DreamShard: Generalizable Embedding Table Placement for Recommender Systems

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Abstract

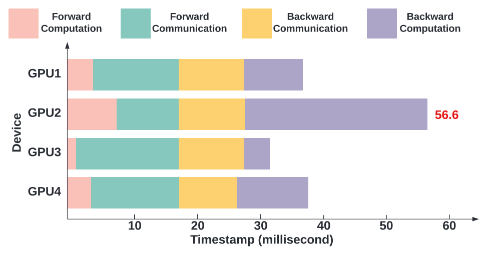
We study embedding table placement for distributed recommender systems, which aims to partition and place the tables on multiple hardware devices (e.g., GPUs) to balance the computation and communication costs. Although prior work has explored learning-based approaches for the device placement of computational graphs, embedding table placement remains to be a challenging problem because of 1) the operation fusion of embedding tables, and 2) the generalizability requirement on unseen placement tasks with different numbers of tables and/or devices. To this end, we present DreamShard, a reinforcement learning (RL) approach for embedding table placement. DreamShard achieves the reasoning of operation fusion and generalizability with 1) a cost network to directly predict the costs of the fused operation, and 2) a policy network that is efficiently trained on an estimated Markov decision process (MDP) without real GPU execution, where the states and the rewards are estimated with the cost network. Equipped with sum and max representation reductions, the two networks can directly generalize to any unseen tasks with different numbers of tables and/or devices without fine-tuning. Extensive experiments show that DreamShard substantially outperforms the existing human expert and RNN-based strategies with up to 19% speedup over the strongest baseline on large-scale synthetic tables and our *production* tables. The code is available at `https://github.com/daochenzha/dreamshard`.

1 Introduction

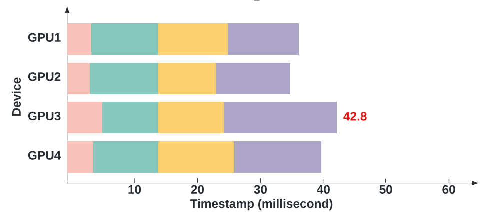
Embedding learning is a commonly used technique to deal with categorical features in deep recommendation models by mapping sparse features into dense vectors [1, 2, 3, 4, 5]. However, the embedding tables can be extremely large due to the large feature sizes [6]. For example, in the YouTube recommendation model, a single categorical feature contains tens of millions of video IDs [7]; the Meta recommendation model demands multi-terabyte memory [8]. Distributed training has been adopted to place the tables on multiple hardware devices such as GPUs [3, 6, 9, 10, 11]. However, even with distributed training, the embedding tables are often still the efficiency bottlenecks. For instance, embedding lookup is shown to dominate the training throughput in the Meta recommendation model [8]. In our internal production model, which has hundreds of tables, embedding lookup accounts for 48% and 65% of the total computation and communication costs, respectively.

How the embedding tables are placed can significantly impact the costs. Figure 1 shows the traces of different placement strategies on a task of placing 50 tables on 4 devices. Typically, embedding lookup consists of four stages. In the forward pass, the sparse indices are mapped into dense vectors (forward computation), which are then sent to the target devices (forward communication).

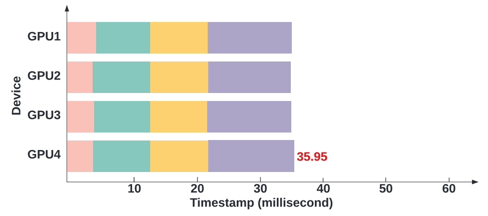
In the backward pass, the gradients of the embedding vectors are sent back from the target devices (backward communication) and applied to the embedding vectors (backward computation). The tables will easily lead to imbalances if not carefully partitioned. The random placement in Figure 1a is bottlenecked by GPU2 with a 56.6 milliseconds latency, while the more balanced placements in Figure 1b and 1c significantly reduce the costs to 42.8 and 35.95 milliseconds, respectively. This work asks: *given a set of embedding tables, how can we identify the best placement of the tables to balance the costs?*



(a) Random placement



(b) The existing best human expert strategy



(c) DreamShard

Figure 1: Visualization of random placement, the existing best human expert strategy, and DreamShard on a task of placing 50 tables on 4 GPUs. The dense computations and communications are omitted in the traces because they do not have an imbalance issue. We provide more visualizations in Appendix L.

