Learning Scheduling Algorithms for Data Processing Clusters

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Abstract
Efficiently scheduling data processing jobs on distributed compute clusters requires complex algorithms. Current systems, however, use simple generalized heuristics and ignore workload characteristics, since developing and tuning a scheduling policy for each workload is infeasible. In this paper, we show that modern machine learning techniques can generate highly-efficient policies automatically.

Decima uses reinforcement learning (RL) and neural networks to learn workload-specific scheduling algorithms without any human instruction beyond a high-level objective such as minimizing average job completion time. Off-the-shelf RL techniques, however, cannot handle the complexity and scale of the scheduling problem. To build Decima, we had to develop new representations for jobs’ dependency graphs, design scalable RL models, and invent RL training methods for dealing with continuous stochastic job arrivals.

Our prototype integration with Spark on a 25-node cluster shows that Decima improves the average job completion time over hand-tuned scheduling heuristics by at least 21%, achieving up to 2× improvement during periods of high cluster load.

1 Introduction
Efficient utilization of expensive compute clusters matters for enterprises: even small improvements in utilization can save millions of dollars at scale [6, §1.2]. Cluster schedulers are key to realizing these savings. A good scheduling policy packs work tightly to reduce fragmentation [24, 25, 58], prioritizes jobs according to high-level metrics such as user-perceived latency [59], and avoids inefficient configurations [20].

Current cluster schedulers, however, rely on heuristics that prioritize generality, ease of understanding, and straightforward implementation over achieving the ideal performance on a specific workload. By using general heuristics like fair scheduling [4, 21], shortest-job-first, and simple packing strategies [24], current systems forego potential performance optimizations. For example, widely-used schedulers ignore readily available information about job structure (i.e., internal dependencies) and efficient parallelism levels for jobs’ input size. Unfortunately, workload-specific scheduling policies that use this information require expert knowledge and significant effort to devise, implement, and validate. For many organizations, these skills are either unavailable or uneconomic since the labor cost exceeds potential savings.

In this paper, we show that modern machine-learning techniques can help side-step this trade-off by automatically learning highly efficient, workload-specific scheduling policies. We present Decima, a general-purpose scheduling service for data processing jobs with dependent stages. Many systems encode job stages and their dependencies as directed acyclic graphs (DAGs) [13, 30, 54, 62]. Efficiently scheduling DAGs leads to hard algorithmic problems whose optimal solutions are intractable [25]. Given only a high-level goal (e.g., minimize average job completion time), Decima uses existing monitoring information and past workload logs to automatically learn sophisticated scheduling policies. For example, instead of a rigid fair sharing policy, Decima learns to give jobs different shares of resources to optimize overall performance, and it learns job-specific parallelism levels that avoid wasting resources on diminishing returns for jobs with little inherent parallelism. The right algorithms and thresholds for these policies are workload-dependent, and achieving them today requires painstaking manual scheduler customization.

Decima learns scheduling policies through experience using modern reinforcement learning (RL) techniques. RL is well-suited to learning scheduling policies because it allows learning from actual workload and operating conditions without relying on inaccurate assumptions. Decima encodes its scheduling policy in a neural network trained via a large number of simulated experiments, during which it schedules a workload, observes the outcome, and gradually improves its policy. However, Decima’s contribution goes beyond merely applying off-the-shelf RL algorithms to scheduling. To successfully learn high-quality scheduling policies, we had to develop novel data and scheduling action representations, and new RL training techniques.

First, cluster schedulers must scale to hundreds of jobs and thousands of machines, and must decide among potentially hundreds of configurations per job (e.g., different levels of parallelism). This leads to much larger problem sizes compared to conventional RL applications (e.g., game-playing [44, 51], robotics control [37, 48]), both in the amount of information available to the scheduler (the state space), and the number of choices it must consider (the action space). 1

1 For example, the state of the game of Go [52] can be represented by $19 \times 19 = 361$ numbers, which also bound the number of legal moves per turn.

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network that makes scheduling decisions. Our neural networks reuse a small set of building block operations for to process job DAGs, irrespective of their sizes and shapes, and to make scheduling decisions, irrespective of the number of jobs or machines. These operations are parametrized functions learned during training, and designed for the scheduling domain — e.g., ensuring that the graph neural network can express properties such as a DAG’s critical path. Our neural network design substantially reduces model complexity compared to naive encodings of the scheduling problem, which is key to efficient learning, fast training, and low-latency scheduling decisions.

Second, conventional RL algorithms cannot train models with continuous streaming job arrivals. The randomness of job arrivals can make it impossible for RL algorithms to tell whether the observed outcome of two decisions differs due to disparate job arrival patterns, or due to the quality the policy’s decisions. Further, RL policies necessarily make poor decisions in early stages of training. Hence, with an unbounded stream of incoming jobs, the policy inevitably accumulates a backlog of jobs from which it can never recover. Spending significant training time exploring actions in such situations fails to improve the policy. To deal with the latter problem, we terminate training “episodes” early in the beginning, and gradually grow their length. This allows the policy to learn to handle simple, short job sequences first, and to then graduate to more challenging arrival sequences. To cope with the randomness of job arrivals, we condition training feedback on the actual sequence of job arrivals experienced, using a recent technique for RL in environments with stochastic input processes [39]. This isolates the contributions of the scheduling policy in the overall feedback, making it feasible to learn policies that handle stochastic job arrivals.

We integrated Decima with Spark and evaluated it in both an experimental testbed and on a workload trace from a large (anonymized) company. Our evaluation shows that Decima outperforms existing heuristics on a 25-node Spark cluster, reducing average job completion time of TPC-H query mixes by at least 21%. Decima’s policies are particularly effective during periods of high cluster load, where it improves the job completion time by up to 2× over existing heuristics. Decima also extends to multi-resource scheduling of CPU and memory, where it improves average job completion time by 32–43% over prior schemes such as Graphene [25].

In summary, we make the following key contributions:

1. A scalable neural network design that can process DAGs of arbitrary shapes and sizes, schedule DAG stages, and set efficient parallelism levels for each job (§5.1–§5.2).
2. A set of RL training techniques that for the first time enable training a scheduler to handle unbounded stochastic job arrival sequences (§5.3).
3. Decima, the first RL-based scheduler that schedules complex data processing jobs and learns workload-specific scheduling policies without human input, and a prototype implementation of it (§6).

(4) An evaluation of Decima both in simulation and in a real Spark cluster, and a comparison with state-of-the-art scheduling heuristics (§7).

2 Motivation

Data processing systems and query compilers such as Hive, Pig, SparkSQL, and DryadLINQ create DAG-structured jobs, which consist of processing stages connected by input/output dependencies (Figure 1). For recurring jobs, which are common in production clusters [2], we may also have reasonable estimates of runtimes and intermediate data sizes. Most cluster schedulers, however, ignore this job structure in their decisions and use e.g., coarse-grained fair sharing [4, 10, 21, 22], rigid priority levels [59], and manual specification of each job’s parallelism [49, §5]. Existing schedulers choose to largely ignore this rich, easily-available job structure information because designing scheduling algorithms that make use of it is a complex task. We illustrate the challenges of using job-specific information in scheduling decisions with two concrete examples: (i) dependency-aware scheduling, and (ii) automatically choosing the right number of parallel tasks.

2.1 Dependency-aware task scheduling

Many job DAGs in practice have tens or hundreds of stages with different durations and numbers of parallel tasks in a complex dependency structure. An ideal schedule ensures that independent stages run in parallel as much as possible, and that no stage ever blocks on a dependency if there are available resources. Ensuring this requires the scheduler to understand the dependency structure and plan ahead. This “DAG scheduling problem” is algorithmically hard: see, e.g., the illustrative example by Grandi et al. [25, §2.2] and the one we describe in detail in Appendix A. Theoretical research [12, 14, 36, 50] has focused mostly on simple instances of the problem that do not capture the complexity of real data processing clusters (e.g., online job arrivals, multiple DAGs, multiple tasks per stage, jobs with different inherent parallelism, overheads for moving jobs between machines, etc.). For example, in a recent paper, Agrawal et al. [3] showed that two simple

![Figure 1: Data-parallel jobs have complex data-flow graphs like the ones shown (TPC-H queries in Spark), with each node having a distinct number of tasks, task durations, and input/output sizes.](image-url)
DAG scheduling policies (shortest-job-first and latest-arrival-processor-sharing) have constant competitive ratio in a basic model with one task per job stage. As our results show (§2.3, §7), these policies are far from optimal in a real Spark cluster.

