}$$

The lower the fragmentation, higher the ability of the cluster to schedule unanticipated large jobs, which is desirable.

[Resource Overshoot %] It measures the total amount of resource shortage in each machine across time t across dimension d, denoted as $S(m,t,d)$, over the total resource capacity of the cluster.

$$\text{Avg Overshoot \%} = 100 \times \sum_{t=0}^{T} \sum_{m} \sum_{d} \frac{S(m,t,d)}{T \times m \times C_d}$$

[# of Machine Used] Total number of machines where at least one TVW was placed at some point of time.

Improvements in Operational Excellence. Fig. 4 and 5 illustrate using Google and Alibaba traces respectively, how TVW-RL can improve the metrics for operational excellence. TVW-RL provides a 30-300% increase in average CPU and memory utilization compared to DeepRM. The benefit is more apparent under low-load conditions as shown in Fig. 4a/5a (and Fig. 4b/5b). We also achieved 68-100% increase in average utilization compared to Tetris across different cluster-load conditions. This is primarily due to efficient packing that requires significantly less number of machines than Tetris as shown in Fig. 4e/5e. Further, the gap between TVW-RL and Tetris in terms of the number of machines required to accommodate the jobs increases with the increase in cluster load. Notice, *Best-Fit* provides higher utilization because it just packs the jobs into the machines without any knowledge of peak or future resource usages. As a consequence, *Best-Fit* suffers from huge over-utilization of the resources as shown in Fig. 4f/5f. On the other hand, over-utilization due to TVW-RL's placement decisions are almost negligible. Tetris and DeepRM already include peak resource usage information in their placement decisions and thus avoid over-utilization. We noticed DeepRM's inability to schedule all the jobs in the available machines at high cluster loads because of excessive resource fragmentation (Fig. 4c/4d and 5c/5d). TVW-RL provides 5-50% reduction in resource fragmentation compared to DeepRM and 6-13% reduction compared to Tetris on Google and Alibaba data.

Robustness Against Noisy Environment. There can be some unknown background process activities (e.g. maintenance process, system noise (Hoefler et al. 2010)) or some TVWs can be noisy. We evaluate TVW-RL's robustness

Metric	Robustness Against Noisy Workloads						Variation of Clustering Algorithms			
	Trained with Noise			Not-trained with Noise				Different Clustering algorithms		
	Noise [0-1]	[0-2]	[0-3]	Noise [0-1]	[0-2]	[0-3]	W/o EC	Aggregate	DTW	Temporal
CPU Util	0.144	0.155	0.132	0.146	0.153	0.157	0.328	0.347	0.345	0.345
MEM Util	0.231	0.243	0.206	0.234	0.240	0.245	0.613	0.653	0.649	0.649
CPU Frag	0.679	0.671	0.706	0.684	0.678	0.677	0.795	0.776	0.779	0.777
MEM Frag	0.652	0.645	0.675	0.657	0.652	0.648	0.734	0.708	0.708	0.723
Machines Used	5.975	5.892	7.033	5.933	5.892	5.933	6.38	6.10	6.12	6.17
%age Overshoot	0.133	0.134	0.055	0.108	0.118	0.132	0.051	0.284	0.24	0.52

Table 2: Robustness against unknown/noisy workloads and Variation of Clustering Algorithms

	Different values of K_u			
Metric	$K_u = 0$	$K_u = 1$	$K_u = 2$	$K_u = 3$
CPU Util	0.103	0.117	0.130	0.179
MEM Util	0.171	0.195	0.216	0.298
CPU Frag	0.701	0.695	0.689	0.627
MEM Frag	0.646	0.64	0.635	0.581
Machines Used	8.967	7.867	7.1	5.167
%age Overshoot	0.0	0.0	0.0	0.145

Table 3: Effect of K_u

against such noisy environments using Google traces, keeping the cluster under 50% load. **First**, we compare TVW-RL's scheduling capability in the presence of a random workload (to simulate random background processes) under two situations: (1) TVW-RL is trained in the presence of another random workload vs. (2) trained without any random workload (we call **not-trained**). The resource values for the random workload are uniformly chosen between [0-1], [0-2], [0-3] units. Recall, capacity of each machine is 8 units. Table 2 shows the comparisons of these two situations. The numbers are averaged over 5 runs (seeds). For [0-1] and [0-2] units of noise, we observe that both the trained and the not-trained versions are similar in most metrics, in fact the not-trained version does slightly better considering the fact that the % overshoot is less. Our hypothesis is that inherent noise introduced by the initial EC creation workflow made TVW-RL's learning robust against some degree of noise. However, as shown in Table 2, not-trained TVW-RL could not anticipate the larger amount of noise (in case of [0-3]) while the trained version was able to spread scheduling over more number of machines. Hence, the percentage of overshoot for the not-trained version is 240% larger than the trained version. This suggests, TVW-RL needs to be trained in the presence of some noisy workloads if anticipated background noise level (defined as: {resource usage by unknown background processes}/{machine capacity}) in the cluster is high (in our case over $\frac{3\times100}{8} = 37.5\%$). **Second**, we perturbed the shape of the TVWs by adding discrete uniformly distributed noise in the range of [-1,1] to the quantized and scaled values of the workloads that ranged from 1-6 units for both CPU and memory. Compared to the setup without noise, CPU and memory utilization dropped by 2% and 7% respectively.

Ablation Study

We performed ablation studies with cluster load of 50%. Extremely low or high loads are unusual in production clusters.

Impact of Distance Metric and EC Creation. We compare the usefulness of creating ECs with different distance metric on TVW-RL's end-to-end performance against a baseline with no EC (w/o EC) mapping in Table 2 (Google traces). We see that EC creation results in better overall utilization and less number of machines used compared to w/o EC because grouping similar workloads helps in reducing the number of labels aiding RL agent's policy learning.

Sensitivity with Reward/Penalty Components. We perform a sensitivity study of the different penalty components, by individually varying the coefficients of each penalty, and observing TVW-RL's ability to mimic the desired behavior. We present selected tables in detail and summarize the rest.

Under-Utilization Penalty. Table 3 (Alibaba traces) shows that TVW-RL can pack workloads more efficiently when K_u is gradually increased in [0-3]. It schedules job on lesser number of active machines (thus increasing avg. resource utilization), while still managing to keep %overshoot low.

Resource Over-Utilization Penalty. We study the effect of the overshoot penalty on TVW-RL by varying K_o as $\{0,$ 15000, 30000, 45000$\}$. We found TVW-RL can bring down overshoot level to 2.20, 0.20, 0.15, 0.09% respectively. This is achieved by progressively increasing the # of machines used from 2 to 6.2, on average. For $K_o = 0$, i.e. without the penalty, overall (CPU,memory) utilization metrics are very high (0.455,0.752) and %overshoot is also high as the scheduler packs more aggressively.

Resource Contention Penalty. We varied K_c in $\{0, 0.1, 1.0, 10.0\}$. CPU and memory utilization decreased from 0.17 to 0.12 and 0.28 to 0.2 respectively, with most significant drop at $K_c = 10$. To avoid the resource contention penalty, the policy network learns to schedule TVWs sparsely, leading to a higher machine usage and lower overall utilization.

Conclusion

We propose a deep reinforcement learning based approach for scheduling time-varying workloads in a shared cluster for optimal alignment of workloads based on their temporal resource-usage characteristics. Our evaluations with two real production cluster traces show that our novel state-space design along with reward formulation help our approach achieve significant improvement in operational metrics for shared clusters, compared to the state-of-the-art baselines.

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