Device placement is essentially a partition problem, which is one of the classical NP-hard combinatorial optimization problems [12]. A recent line of research uses reinforcement learning (RL) for device placement of computational graphs [13, 14, 15, 16, 17, 18, 19, 20]. For example, [13] proposed to train an RNN controller with content-based attention to predict the placement. Other studies advanced [13] in different ways, such as using hierarchical models [14], more sophisticated RL algorithms [15], and graph neural networks [16].

However, embedding table placement remains to be an open and challenging problem due to the operation fusion [21] of tables and the generalizability requirement. **1)** Modern embedding implementations (e.g., FBGEMM [22]), use a single operation to subsume multiple tables for acceleration. The speedup of the fused operation over the sum of the single-table operation costs is not constant and depends on the characteristics of the fused tables (e.g., table dimensions). Our analysis finds that the speedups vary significantly across different table combinations, ranging from 1X to 3X (Figure 12 in Appendix A.3.2). Thus, we not only need to reason about cost balance but also how the tables should be fused to maximize the speedup. **2)** In real-world scenarios, the adopted embedding tables and the available devices can change frequently (e.g., machine learning engineers/researchers may conduct concurrent experiments with various table combinations and numbers of devices). Thus, a practical algorithm should generalize to tasks with unseen tables, different numbers of tables, and different numbers of devices. It is non-trivial to achieve this with the existing device placement approaches.

To this end, we introduce DreamShard, an RL approach for embedding table placement. DreamShard achieves the reasoning of operation fusion and generalizability with two novel ideas. **1)** It learns a cost network to directly predict the costs of the fused operations. Specifically, the network takes as input the table features (e.g., table dimension) of each single-table and outputs the computation and communication costs. **2)** It trains a policy network by interacting with an estimated Markov decision process (MDP) without real GPU execution, where the states and the rewards are estimated by the predictions of the cost network. Equipped with sum reductions for the table representations and max reductions for the device representations, the two networks can directly generalize to unseen placement tasks with different numbers of tables and/or devices without fine-tuning.

Extensive experiments show that DreamShard outperforms the existing human expert and RNN-based [13] strategies on open-sourced synthetic tables [23] and our *production* tables, achieving up to 19% speedup over the strongest baseline. Moreover, it can generalize to unseen tasks that have different numbers of tables and/or devices with neglectable performance drop (< 0.5 milliseconds). Additionally, its inference is very efficient. It can place hundreds of tables in less than one second.

2 Generalizable Embedding Table Placement Problem

The embedding table placement problem seeks a device placement[1] of all the tables such that the overall cost (in terms of execution time) is minimized (we provide a background for the distributed training of recommendation models in Appendix A.1). Consider M embedding tables $\{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_M\}$ and D devices, where $\mathbf{e}_i \in \mathbb{R}^N$ denotes the table features that characterize the embedding lookup patterns. In our work, we use 21 table features, including hash size, dimension, table size, pooling factor, and distribution (their definitions are provided in Appendix A.2). A placement $\mathbf{a} = [a_1, a_2, ..., a_M]$, where $a_i \in \{1, 2, ..., D\}$, assigns each table to a device. Let $c(\mathbf{a})$ denote the cost measured on GPUs. The goal of embedding table placement is to find the $\mathbf{a}$ such that $c(\mathbf{a})$ is minimized. Due to the NP-hardness of the partition problem [12], identifying the exact solution demands extensive computational overhead. Thus, the state-of-the-art algorithms often approximate the optimal partition via sampling with RL [24, 13]. However, sampling remains expensive because obtaining $c(\mathbf{a})$ requires running operations on GPUs. Given that the embedding tables and the available devices can frequently change, we wish to approximate the best $\mathbf{a}$ without GPU execution.