Hence, designing an algorithm to generate optimal schedules for all possible DAG combinations is intractable [25, 40]. Existing schedulers therefore ignore this challenge: they enqueue tasks from a stage as soon as it becomes available, or run stages in an arbitrary order.

### 2.2 Setting the right level of parallelism

In addition to understanding dependencies, an ideal scheduler must also understand how to best split limited resources among jobs. Jobs vary in the amount of data that they process, and in the amount of parallel work available. A job with large input or large intermediate data can efficiently harness additional parallelism; by contrast, a job running on small input data, or one with less efficiently parallelizable operations, sees diminishing returns beyond modest parallelism.

Figure 2 illustrates this with the job runtime of two TPC-H [55] queries running on Spark as they are given additional resources to run more parallel tasks. Even when both process 100 GB of input, Q2 and Q9 exhibit widely different scalability: Q9 sees significant speedup up to 40 parallel tasks, while Q2 only obtains marginal returns beyond 20 tasks. When Q9 runs on a smaller input of 2 GB, however, it needs no more than ten parallel tasks. For all jobs, assigning additional parallel tasks beyond a “sweet spot” in the curve adds only diminishing gains. Hence, the scheduler should reason about which job will see the largest marginal gain from extra resources and accordingly pick the sweet spot for each job.

Existing schedulers largely side-step this problem. Most burden the user with the choice of how many parallel tasks to use [49, §5], or rely on a separate “auto-scaling” component based on coarse heuristics [5, 20]. Indeed, many fair scheduling policies [21, 31] divide resources without paying attention to their decisions’ efficiency: sometimes, an “unfair” schedule results in a more efficient overall execution.

### 2.3 An illustrative example on Spark

The aspects described are just two examples of how schedulers can exploit knowledge of the workload. To achieve the best performance, schedulers must also respect other considerations, such as the execution order (e.g., favoring short jobs) and avoiding resource fragmentation [24, 59]. Considering all these dimensions together—as Decima does—makes a substantial difference. We illustrate this by running a mix of ten randomly chosen TPC-H [55] queries with input sizes drawn from a long-tailed distribution on a Spark cluster with 50 parallel task slots. Figure 2 visualizes the schedules imposed by (a) Spark’s default FIFO scheduling; (b) a shortest-job-first (SJF) policy that strictly prioritizes short jobs; (c) a more realistic, fair scheduler that dynamically divides task slots between jobs; and (d) a scheduling policy learned by Decima.

We measure average job completion time (JCT) over the ten jobs. Having access to the graph structure helps Decima improve average JCT by 45% over the naive FIFO scheduler, and by 19% over the fair scheduler. It achieves this speedup (i) by completing short jobs quickly, as five jobs finish in the first 40 seconds; and (ii) by maximizing parallel-processing efficiency. SJF dedicates all task slots to the next-smallest job in order to finish it early (but inefficiently); by contrast, Decima runs jobs near their parallelism sweet spot. By controlling parallelism, Decima reduces the total time to complete all jobs by 30% compared to SJF. Further, unlike fair scheduling, Decima partitions task slots non-uniformly across jobs, improving average JCT by 19%.

Designing general-purpose heuristics to achieve these benefits is difficult, as each additional dimension (DAG structure, parallelism, job sizes, etc.) increases complexity and introduces new edge cases. Decima opens up a new option: using data-driven techniques, it automatically learns workload-specific policies that can reap these gains. Decima does so without requiring human guidance beyond a high-level goal (e.g., minimal average JCT), and without explicitly modeling the system or the workload.

### 3 The DAG scheduling problem in Spark

Decima is a general framework for learning scheduling algorithms for DAG-structured jobs. For concreteness, we describe its design in the context of the Spark system.

A Spark job consists of a DAG whose nodes are the execution stages of the job. Each stage represents an operation that the system runs in parallel over many shards of the stage’s input data. The inputs are the outputs of one or more parent stages, and each shard is processed by a single task. A stage’s tasks become runnable as soon as all parent stages have completed. How many tasks can run in parallel depends on the number of executors that the job holds. Usually, a stage has more tasks than there are executors, and the tasks therefore run in several “waves”. Executors are assigned by the Spark master based on user requests, and by default stick to

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2 See §7 for details of the workload and our cluster setup.
4 Overview and Design Challenges

Decima represents the scheduler as an agent that uses a neural network (henceforth called the policy network) to make decisions. On scheduling events — e.g., a stage completion (which frees up executors), or a job arrival (which adds a DAG) — the agent takes as input the current state of the cluster and outputs a scheduling action. At a high level, the state captures the status of the DAGs in the scheduler’s queue and the executors, while the actions determine which DAG stages executors work on at any given time.

Decima trains its neural network using RL through a large number of offline (simulated) experiments. In these experiments, Decima attempts to schedule a workload, observes the outcome, and provides the agent with a reward after each action. The reward is set based on Decima’s high-level scheduling objective (e.g., minimize average JCT). The RL algorithm uses this reward signal to gradually improve the scheduling policy. Appendix B provides a brief primer on RL.

Decima’s RL framework (Figure 4) is general and it can be applied to a variety of systems and objectives. In §5, we describe the design for scheduling DAGs on a set of identical executors to minimize average JCT. Our results in §7 will show how to apply the same design to schedule multiple resources (e.g., CPU and memory), optimize for other objectives like makespan [47], and learn qualitatively different policies depending on the underlying system (e.g., with different overheads for moving jobs across machines).

Challenges. Decima’s design tackles three key challenges:

1. Scalable state information processing. The scheduler must consider a large amount of dynamic information to make scheduling decisions: hundreds of job DAGs, each with dozens of stages, and executors with different status (e.g., currently assigned to different jobs). Processing all of this information via neural networks is challenging, particularly because neural networks usually require fixed-sized vectors as input.

2. Huge space of scheduling decisions. The scheduler must map potentially thousands of runnable stages to available executors. The exponentially large space of mappings poses a challenge for RL algorithms, which must “explore” the action space to learn a good policy.

3. Training for continuous stochastic job arrivals. It is important to train the scheduler to handle continuous randomly-arriving jobs over time. However, training with a continuous job arrival process is non-trivial because RL algorithms typically require training “episodes” with a finite time horizon. Further, we find that randomness in the job arrival process creates difficulties for RL training due to the variance and noise it adds to the reward signal.

Figure 3: Decima improves average JCT of 10 random TPC-H queries by 45% over Spark’s FIFO scheduler, and by 19% over a fair scheduler on a cluster with 50 task slots (executors). Different queries in different colors; vertical red lines are job completions; purple means idle.
5 Design

This section describes Decima’s design, structured according to how it addresses the three aforementioned challenges: scalable processing of the state information (§5.1), efficiently encoding scheduling decisions as actions (§5.2), and RL training with continuous stochastic job arrivals (§5.3).

5.1 Scalable state information processing

On each state observation, Decima must convert the state information (job DAGs and executor status) into features to pass to its policy network. One option is to create a flat feature vector containing all the state information. However, this approach cannot scale to arbitrary number of DAGs of arbitrary sizes and shapes. Further, even with a hard limit on the number of jobs and stages, processing a high-dimensional feature vector would require a large policy network that would be difficult to train.

To achieve scalability, Decima uses a graph neural network, which encodes or “embeds” the state information (e.g., attributes of job stages, DAG dependency structure, etc.) in a set of embedding vectors. Our method is based on graph convolutional neural networks [7, 16, 34], but it is customized for scheduling. Table 1 defines the notation we use.

The graph embedding takes as input the job DAGs whose nodes carry a set of stage attributes (e.g., the number of remaining tasks, expected task duration, etc.), and it outputs three different types of embeddings:

1. **Per-node embeddings**, which capture information about the node and its children (containing, e.g., aggregated work along the critical path starting from the node);
2. **Per-job embeddings**, which aggregate information across an entire job DAG (containing, e.g., the total work in the job); and
3. A global embedding, which combines information from all per-job embeddings into a cluster-level summary (containing, e.g., the number of jobs and the cluster load).

Importantly, what information to store in these embeddings is not hard-coded—Decima automatically learns what is statistically important and how to compute it from the input DAGs through end-to-end training. In other words, the embeddings can be thought of as feature vectors that the graph neural network learns to compute without manual feature engineering. Decima’s graph neural network is scalable because it reuses a common set of operations as building blocks to compute the above embeddings. These building blocks are themselves implemented as small neural networks that operate on relatively low-dimensional input vectors.

**Per-node embeddings.** Given the vectors \( \mathbf{x}_v \) of stage attributes corresponding to the nodes in DAG \( G_i \), Decima builds a per-node embedding \( \{ (G_i, \mathbf{x}_v) \mapsto \mathbf{e}_v \} \). The result \( \mathbf{e}_v \) is a vector (e.g., in \( \mathbb{R}^16 \)) that captures information from all nodes reachable from \( v \) (i.e., \( v \)'s child nodes, their children, etc.). To compute these vectors, Decima propagates information from children to parent nodes in a sequence of message passing steps, starting from the leaves of the DAG (Figure 5a). In each message passing step, a node \( v \) whose children have aggregated messages from all of their children (shaded nodes in Figure 5a’s examples) computes its own embedding as:

\[
\mathbf{e}_v = g \sum_{u \in \xi(v)} f(\mathbf{e}_u) + \mathbf{x}_v, \tag{1}
\]

where \( f(\cdot) \) and \( g(\cdot) \) are non-linear transformations over vector inputs, implemented as (small) neural networks, and \( \xi(v) \) denotes the set of \( v \)'s children. The first term is a general, non-linear aggregation operation that summarizes the embeddings of \( v \)'s children; adding this summary term to \( v \)'s feature vector \( (\mathbf{x}_v) \) yields the embedding for \( v \). Decima reuses the same non-linear transformations \( f(\cdot) \) and \( g(\cdot) \) at all nodes, and in all message passing steps.

Most existing graph neural network architectures [16, 17, 34] use aggregation operations of the form \( \mathbf{e}_v = \sum_{u \in \xi(v)} f(\mathbf{e}_u) \) to compute node embeddings. However, we found that adding a second non-linear transformation \( g(\cdot) \) in Eq. (1) is critical for learning strong scheduling policies. The reason is that without \( g(\cdot) \), the graph neural network cannot compute certain useful features for scheduling. For example, it cannot compute the critical path [32] of a DAG, which requires a max operation across the children of a node during message passing. Combining two non-linear transforms \( f(\cdot) \) and \( g(\cdot) \) enables Decima to express a wide variety of aggregation functions. For example, if \( f \) and \( g \) are identity transformations, the aggregation sums the child node embeddings; if \( f \sim \log(n) \), \( g \sim \exp(n \times \cdot) \), and \( n \to \infty \), the aggregation computes the max of the child node embeddings.

**Per-job and global embeddings.** The graph neural network also computes a summary of all node embeddings for each DAG \( G_i \), \( \{ (\mathbf{x}_v^i, \mathbf{e}_v^i, v \in G_i) \mapsto \mathbf{y}^i \} \); and a global summary across all DAGs, \( \{ \mathbf{y}^1, \mathbf{y}^2, \ldots \} \mapsto \mathbf{z} \). To compute these embeddings, Decima adds a summary node to each DAG, which has all the nodes in the DAG as children (the squares in Figure 5b). These DAG-level summary nodes are in turn children of a single global summary node (the triangle in Figure 5b). The embeddings for these summary nodes are also computed using Eq. (1). Each level of summarization has its own non-linear transformations \( f \) and \( g \); in other words, the graph

<table>
<thead>
<tr>
<th>entity</th>
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<tbody>
<tr>
<td>job</td>
<td>( i )</td>
<td>per-node feature vector</td>
<td>( \mathbf{x}_v^i )</td>
</tr>
<tr>
<td>stage (DAG node)</td>
<td>( v )</td>
<td>per-node embedding</td>
<td>( \mathbf{e}_v^i )</td>
</tr>
<tr>
<td>node ( v )'s children</td>
<td>( \xi(v) )</td>
<td>per-job embedding</td>
<td>( \mathbf{y}^i )</td>
</tr>
<tr>
<td>job ( i )'s DAG</td>
<td>( G_i )</td>
<td>global embedding</td>
<td>( \mathbf{z} )</td>
</tr>
<tr>
<td>job ( i )'s parallelism</td>
<td>( l_i )</td>
<td>node score</td>
<td>( q_i )</td>
</tr>
<tr>
<td>non-linear functions</td>
<td>( f, g, q, w )</td>
<td>parallelism score</td>
<td>( w_i )</td>
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Table 1: Notation used throughout §5.
neural network uses six non-linear transformations in total, two for each level of summarization.

5.2 Encoding scheduling decisions as actions

The key challenge for encoding scheduling decisions lies in the learning and computational complexities of dealing with large action spaces. As a naive approach, consider a solution, that given the embeddings from §5.1, returns the assignment for all executors to job stages in one shot. This approach has to choose actions from an exponentially large set of combinations. On the other extreme, consider a solution that invokes the scheduling agent to pick one stage every time an executor becomes available. This approach has a much smaller action space (O(# stages)), but it requires long sequences of actions to schedule a given set of jobs. In RL, both large action spaces and long action sequences increase sample complexity and slow down training [53].

Decima balances the size of the action space and the number of actions required by decomposing scheduling decisions into a series of actions, which output (i) a stage designated to be scheduled next, and (ii) an upper limit on the number of executors to use for that stage’s job. Scheduling events. Decima invokes the scheduling agent when the set of runnable stages — i.e., stages whose parents have completed and which have at least one waiting task — in any job DAG changes. Such scheduling events happen when (i) a stage runs out of tasks (i.e., needs no more executors), (ii) a stage completes, unlocking the tasks of one or more of its children, or (iii) a new job arrives to the system.

At each scheduling event, the agent schedules a group of free executors in one or more actions. Specifically, it passes the embedding vectors from §5.1 as input to the policy network, which outputs a two-dimensional action (v, l), consisting of a stage v and the parallelism limit l, for v’s job i. If job i currently has fewer than l_i executors, Decima assigns executors to v up to the limit. If there are still free executors, Decima invokes the agent again to select another stage and parallelism limit. This process repeats until all the executors have been assigned, or there are no more runnable stages. Decima ensures that this process completes in a finite number of steps by enforcing that the parallelism limit l_i is greater than the number of executors currently allocated to job i, so that at least one new executor is scheduled with each action.

Stage selection. Figure 6 visualizes Decima’s policy network. For a scheduling event at time t, during which the state is s_t, the policy network selects a stage to schedule as follows. For a node v in job i, it computes a score q_{v}^t \triangleq q(e_v^t, y^t, z), where q(·) is a score function that maps the embedding vectors (output from the graph neural network in §5.1) to a scalar value. Similar to the embedding step, the score function is also a non-linear transformation implemented as a neural network. The score q_{v}^t represents the priority of scheduling node v. Decima then uses a softmax operation [11] to compute the probability of selecting node v based on the priority scores:

\[ P(\text{node} = v) = \frac{\exp(q_{v}^t)}{\sum_{u \in A_t} \exp(q_{u}^t)}, \]  

where j(u) is the job of node u, and A_t is the set of nodes that can be scheduled at time t.

Parallelism limit selection. For each job i, Decima’s policy network also computes a score w_i^t \triangleq w(y^t, z, l) for assigning parallelism limit l to job i, using another score function w(·). Similar to stage selection, Decima applies a softmax operation on these scores to compute the probability of selecting a parallelism limit (Figure 6).

Importantly, the same score function w(·) is used for all jobs and all parallelism limit values. This is possible because the score function takes the parallelism l as one of its inputs. Without using l as an input, we cannot distinguish between different parallelism limits, and would have to use separate functions for each limit. Since the number of possible limits can be as large as the number of executors, reusing the same score function significantly reduces the number of parameters in the policy network and speeds up training (Figure 15a). Decima controls the parallelism at the job level, as opposed to the node level. This trades off some ability to make fine-grained parallelism decisions for a model that is much easier to train. In particular, restricting Decima to job-level
parallelism control reduces the space of scheduling policies that it must explore and optimize over during training. Our experiments show that this coarser control does not degrade Decima’s performance while substantially accelerating training (Figure 15a).

5.3 Training

The primary challenge for training Decima is how to train with continuous stochastic job arrivals. To explain the challenge, we first describe the RL algorithms used for training.