Motivated by this, we study the *generalizable embedding table placement* (GETP) problem. Let $\mathcal{E}$ be the space of all the embedding tables. A placement task can be denoted as $T_i = (\mathcal{E}_i, D_i)$, where $\mathcal{E}_i \subseteq \mathcal{E}$ is a set of tables, and D_i is the number of devices. Given N_{train} training tasks $\mathcal{T}_{\text{train}} = \{T_1, T_2, ..., T_{N_{\text{train}}}\}$, and N_{test} testing tasks $\mathcal{T}_{\text{test}} = \{T_1, T_2, ..., T_{N_{\text{test}}}\}$, the goal is to train a placement policy based on $\mathcal{T}_{\text{train}}$ (GPU execution is allowed during training) such that the learned policy can minimize the costs for the tasks in $\mathcal{T}_{\text{test}}$ without GPU execution.

3 DreamShard Framework

We present DreamShard, an RL framework based on estimated MDP, to tackle the GETP problem. An overview of the framework is shown in Figure 2. The key idea is to formulate the table placement process as an MDP (Section 3.1) and train a cost network to estimate its states and rewards (Section 3.2). A policy network with a tailored generalizable network architecture is trained by efficiently interacting with the estimated MDP (Section 3.3). The two networks are updated iteratively to improve the state/reward estimation and the placement policy.

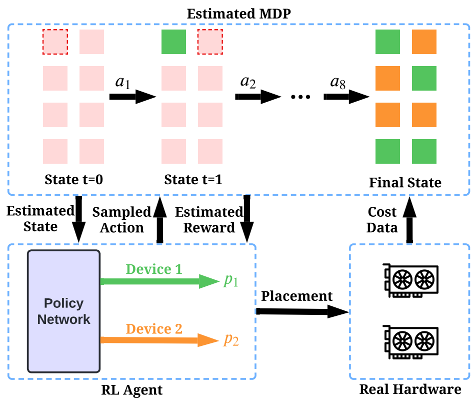


Figure 2: DreamShard framework. The agent interacts with the estimated MDP, which is trained with the cost data collected from GPUs.

3.1 MDP Formulation

Given embedding tables $\{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_M\}$ and D devices, we aim to generate a placement $\mathbf{a} = [a_1, a_2, ..., a_M]$. The key idea is to place the tables one by one at each step, where the state characterizes the tables that have been placed so far, the action is the device ID, and the reward represents the execution time on GPUs. Specifically, at a step t, the state $s_t = \{s_{t,d}\}_{d=1}^{D}$ is all the table features of the tables placed on all the devices, where $s_{t,d} = \{\mathbf{e}_i | i \in \mathcal{P}_d\}$ denotes all the table features corresponding to device d ($\mathcal{P}_d$ is the set of table IDs that have been placed on device d). We further augment the raw features with cost features which are obtained by collecting the operation computation and communication times from GPUs (Appendix A.3 provides a comprehensive analysis of the cost features). Formally, the augmented state is defined as $\widetilde{s}_t = \{s_t, \{\mathbf{q}_{t,d}\}_{d=1}^{D}\}$, where $\mathbf{q}_{t,d} \in \mathbb{R}^3$ has three elements representing forward computation time, backward computation time, and backward communication time for the current operation in device d (we provide detailed explanations of why forward communication time is excluded in Appendix A.4). We find that the augmented cost features can significantly boost the performance, evidenced by the ablations in Table 3. The action $a_t \in \mathcal{A}_t$ is an integer specifying the device ID, where $\mathcal{A}_t$ is the set of legal actions at step t. A device ID is considered legal if placing the current table on the corresponding device does not cause a memory explosion. The reward r_t is 0 for all the intermediate steps, and the reward at the final step M is the negative of the cost, i.e., $r_M = -c(\mathbf{a})$, which encourages the agent to achieve lower cost.

[1]In this work, we focus on GPU devices, where all the GPU devices are identical, which is the most common configuration in our production. We defer the mixed scenarios of both GPUs and CPUs to future work.

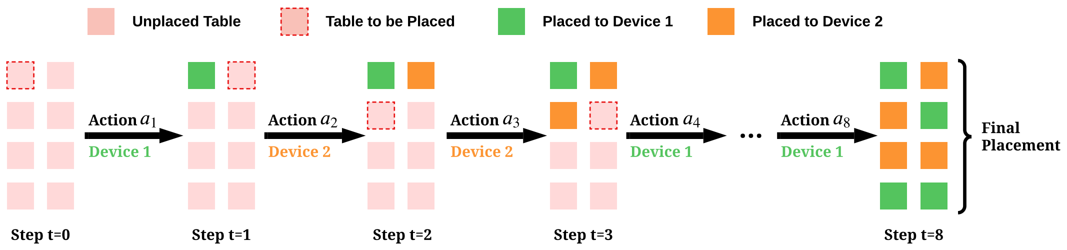


Figure 3: MDP formulation of embedding table placement.