RL training proceeds in episodes. Each episode consists of multiple scheduling events, and each scheduling event includes one or more actions. Let \( T \) be the total number of actions in an episode (\( T \) can vary across different episodes), and \( t_k \) be the wall clock time of the \( k^{th} \) action. To guide the RL algorithm, Decima gives the agent a reward \( r_k \) after each action based on its high-level scheduling objective. For example, if the objective is to minimize the average JCT, Decima penalizes the agent \( r_k = -(t_k - t_{k-1})j_k \) after the \( k^{th} \) action, where \( j_k \) is the number of jobs in the system during the interval \([t_{k-1}, t_k)\). The goal of the RL algorithm is to minimize the expected time-average of the penalties: 

\[
\mathbb{E} \left[ 1/T \sum_{k=1}^{T} (t_k - t_{k-1})j_k \right].
\]

This objective minimizes the average number of jobs in the system, and hence, by Little’s law [15, §5], it effectively minimizes the average JCT.

Decima uses a policy gradient algorithm for training. The main idea in policy gradient methods is to learn by performing gradient descent on the neural network parameters using the rewards observed during training. Notice that all of Decima’s operations, from the graph neural network (§5.1) to the policy network (§5.2), are differentiable. For conciseness, we denote all of the parameters in these operations jointly as \( \theta \), and the scheduling policy as \( \pi_\theta(s_t, a_t) \)—defined as the probability of taking action \( a_t \) in state \( s_t \).

Consider an episode of length \( T \), where the agent collects \((state, action, reward)\) observations, i.e., \((s_k, a_k, r_k)\), at each step \( k \). The agent updates the parameters \( \theta \) of its policy \( \pi_\theta(s_t, a_t) \) using the REINFORCE policy gradient algorithm [61]:

\[
\theta \leftarrow \theta + \alpha \sum_{k=1}^{T} \nabla_\theta \log \pi_\theta(s_k, a_k) \left( \sum_{k'=k}^{T} r_{k'} - b_k \right). \tag{3}
\]

Here, \( \alpha \) is the learning rate and \( b_k \) is a baseline used to reduce the variance of the policy gradient [60]. An example of a baseline is a “time-based” baseline [26, 38], which sets \( b_k \) to the cumulative reward from step \( k \) onwards, averaged over all training episodes. Intuitively, \( (\sum_{k'} r_{k'} - b_k) \) estimates how much better (or worse) the total reward is (from step \( k \) onwards) in a particular episode compared to the average case; and \( \nabla_\theta \log \pi_\theta(s_k, a_k) \) provides a direction in the parameter space to increase the probability of choosing action \( a_k \) at state \( s_k \). As a result, the net effect of this equation is to increase the probability of choosing an action that leads to a better-than-average reward.\(^4\)

\(^4\)The update rule in Eq. (3) aims to maximize the sum of rewards during an episode. To maximize the time-average of the rewards, Decima uses a slightly modified form of this equation. See appendix B for details.

Challenge #1: Training with continuous job arrivals. To learn a robust scheduling policy, the agent has to experience “streaming” scenarios, where jobs arrive continuously over time, during training. Training with “batch” scenarios, where all jobs arrive at the beginning of an episode, leads to poor policies in streaming settings (e.g., see Figure 14). However, training with a continuous stream of job arrivals is non-trivial. In particular, initially, the agent’s policy is very poor (e.g., initial parameters are random). Therefore, in early episodes, the agent cannot schedule jobs as quickly as they arrive, and a large queue of jobs builds up in almost every episode. Exploring such conditions does not help the agent learn meaningful scheduling policies.

To avoid wasting training time, we terminate initial episodes early so that the agent can reset and try again from an idle state. We gradually increase the episode length throughout the training process. Thus, initially, the agent learns to schedule short sequences of jobs. As its scheduling policy improves, we increase the episode length, making the problem more challenging. The concept of gradually increasing job sequence length—and therefore, problem complexity—during training is a realization of curriculum learning [8] for cluster scheduling.

One subtlety about this method is that the termination cannot be deterministic. Otherwise, the agent can learn to predict when an episode terminates, and defer scheduling certain large jobs until the termination time. This turns out to be the optimal strategy over a fixed time horizon. Since the agent is not penalized for the remaining jobs at termination, it is better to strictly schedule short jobs even if it means starving some large jobs. We have found that this behavior leads to indefinite starvation of some jobs at run-time (where jobs arrive indeﬁnitely). To prevent this behavior, we use a memoryless termination process. Specifically, we terminate each training episode after a time \( \tau \), drawn randomly from an exponential distribution. As explained above, the mean episode length increases during training up to a large value (e.g., a few hundreds of job arrivals on average).

Challenge #2: Variance caused by stochastic job arrivals. Next, for a policy to generalize well in a streaming setting, the training episodes must include many different job arrival patterns. This creates a new challenge: different job arrival patterns have a large impact on performance, resulting in vastly different rewards. Consider, for example, a scheduling action at the time \( t \) shown in Figure 7. If the arrival sequence following this action consists of a burst of large jobs (e.g., job sequence 1), the job queue will grow large, and the agent will incur large penalties. On the other hand, a light stream of...
jobs (e.g., job sequence 2) will lead to short queues and small penalties. The problem is that this difference in reward has nothing to do with the action at time $t$ — it is caused by the randomness in the job arrival process. Since the RL algorithm uses the reward to assess the goodness of the action, such variance adds noise and impedes effective training.

To resolve this problem, we build upon a recently-proposed variance reduction technique for “input-driven” environments [39], where an exogenous, stochastic input process (e.g., Decima’s job arrival process) affects the dynamics of the system. The main idea is to fix the same job arrival sequence in multiple training episodes, and compute separate baselines specifically for each arrival sequence. In particular, instead of computing the baseline $b_k$ in Eq. (3) by averaging over episodes with different arrival sequences, we average over only episodes with the same arrival sequence. During training, we repeat this procedure for a large number of randomly-sampled job arrival sequences. This method removes the variance caused by the job arrival process entirely, enabling the policy gradient algorithm to assess the goodness of different actions much more accurately (see Figure 14). For the implementation details of training and the hyperparameter settings, we refer the readers to Appendix C.

6 Implementation

We have implemented Decima as a pluggable scheduling service that parallel data processing platforms can communicate with over an RPC interface. In §6.1, we describe the integration of Decima with Spark. Next, we describe our Python-based training infrastructure which includes an accurate Spark cluster simulator (§6.2).

6.1 Spark integration

A Spark cluster3 runs multiple parallel applications, which contain one or more jobs that together form a DAG of processing stages. The Spark master manages application execution and monitors the health of many workers, which each split their resources between multiple executors. Executors are created for, and remain associated with, a specific application, which handles its own scheduling of work to executors. Once an application completes, its executors terminate. Figure 8 illustrates this architecture.

To integrate Decima in Spark, we made two major changes:

1. Each application’s DAG scheduler contacts Decima on startup and whenever a scheduling event occurs. Decima responds with the next stage to work on and the parallelism limit as described in §5.2.

2. The Spark master contacts Decima when a new job arrives to determine how many executors to launch for it, and whether to preempt any existing executors.

State observations. In Decima, the feature vector $x^i_v$ (§5.1) of a node $v$ in job DAG $i$ consists of: (i) the number of tasks remaining in the stage, (ii) the average task duration, (iii) the number of executors currently working on the node, (iv) the number of available executors, and (v) whether available executors are local to the job. Our implementation uses these features but it can readily incorporate more signals.

Neural network architecture. The graph neural network’s six transformation functions $f(·)$ and $q(·)$ (§5.1) (two each for node-level, job-level, and global embeddings) and the policy network’s two score functions $q(·)$ and $w(·)$ (§5.2) are implemented using two-hidden-layer neural networks, with 32 and 16 hidden units on each layer. Since these neural networks are reused for all jobs and all parallelism limits, Decima’s model is lightweight—it consists of 12,736 parameters (50KB) in total. Mapping the cluster state to a scheduling decision takes less than 15ms (Figure 15b).

6.2 Spark simulator

Decima’s training happens offline using a faithful simulator that has access to profiling information (e.g., task durations) from a real Spark cluster (§7.2) and the job run time characteristics from an industrial trace (§7.3). To faithfully simulate how Decima’s decisions interact with a cluster environment, our simulator has to captures several real-world effects:

1. The first “wave” of tasks from a particular stage often runs slower than subsequent tasks. This is due to Spark’s pipelined task execution [46], JIT compilation [35] of task code, and warmup costs (e.g., making TCP connections to other executors). Decima’s simulated environment thus picks the actual runtime of first-wave tasks from a different distribution than later waves.

3We discuss Spark’s “standalone” mode of operation here (http://spark.apache.org/docs/latest/spark-standalone.html); YARN-based deployments can, in principle, use Decima, but require modifying both Spark and YARN.
7 Evaluation

We evaluated Decima on a real Spark cluster testbed and in simulations with a production workload from a large company. Our experiments address the following questions:

1. How does Decima perform compared to carefully-tuned heuristics in a real Spark cluster (§7.2)?
2. Can Decima’s learning generalize to a multi-resource setting with different machine configurations (§7.3)?
3. How does each of our key ideas contribute to Decima’s performance; how does Decima adapt when scheduling environments change; and how fast does Decima train and take scheduling decisions after training?

7.1 Existing baseline algorithms

In our evaluation, we compare Decima’s performance to that of seven baseline algorithms:

1. Spark’s default FIFO scheduling, which runs jobs in the same order they arrive in and grants as many executors to each job as the user requested.
2. A shortest-job-first critical-path heuristic (SJF-CP), which prioritizes jobs based on their total work, and within each job runs tasks from the next stage on its critical path.
3. Simple fair scheduling, which gives each job an equal fair share of the executors and round-robins over tasks from runnable stages to drain all branches concurrently.
4. Naive weighted fair scheduling, which assigns executors to jobs proportional to their total work.
5. A carefully-tuned weighted fair scheduling that gives each job \( T_i^a / \sum_j T_j^a \) of total executors, where \( T_j \) is the total work of each job \( j \) and \( \alpha \) is a tuning factor. Notice that \( \alpha = 0 \) reduces to simple fair scheme and \( \alpha = 1 \) means naive weighted fair. We sweep through \( \alpha \in \{-2, -1.9, ..., 2\} \) for the optimal factor.
6. The standard multi-resource packing algorithm from Tetris [24], which greedily schedules the stage that maximizes the dot product of the requested resource vector and the available resource vector.
7. Graphene*, an adaptation of Graphene [25] for Decima’s discrete executor classes. Graphene* detects and groups “troublesome” nodes using Graphene’s algorithm [25, §4.1], and schedules them together with optimally tuned parallelism as in (5), achieving the essence of Graphene’s planning strategy (details in Appendix E).

7.2 Spark cluster

We use an OpenStack cluster running Spark v2.2, modified as described in §6.1, in the Chameleon Cloud testbed. The cluster consists of 25 worker VMs, each running two executors on an m1.xlarge instance (8 CPUs, 16 GB RAM) and a master VM on an m1.xxlarge instance (16 CPUs, 32 GB RAM). Our experiments consider (i) batched arrivals, in which multiple jobs start at the same time and run until completion, and (ii) continuous arrivals, in which jobs arrive with stochastic interarrival distributions or follow a trace.

Batched arrivals. We randomly sample jobs from six different input sizes (2, 5, 10, 20, 50, and 100 GB) and all 22 TPC-H [55] queries, producing a heavy-tailed distribution: 23% of the jobs contain 82% of the total work. A combination of 20 random jobs (unseen in training) arrives as a batch at the start of the experiment, and we measure their average JCT. Figure 9a shows a cumulative distribution of the average JCT achieved over 100 experiments. There are three key observations from the results. First, SJF-CP and fair scheduling, albeit simple, outperform the FIFO policy by 1.6× and 2.5×

https://www.chameleoncloud.org
on average. Importantly, the fair scheduling policies outperform SJF-CP since they work on multiple jobs, while SJF-CP focuses all executors exclusively on the shortest job.

Second, perhaps surprisingly, unweighted fair scheduling outperforms fair scheduling weighted by job size (“naive weighted fair”). This is because weighted fair scheduling grants smaller jobs fewer executors than their fair share, slowing them down and increasing average JCT. Our tuned weighted fair heuristic (“opt. weighted fair”) counters this effect by calibrating the weights for each job on each experiment (§7.1).

The optimal $\alpha$ is usually around $-1$, i.e., the heuristic grants a number of executors inversely proportional to job size. This policy effectively focuses on the small jobs in the beginning, and later shifts to run large jobs in parallel; it outperforms fair scheduling by 11% on average.

Finally, Decima outperforms all baseline algorithms and improves the average JCT by 21% over the closest heuristic (“opt. weighted fair”). This is because Decima prioritizes jobs better, assigns efficient executor shares to different jobs, and leverages the job DAG structure (§7.4 breaks down the benefit of each of these factors). Decima autonomously learns this policy through end-to-end RL training, while the best-performing baseline algorithms required careful tuning.

**Continuous arrivals.** We randomly sample 1,000 TPC-H jobs of six different sizes, and model their arrival as a Poisson process with an average interarrival time of 45 seconds. The resulting cluster load is about 85%. At this cluster load, jobs arrive faster than most heuristic-based scheduling policies can complete them. Figure 9b shows that Decima outperforms the only baseline algorithm that can keep up (“opt. weighted fair”); Decima’s average JCT is 29% lower. In particular, Decima shines during busy, high-load periods, where scheduling decisions have a much larger impact than when cluster resources are abundant. Figure 10a shows that Decima maintains a lower concurrent job count than the tuned heuristic particularly during the busy period in hours 7–9, where Decima completes jobs about 2× faster (Figure 10b).

Decima’s performance gain comes from finishing small jobs faster, as the concentration of red points in the lower-left corner of Figure 10c shows. Decima achieves this by assigning more executors to the small jobs (Figure 10d). The right number of executors for each job is workload-dependent: indiscriminately giving small jobs more executors would use cluster resources inefficiently (§2.2). For example, SIF-CP’s strict giving all available executors to the smallest job, but this inefficient use of executors inflates total work, and SJF-CP therefore accumulates a growing backlog of jobs. Decima’s executor assignment, by contrast, results in similar total work as with the hand-tuned heuristic. Figure 10e shows this: jobs below the diagonal have smaller total work with Decima than with the heuristic, and ones above have larger total work in Decima. Most small jobs are on the diagonal, indicating that Decima only increases the parallelism limit when extra executors are still efficient. Consequently, Decima successfully balances between giving small jobs extra resources to finish them sooner and using the resources efficiently.

**7.3 Multi-dimensional resource packing**

The standalone Spark scheduler used in our previous experiments only provides jobs with access to predefined executor slots. More advanced cluster schedulers, such as YARN [57] or Mesos [29], allow jobs to specify their tasks’ resource requirements and create appropriately-sized executors. Packing tasks with multi-dimensional resource needs (e.g., (CPU, memory)) onto fixed-capacity servers adds further complexity to the scheduling problem [24, 25]. We use a production trace from a large company to investigate if Decima can learn good multi-dimensional scheduling policies with the same core approach.

**Industrial trace.** The trace contains about 20,000 jobs from a production cluster. Many jobs have complex DAGs; 59% have four or more stages, and some have hundreds. We run the experiments using our simulator (§6.2) with up to 30,000 executors. We set this parameter according to the maximum number of concurrent tasks in the trace.

**Multi-resource environment.** We modify Decima’s environment to provide several discrete executor classes with different memory sizes. Tasks now require a minimum amount of CPU and memory, i.e., a task must fit into the executor that runs it. Tasks can run in executors larger than or equal to their resource request. Decima now chooses a DAG stage to schedule, a parallelism level, and an executor class to use. Our experiments use four executor types, each with 1 CPU.
avg. JCT 67.3 sec, makespan 119.6 sec
Avg. JCT 61.4 sec, makespan 114.3 sec
Avg. JCT 74.5 sec, makespan 102.1 sec

(a) Average JCT objective.  (b) Avg. JCT, with zero-cost executor motion.  (c) Minimal makespan objective.

Figure 13: Decima learns qualitatively different policies depending on the environment (e.g., costly (a) vs. free executor migration (b)) and the objective (e.g., average JCT (a) vs. makespan (c)). Red lines at job completions, colors indicate tasks in different jobs, dark purple is idle.

Results. We run simulated multi-resource experiments on continuous job arrivals according to the trace. Figure 11a shows the results for Decima and three other algorithms: the optimally tuned weighted-fair heuristic, Tetris, and Graphene*. Decima achieves a 32% lower average JCT than the closest competing algorithm (Graphene*), suggesting that it learns a good policy in the multi-resource environment.