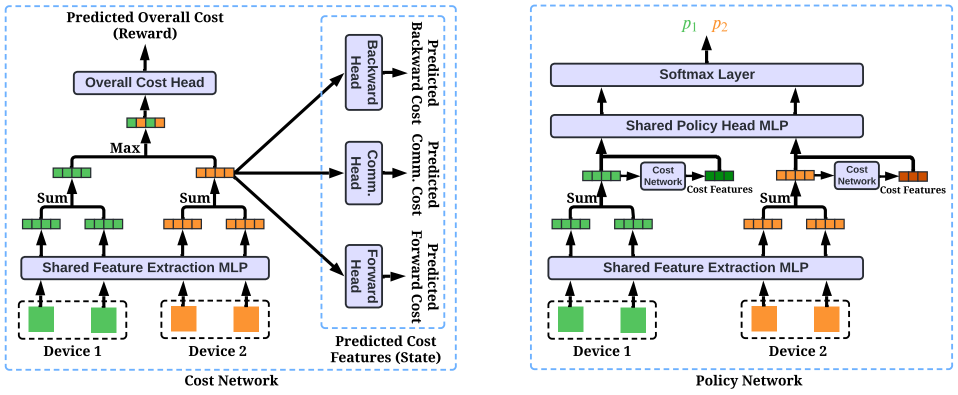


Figure 4: DreamShard's cost network (**left**) and policy network (**right**).

The procedure is illustrated for an example task of placing 8 tables $\{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_8\}$ on 2 devices in Figure 3. At step 0, no table has been placed so $s_0 = \{\{\}, \{\}\}$ and the augmented state $\widetilde{s}_0 = \{s_0, \{\mathbf{q}_{0,0}, \mathbf{q}_{0,1}\}\}$, where both $\mathbf{q}_{0,0}$ and $\mathbf{q}_{0,1}$ are zero vectors (i.e., $[0, 0, 0]$) since all the computation and communication times are 0 as well. Then the action $a_0 = 1$ makes the MDP transit to the next state $s_1 = \{\{\mathbf{e}_1\}, \{\}\}$ with its corresponding augmented state $\widetilde{s}_1 = \{s_1, \{\mathbf{q}_{1,0}, \mathbf{q}_{1,1}\}\}$, where $\mathbf{q}_{1,0}$ becomes a non-zero vector containing the computation and communication costs by running $\{\mathbf{e}_1\}$ and $\{\}$ on GPUs. We repeat the above process, and finally at step 8, we have $s_8 = \{\{\mathbf{e}_1, \mathbf{e}_4, \mathbf{e}_7, \mathbf{e}_8\}, \{\mathbf{e}_2, \mathbf{e}_3, \mathbf{e}_5, \mathbf{e}_6\}\}$. The corresponding $\mathbf{q}_{8,1}$, and $\mathbf{q}_{8,2}$ are the measured times of running $\{\mathbf{e}_1, \mathbf{e}_4, \mathbf{e}_7, \mathbf{e}_8\}$ and $\{\mathbf{e}_2, \mathbf{e}_3, \mathbf{e}_5, \mathbf{e}_6\}$ on two devices. The action sequence $\mathbf{a} = [a_1, a_2, ..., a_8]$ is the generated placement, which is then evaluated on GPUs to obtain the reward.

Discussion 1. The MDP enjoys two desirable properties. **1)** The legal action $\mathcal{A}_t$ can guarantee that the generated placement satisfies the memory constraints. **2)** The one-by-one placement enables the agent to be generalized across different numbers of tables. For example, an agent trained on an MDP with very few tables can be applied to another MDP with more tables by simply executing more steps.