Decima’s policy is qualitatively different to Graphene**. Figure 12a breaks Decima’s improvement over Graphene down by jobs’ total work. Decima completes jobs faster than Graphene* for all job sizes, but its gain is particularly large for small jobs. The reason is that Decima learns to use “oversized” executors when they can help finish nearly-completed small jobs when insufficiently many right-sized executors are available. Figure 12b illustrates this: Decima uses 39% more executors of the largest class on the jobs with smallest 20% total work (full profiles in Appendix F). In other words, Decima trades off memory fragmentation against clearing the job queue more quickly. This trade-off makes sense because small jobs (i) contribute more to the average JCT objective, and (ii) only fragment resources for a short time. By contrast, Tetris greedily packs tasks into the best-fitting executor class and achieves the lowest memory fragmentation. Decima’s fragmentation is within 4%–13% of Tetris’s, but Decima’s average JCT is 52% lower, as it learns to balance the trade-off well. This requires respecting workload-dependent factors, such as the DAG structure, the threshold for what is a “small” job, and others. Heuristic approaches like Graphene attempt to balance those factors via additive score functions and extensive tuning, while Decima learns them without such inputs.

We also repeat this experiment with the TPC-H workload, using 200 executors and sampling each TPC-H DAG node’s memory request from (0, 1]. Figure 11b shows that Decima outperforms the competing algorithms by even larger margins (e.g., 43% over Graphene*). This is because the industrial trace lacks work inflation measurements for different levels of parallelism, which we provide for TPC-H. Decima learns to use this information to further calibrate executor assignment.

7.4 Decima deep dive

Finally, we demonstrate the wide range of scheduling policies Decima can learn, and break down the impact of our key ideas and techniques on Decima’s performance. In appendices, we further evaluate Decima’s optimality via an exhaustive search of job orderings (Appendix G), the robustness of its learned policies to changing environments (Appendix H), and Decima’s sensitivity to incomplete information (Appendix I).

Learned policies. Decima outperforms other algorithms because it can learn different policies depending on the high-level objective, the workload, and environmental conditions. When Decima optimizes for average JCT (Figure 13a), it learns to share executors for small jobs to finish them quickly and avoids inefficiently using too many executors on large jobs (§7.2). Decima also keeps the executors working on tasks from the same job to avoid the overhead of moving executors (§6.1). However, if moving executors between jobs is free — as is effectively the case for long tasks, or for systems without JVM spawn overhead — Decima learns a policy that eagerly moves executors among jobs (cf. the frequent color changes in Figure 13b). Finally, given a different objective of minimizing the overall makespan for a batch of jobs, Decima learns yet another different policy (Figure 13c). Since only the final job’s completion time matters for a makespan objective, Decima no longer works to finish jobs early. Instead, many jobs complete together at the end of the batched workload, which gives the scheduler more choices of jobs throughout the execution, increasing cluster utilization.

Impact of learning architecture. We validate that Decima uses all raw information provided in the state and requires all its key design components by selectively omitting components. We run 1,000 continuous TPC-H job arrivals (as in §7.2) on a simulated cluster with different loads, and train five different variants of Decima on each of the loads.

Figure 14 shows that removing any one component from Decima results in worse average JCTs than the tuned weighted-fair heuristic at a high cluster load. There are four takeaways from this result. First, parallelism control has the greatest impact on Decima’s performance. Without parallelism control, Decima assigns all available executors to a single stage at
every scheduling event. Even at a moderate cluster load (e.g., 55%), this leads to an unstable policy that cannot keep up with the arrival rate of incoming jobs. Second, omitting the graph embedding (i.e., directly taking raw features on each node as input to the score functions in §5.2) makes Decima unable to estimate remaining work in a job and to account for other jobs in the cluster. Consequently, Decima has no notion of small jobs or cluster load, and its learned policy quickly becomes unstable as the load increases. Third, using unfixed job sequences across training episodes increases the variance in the reward signal (§5.3). As the load increases, job arrival sequences become more varied, which increases variance in the reward. At cluster load larger than 75%, reducing this variance via synchronized termination improves average JCT by 2x when training Decima, illustrating that variance reduction is key to learning high-quality policies in long-horizon scheduling problems. Fourth, training only on batched job arrivals cannot generalize to continuous job arrivals. When trained on batched arrivals, Decima learns to systematically defer large jobs, as this results in the lowest sum of JCTs (lowest sum of penalties). With continuous job arrivals, this policy starves large jobs indefinitely as the cluster load increases and jobs arrive more frequently. Consequently, Decima underperforms the tuned weighted-fair heuristic at loads above 65% when trained on batched arrivals.

Training and inference performance. Figure 15a shows Decima’s learning curve (in blue) on continuous TPC-H job arrivals (§7.2), testing snapshots of the model every 100 iterations on (unseen) job arrival sequences. Each training iteration takes about 5 seconds. Decima’s design (§5.3) is crucial for training efficiency: omitting the parallelism limit values in the input (yellow curve) forces Decima to use separate score functions for different limits, significantly increasing the number of parameters to optimize over; putting fine-grained parallelism control on nodes (green curve) slows down training as it increases the space of algorithms Decima must explore.

Figure 15b shows cumulative distributions of the time Decima takes to make a scheduling action (in red) and the time interval between scheduling events (in blue) in our Spark testbed (§7.2). The average scheduling delay for Decima is less than 15ms, while the interval between scheduling events is typically in the scale of seconds. In less than 5% of the cases, the scheduling interval is shorter than the scheduling delay (e.g., when the cluster requests for multiple scheduling actions in a single scheduling event). Thus Decima’s scheduling delay imposes no measurable overhead on task runtimes.

8 Related Work

There is little prior work on applying machine learning techniques to cluster scheduling. DeepRM [38], which uses RL to train a neural network for multi-dimensional resource packing, is closest to Decima in aim and approach. However, DeepRM’s learning model does not support DAG-structured jobs and its training procedure cannot handle continuous job arrivals. Mirhoseini et al.’s work on learning device placement in TensorFlow (TF) computations [43] also uses RL. It uses recurrent neural networks to scan through all nodes instead of using a scalable graph neural network. Moreover, the objective is to schedule a single TF job well, and the model cannot generalize to unseen job combinations [42].

Paragon [18] and Quasar [19] use collaborative filtering to match workloads to different machine types and avoid interference; their goal is complementary to Decima’s. Tetrisched [56], like Decima, plans ahead in time, but uses a constraint solver to optimize job placement and requires the user to supply explicit constraints with their jobs. Firmament [23] also uses a constraint solver and achieves high-quality placements, but requires an administrator to configure an intricate scheduling policy. Graphene [25] uses heuristics to schedule job DAGs, but cannot set appropriate parallelism levels. Some systems “auto-scale” parallelism levels to meet job deadlines [20] or opportunistically accelerate jobs using spare resources [49, §5]. As general-purpose cluster managers like Borg [59], Mesos [29], or YARN [57] support many different applications, workload-specific scheduling policies are difficult to apply at this level. However, Decima could run as a framework atop Mesos or Omega [49].

9 Conclusion

Decima demonstrates that automatically learning complex cluster scheduling policies using reinforcement learning is feasible, and that the learned policies are flexible and efficient. Decima’s learning innovations, such as its graph embedding technique and the training framework for streaming, may be applicable to other systems processing DAGs (e.g., query
optimizers). We will open-source Decima, our models, and our experimental infrastructure.

References


Appendices

A An illustrative example of dependency-aware job scheduling

Figure 16 shows a common example: a DAG with two branches that converge in a join stage. A simple critical path heuristic would choose to work on the right branch, which contains a larger aggregate work: 90 task-seconds vs. 10 in the left branch. Once the orange stage finishes, however, the final join stage cannot yet run, since its other parent stage (in green) is still incomplete. Completing it next, followed by the join stage — as a critical-path schedule would — results in an overall makespan of $28 + 3\epsilon$. The optimal schedule, by contrast, completes this DAG in $20 + 3\epsilon$ time, a 29% improvement. Intuitively, an ideal schedule allocates resources such that both branches reach the final join stage at the same time, and execute it without blocking.

B Background on Reinforcement Learning

In this section, we briefly review reinforcement learning (RL) techniques that we use in this paper. We refer the readers to [53] for a detailed survey and rigorous derivations.