Discussion 2. A straightforward idea to solve the MDP is to greedily place the current table on the device with the lowest cost at each step, where the cost function can be one of or a combination of the state features (e.g., the sum of the table dimensions, or the sum of all the cost features). However, greedy heuristics are often sub-optimal. Thus, we seek a learning-based algorithm to explore various placement possibilities and make comprehensive decisions based on all the state features.

3.2 Learning an Estimated MDP

Interacting with the above MDP is computationally expensive since obtaining the cost features and the reward requires GPU execution. Motivated by world models [25, 26], we build an estimated MDP by approximating the cost features and the reward with a cost network. Let f_{cost} denote the cost network. f_{cost} takes as input the raw table features s_t, and predicts cost features $\{\mathbf{q}_{t,d}\}_{d=1}^{D}$ and the overall cost $c(\mathbf{a})$. f_{cost} is trained with mean squared error (MSE) loss using the cost data collected from the GPUs. Once trained, it can predict the cost features or the reward with a single forward pass without GPU execution. However, it is non-trivial to design the architecture of f_{cost} because it needs

Algorithm 1 Training of DreamShard

```
1: Input: Training tasks $\mathcal{T}_{\text{train}}$, the number of data collection steps $N_{\text{collect}}$, the number of cost
   network update steps $N_{\text{cost}}$, the batch size for updating the cost network $N_{\text{batch}}$, the number RL
   update steps $N_{\text{RL}}$, the number of considered episodes in each RL update $N_{\text{episode}}$
2: Initialize a cost network, a policy network, and a buffer
3: for iteration = 1, 2, ... until convergence do
4:     for step = 1, 2, ... $N_{\text{collect}}$ do                    ▷ Collect cost data from GPUs
5:         Randomly sample a training task from $\mathcal{T}_{\text{train}}$
6:         Generate a placement by interacting with the estimated MDP using the policy network
7:         Evaluate the placement on the hardware and store the collected cost data to the buffer
8:     end for
9:     for step = 1, 2, ... $N_{\text{cost}}$ do          ▷ Update the cost network (no GPU execution)
10:        Randomly sample $N_{\text{batch}}$ cost data from the buffer
11:        Update the cost network based on MSE loss (Eq. 1 in Appendix B.4.1)
12:    end for
13:    for step = 1, 2, ... $N_{\text{RL}}$ do          ▷ Update the policy network (no GPU execution)
14:        Randomly sample a training task from $\mathcal{T}_{\text{train}}$
15:        Collect $N_{\text{episode}}$ episodes by interacting with the estimated MDP using the policy network
16:        Update the policy network based on the policy gradient loss (Eq. 2 in Appendix B.4.1)
17:    end for
18: end for
```

to accommodate different numbers of devices (i.e., s_t can have variable sizes), and different numbers of tables in each device (i.e., $s_{t,d}$ can have variable lengths).

The left-hand side of Figure 4 shows DreamShard's generalizable design of f_{cost}, which is based on two key ideas. **First,** it uses a shared MLP to map raw table features into table representations. For any unseen tables, this MLP can be directly applied to extract table representations. **Second,** it enables a fixed-dimension representation for each device with sum reductions (i.e., the element-wise sum of the table representations in the device), and similarly for the overall representation across devices with max reductions (Appendix B.3 compares different reduction choices and finds that this sum-max combination leads to the most accurate prediction). The reduced representations are then followed by multiple MLP heads for cost predictions. For unseen tasks with different numbers of tables and/or devices, the reductions will always lead to fixed-dimension device/overall representations, so that the prediction heads can be directly applied. Appendix B.1 provides more details.

3.3 Training the Policy Network on the Estimated MDP

Generalizable policy network architecture. Let π be the policy network. π maps the augmented state $\widetilde{s}_t = \{s_t, \{\mathbf{q}_{t,d}\}_{d=1}^{D}\}$ to action a_t, i.e., $a_t = \pi(\widetilde{s}_t)$. π also adopts a generalizable design, shown in the right-hand side of Figure 4. Like f_{cost}, π uses a shared MLP and sum reductions to produce a fixed-dimension representation, which is then concatenated with the cost features to obtain the device representation. To accommodate the potentially variable action space (i.e., the number of available devices may vary), a shared MLP will process each device representation separately to obtain a confidence score, followed by a Softmax layer to produce action probabilities. This design allows π to generalize across different numbers of devices. Appendix B.2 provides more details.