Reinforcement learning. Consider the general setting in Figure 17, where an RL agent interacts with an environment. At each step $k$, the agent observes some state $s_k$, and takes an action $a_k$. Following the action, the state of the environment transitions to $s_{k+1}$ and the agent receives a reward $r_k$ as feedback. The state transitions and rewards are stochastic and assumed to be Markov: the state transition to $s_{k+1}$ and the reward $r_k$ depend only on the state $s_k$ and the action $a_k$ at step $k$ (i.e., they are conditionally independent of the past).

In the general RL setting, it is important to note that the agent can only control its actions; and it has no a priori knowledge of the state transition probabilities or the reward function. However, by interacting with the environment, the agent can learn these quantities during training.

For training, RL proceeds in episodes. Each episode consists of a sequence of (state, action, reward) observations — i.e., $(s_k, a_k, r_k)$ at each step $k \in [0, 1, \ldots, T]$, where $T$ is the episode length. For ease of understanding, we will first describe an RL formulation that maximizes the total reward: $E \left[\sum_{k=0}^{T} r_k\right]$. However, in our scheduling problem, the average reward formulation (§5.3) is more suitable. We will later describe how to modify the reward signal to convert the objective to the average reward setting.

Policy. The agent picks actions based on a policy $\pi(s_k, a_k)$, defined as a probability of taking action $a_k$ at state $s_k$. In most practical problems, the number of possible {state, action} pairs is too enormous, making it infeasible to store the policy in a lookup table. It is therefore common to use function approximators [9, 41], with a manageable number of adjustable parameters, $\theta$, to represent the policy as $\pi_\theta(s_k, a_k)$. Many forms of function approximators can be used to represent the policy. For instance, linear combinations of features of the state/action space (i.e., $\pi_\theta(s_k, a_k) = \theta^T \phi(s_k, a_k)$) are a popular choice. Neural networks [27] have recently been used successfully as function approximators to solve large-scale RL tasks [45, 52]. An advantage of neural networks is that they do not need hand-crafted features; and they are end-to-end differentiable for training.

Policy gradient methods. We focus on a class of RL algorithms that perform training by using gradient-descent on the policy parameters. Recall that the objective is to maximize the expected total reward; the gradient of this objective is given by [53, §13.2]:

$$\nabla_{\theta} E_{\pi_\theta} \left[ \sum_{k=0}^{T} r_k \right] = E_{\pi_\theta} \left[ \sum_{k=0}^{T} \nabla_{\theta} \log \pi_\theta(s_k, a_k) Q^\pi_\theta(s_k, a_k) \right],$$

where $Q^\pi_\theta(s_k, a_k)$ is the expected total discounted reward from (deterministically) choosing action $a_k$ in state $s_k$, and subsequently following policy $\pi_\theta$. The key idea in policy gradient methods is to estimate the gradient by using the trajectories of execution following the current policy. Following the Monte Carlo Method [28], the agent samples multiple trajectories and uses the empirical total discounted reward, $v_k$, as an unbiased estimate of $Q^\pi_\theta(s_k, a_k)$. It then updates the policy parameters via gradient descent:

$$\theta \leftarrow \theta + \alpha \sum_{k=0}^{T} \nabla_{\theta} \log \pi_\theta(s_k, a_k) v_k,$$

where $\alpha$ is the learning rate. This equation results in the REINFORCE algorithm [61]. The intuition of REINFORCE is that the direction $\nabla_{\theta} \log \pi_\theta(s_k, a_k)$ gives how to change the policy parameters in order to increase $\pi_\theta(s_k, a_k)$ (the probability of action $a_k$ at state $s_k$). Equation 5 takes a step in this direction; the size of the step depends on how large is the return $v_k$. The net effect is to reinforce actions that empirically lead to better returns. Appendix C describes the implementation details of this training method.

Average reward formulation. For our scheduling problem, a better fitting objective is the average reward formulation,
Algorithm 1 presents the pseudocode for Decima’s training framework using TensorFlow [1]. Each iteration of training maximizes the average reward objective. We implement Decima’s neural network architecture is described in §6.1. For continu-
ous job arrivals, the moving window for estimating episode termination probability decays linearly from a small initial mean \( \tau \) to \( \tau \rightarrow \infty \). This step terminates the initial episode early to avoid wasting training time (see challenge #1 in §5.3). Then, we sample a job sequence (line 4) and use it to collect \( N \) episodes of experience (line 5). Importantly, the baseline \( b_k \) in line 8 is computed with the same job sequence to reduce the variance caused by the randomness in the job arrival process (see challenge #2 in §5.3). Line 10 is the policy gradient REINFORCE algorithm described in Eq. (3). Line 13 increases the average episode length (i.e., the curriculum learning procedure for challenge #1 in §5.3). Finally, we update Decima’s policy parameter \( \theta \) in line 14.

The hyperparameter setting for training Decima is the following. The number of incoming jobs is capped at 2000. The episode termination probability decays linearly from \( 5 \times 10^{-8} \) to \( 5 \times 10^{-3} \) throughout training. The learning rate \( \alpha \) is \( 1 \times 10^{-3} \) and we use Adam optimizer [33] for gradient descent. The neural network architecture is described in §6.1. For continuous job arrivals, the moving window for estimating \( \hat{\tau} \) spans \( 10^3 \) time steps (see the average reward formulation in Appendix B); We train Decima for at least 50,000 iterations for all experiments. During training, there are 16 workers to compute the episodes (with the same job sequence) in parallel for speedup. Evaluations in §7 are all performed on unseen test job sequences (e.g., unseen TPC-H job combinations, unseen part of the company trace, etc.). We implement Decima’s training framework using TensorFlow [1]. Each iteration of training, including interaction with the simulator, model inference and model update from all training workers, takes roughly 1.5 seconds on a machine with Intel Xeon E5-2640 CPU and Nvidia Tesla P100 GPU.

Algorithm 1 Policy gradient method to train Decima.

```
1: \textbf{for} each iteration \textbf{do}
2: \hspace{1em} \Delta \theta \leftarrow 0
3: \hspace{1em} Sample episode length \( \tau \sim \text{exponential}(\tau_{\text{mean}}) \)
4: \hspace{1em} Sample a job arrival sequence
5: \hspace{1em} Run episodes \( i = 1, \ldots, N \):
6: \hspace{2em} \{s_i^k, a_i^k, \tau_i^k, r_i^k\} \sim \pi_{\theta}
7: \hspace{1em} Compute total reward: \( R^k_i = \sum_{\tau_i^k=1}^{\tau_i^k} r_i^k \)
8: \hspace{1em} for \( k = 1 \) to \( \tau \) \textbf{do}
9: \hspace{2em} compute baseline: \( b_k = \frac{1}{N} \sum_{i=1}^{N} R^k_i \)
10: \hspace{2em} for \( i = 1 \) to \( N \) \textbf{do}
11: \hspace{3em} \Delta \theta \leftarrow \Delta \theta + \nabla_{\theta} \log \pi_{\theta}(s_i^k, a_i^k)(R^k_i - b_k)
12: \hspace{1em} end for
13: \hspace{1em} end for
14: \hspace{1em} \theta \leftarrow \theta + \alpha \Delta \theta
15: \textbf{end for}
```

C Implementation details of training

Algorithm 1 presents the pseudocode for Decima’s training procedure as described in §5.3. In particular, line 3 samples the episode length \( \tau \) from an exponential distribution, with a small initial mean \( \tau_{\text{mean}} \). To convert the objective from sum-of-rewards to average reward, we replace the reward \( r_k \) with a differential reward. Operationally, at every step \( k \), the environment modifies the reward to the agent as \( r_k \leftarrow r_k - \hat{\tau} \), where \( \hat{\tau} \) is a moving average of the rewards across a large number of previous steps (across many training episodes). With this modification, we can reuse the same policy gradient method in Equation (4) and (5) to find the optimal policy. We refer the readers to Sutton and Barto [53, §10.3, §13.6] for mathematical details on how this approach optimizes the average reward objective.

D Simulator fidelity

Figure 18 shows how simulated and real Spark differs in terms of job completion time for 10 runs of TPC-H job sets (§7.2). The results show that the simulator closely matches the actual run time of each job, even we run multiple jobs together in the clusters. Importantly, capturing all first-order effect in the Spark environment is crucial to achieve such accuracy (§6.2). For example, without modeling the executor moving delay, the simulated runtime incurs a consistent negative offset. Training in such environment would therefore result in a policy that moves executor more often than intended (§7.4). Also, omitting the waves and stretches artifacts significantly increase the variance in simulated runtime, making it unfaithful to reflect the real cluster. Only when all the factors are consider, can we achieve the small discrepancy between real and simulation as shown in Figure 18.

E Competing heuristics in multi-resource scheduling environment

When evaluating Decima’s performance in multi-resource scheduling environment (§7.3), we compare with several heuristics. First, we consider the optimally tuned weighted fair heuristic from §7.2. This heuristic grants each job an executor share based on the total work in the job. Then the heuristic chooses a stage the same way as in §7.2. Among the available executor types, the heuristic exhausts the best-fitting category before choosing any others. The scheduler ensures that the aggregate allocated resources (across different executor types) do not exceed the job’s weighted fair share.

Second, we compare to the standard resource-packing algorithm from Tetris [24]. To maximize resource utilization, we
select the DAG node that yields the largest dot product of requested resource vector and available resource vector for each executor type. Then we greedily grant as much parallelism as the tasks need in this node.

The two heuristics lack each other’s key scheduling ingredients (fairness and packing), and neither understands the DAG structure. Finally, we compare to Graphene [25], whose hybrid heuristic combines these factors. Our multi-resource scheduling environment with discrete executor classes differs from the original Graphene setting, which assumes continuous, infinitely divisible resources. We adapted the Graphene algorithm for discrete executors, but kept its essence: specifically, we estimate and group the “troublesome” nodes the same way [25, §4.1]. To ensure that troublesome nodes are scheduled at the same time, we dynamically suppress the priority on all troublesome nodes of a DAG until all of these nodes are available in the frontier. We also include parallelism control by sharing the executors according to the optimally tuned weighted partition heuristic; and we pack resources by prioritizing the executor type that best fits the resource request. In the end, we perform a grid search on all the hyper-parameters (e.g., threshold for picking troublesome nodes) in this heuristic for the best scheduling performance in each of the experiments in §7.3.

**F Further analysis on multi-resource scheduling**

As discussed in §7.3, Decima is able to achieve 32% – 43% better average JCT than competing heuristics with continuous job arrivals in the multi-resource environment. Decima achieves this performance by carefully fragmenting memory resource at times. Further, Figure 12b show that Decima selectively borrows large executors if they can help finishing short jobs quickly and increase the cluster throughput during streaming.

This effect is also evident when examining the time series of job duration and executor usage. In Figure 19, Decima maintains an overall smaller number of concurrent jobs. During congested periods (e.g., around snapshot 50 in Figure 19a1), Decima is robust and cleans up the backlogged jobs in the queue. During these periods, Decima manages to assign more executors (e.g., by sometimes borrowing large executors) to each job than Graphene∗ (Figure 19a2 and 19b2). As a consequence, Decima achieves significantly better JCT and cluster throughput when the cluster load is high (Figure 19a3 and 19b3).

Figure 20a and 20b show a full profile of comparison on executor assignment between Decima and Graphene∗ (Figure 12b is the first column of this profile). Overall, Decima tends to assign more executors per job compared to Graphene∗. This helps Decima complete some jobs then move on to others, instead of making progress on many jobs concurrently but slowly (similar to the behavior we discussed in §7.2). Moreover, Decima uses more large executors on small jobs. This aggressive allocation of large executors leads to effectively better job duration during the busy periods (Figure 19a3 and 19b3). The trade-off between resource fragmentation and prioritizing small jobs can be tedious to balance; Decima automatically learns a strong scheduler by interacting with the multi-resource cluster environment.

**G Optimality of Decima**

In §7, we show Decima is able to rival or outperform existing scheduling schemes in a wide range of complex cluster environments, including a real Spark testbed, real-world cluster trace simulations and a multi-resource packing environment. However, the optimality of Decima in those environments remains unknown due to the intractability of computing exact optimal scheduling solutions [25, 40], or tight lower bounds.7 Nevertheless to understand Decima’s optimality, we test Decima in simplified settings where a brute-force search over different scheduling configurations is possible as a near-optimal baseline for comparison.

We consider the Spark executor based scheduling framework simulated in §6.2 with average JCT objective for a batch of jobs. To simplify the environment, we turn off the “wave”

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7In our scheduling settings (e.g., Spark’s executor based scheduling), we find lower bounds based on total work or critical path to be too loose to unveil meaningful information of how optimal Decima stands.
Figure 19: Time-series of different scheduling statistics in the extended Spark multi-resource environment. The comparison is between Decima and the best comparing heuristic Graphene∗. During busy periods, Decima finishes jobs faster and maintains a significantly lower concurrent jobs by aggressively and selectively borrow large executors.

Figure 20: Profiling of executor assignments on jobs with different sizes.

Figure 21: Comparing Decima with near optimal heuristics in a simplified scheduling environment.

To find a good schedule for a batch of \( n \) jobs, we consider exhaustive search over all \( n! \) possible job orderings, and select the ordering having the lowest average JCT. To make the exhaustive search feasible, we reduce the number of batch jobs to 10. For a fixed job ordering, at each scheduling event (§5.2), we select the unfinished job appearing earliest in the order (we use critical path to choose the order of nodes within each job) to assign to available executors. By enumerating over all possible job orderings, the algorithm is guaranteed to find a schedule where jobs finish in order of their respective sizes thus resulting in small average JCT. We believe this policy to be close to optimal, as we have empirically observed job orderings to have a dominating effect on the average JCT in TPC-H workloads (§7.4).

Next, we train an unmodified Decima agent in this environment with the same batch setting as in §7.2. We compare the performance of Decima with our exhaustive search baseline, a shortest-job-first critical-path heuristic, and the optimally tuned weighted fair scheduler (described in §7.2). The results are shown in Figure 21.

We make three key observations. First, different from the results in real spark (Figure 9), the SJF-CP scheme outperforms the optimally tuned weighted fair scheduler. This is expected because SJF-CP strictly favors small jobs to optimize for the average JCT (any misassignment of executors off the shortest job would hurt the performance). Second, the exhaustive search heuristic performs better than SJF-CP scheme. This is due to SJF-CP not exploiting information about the DAG structure or the current cluster state—beyond just the critical path or total work—resulting in a suboptimal packing. Whereas by trying out different job orderings, the exhaustive search heuristic is able to find a schedule in which jobs are not only ordered correctly, but also pack well. Third, remarkably, Decima matches or achieves slightly better average JCT—on average, Decima reduces the JCT by 9%. We found that Decima is better at dynamically packing jobs based on their current structure at run time (e.g., how much work remains on each dependency path). It enables Decima to outperform the heuristic that strictly follows the order determined in a static exhaustive search. This experiment hallmarks Decima’s ability to automatically search for a near optimal scheduling.
Decima training scenario | average JCT (1k seconds)
---|---
Decima trained with 10 jobs | 3.54 ± 0.45
Decima trained with 150 jobs | 3.29 ± 0.68
Decima trained with 1k executors | 0.63 ± 0.07
Decima trained with 10k executors | 0.61 ± 0.09

Table 2: Decima generalizes well to deployment scenarios in which the workload or cluster differ from the training setting.

Figure 22: Decima performs worse on unseen jobs without task duration estimates, but still outperforms the best heuristic.

algorithm, by interacting with the cluster with only the raw observation of the job states.

H Generalizing Decima to different deployment environments

Practical clusters often have varying workloads, and their available resources also change over time. Ideally, Decima would generalize from a model trained for a specific load and cluster size to similar workloads with different parameters. To test this, we train Decima’s agent on a scaled-down version of the industrial workload, using with 15\times fewer concurrent jobs and 10\times fewer executors than in the test setting.

Table 2 shows how the performance of this agent compares with that of one trained on the real workload and cluster size.

Decima is robust to changing parameters: it generalizes to 15\times more jobs with a 7% worse average JCT, and to a 10\times larger cluster with a 3% worse average JCT. Generalization to a larger cluster is robust as the policy correctly limits jobs’ parallelism even if vastly more resources are available. By contrast, generalizing to a workload with many more jobs is harder, as the smaller-scale training lacks experiences with complex job combinations.

I Decima with incomplete information

In a real cluster, Decima will occasionally encounter unseen jobs without reliable task duration estimates. Unlike heuristics that fundamentally rely on profiling information (e.g., weighted fair scheduling based on total work), Decima can still work with the remaining information and extract a reasonable scheduling policy. Running the same setting in §7.2, Figure 22 shows that training without task durations yields a policy that still outperforms the best heuristic, as Decima can still exploit the graph structure and other information such as the correlation between number of tasks and the efficient parallelism point.