Training and inference. Algorithm 1 summarizes the training procedure of DreamShard, which iteratively executes the following: **1)** collect cost data from GPUs based on the placements generated by the current policy, **2)** update the cost network with the previously collected cost data, and **3)** update the policy network by interacting with the current estimated MDP. Throughout the training process, the estimated MDP gradually becomes more accurate, and the resultant policy network tends to generate better placements. Appendix B.4.2 provides more details of the training procedure. For the inference, the trained cost network and policy network can be directly applied to unseen tasks to generate placements without GPU execution, which is summarized by Algorithm 2 in Appendix B.4.3.

4 Experiments

Our experiments aim to answer the following research questions. **RQ1:** How does DreamShard compare with the existing human expert and RL-based placement strategies? **RQ2:** Can DreamShard generalize to placement tasks with different numbers of tables and/or devices? **RQ3:** How efficient is the training of DreamShard? **RQ4:** How do the hyperparameters influence the performance of DreamShard? **RQ5:** How does each component of DreamShard contribute to the performance? **RQ6:** How accurate is the estimated MDP and to what extend can it accelerate the training and inference?

4.1 Experimental Setup

Datasets. Academic recommendation datasets are often too small to enable a meaningful evaluation because the cost will always be very small no matter how the tables are placed. Thus, we use two industrial-scale datasets. **DLRM**[2] is a large-scale synthetic dataset with 856 tables, recently released by Meta. It shares memory access reuse patterns similar to those arising in Meta production workloads. **Prod** is an internal large-scale dataset for production recommendation models. It has a similar scale as DLRM. The main difference is that DLRM only has a fixed dimension for all the tables, while Prod is more challenging with diverse table dimensions, ranging from 4 to 768. For reproducibility, we mainly focus on the DLRM dataset since it is open-sourced. We only report the main results on the Prod dataset for verification purposes. We provide more details in Appendix C.

Baselines. We compare DreamShard against human expert strategies from previous work [27, 8, 28], including **size-based**, **dim-based**, **lookup-based**, **size-lookup-based** greedy balancing strategies. We also include an **RNN-based** RL algorithm [13], which uses RNN architecture to map operators to devices. Since the feature extraction layers of the RNN-based method were designed for other operations instead of embedding tables, for a fair comparison, we adapt [13] by making it have the same feature extraction layers as in DreamShard. We provide more details in Appendix D.

Configurations. To evaluate the generalizability of DreamShard, we randomly divide the tables into a training pool $\mathcal{E}^{\text{train}}$ and a testing pool $\mathcal{E}^{\text{test}}$. The two pools have the same number of tables but they are not overlapped. A sharding task T_i is constructed by randomly sampling a subset of $|\mathcal{E}_i|$ tables from a pool, where the number of tables $|\mathcal{E}_i| \in \{10, 20, 30, 40, 50, 60, 70, 80, 90, 100\}$ for the DLRM dataset, and $|\mathcal{E}_i| \in \{20, 40, 80\}$ for the Prod dataset. For all the experiments, we randomly sample 50 training and 50 testing tasks from $\mathcal{E}^{\text{train}}$ and $\mathcal{E}^{\text{test}}$, respectively. DreamShard is trained on the training tasks and will be evaluated on unseen tables in the testing tasks. We denote placement tasks with different numbers of tables and devices using the format of `dataset-num_tables` (`num_devices`). For example, DLRM-30 (4) suggests that there are 30 tables sampled from the DLRM dataset in each training/testing task with 4 available devices. We provide more details in Appendix E.

Implementation Details. We use the same hyperparameters for all the experiments with $N_{\text{collect}} = 10$, $N_{\text{cost}} = 300$, $N_{\text{batch}} = 64$, $N_{\text{RL}} = 10$, $N_{\text{episode}} = 10$, 10 training iterations, and an entropy weight of 0.001 in the policy gradient. 2080 Ti GPUs and V100 GPUs are used for the DLRM (except that we use V100 for experiments with 8 GPUs) and Prod datasets, respectively. All the experiments are run 5 times, and we report the mean and the standard deviation. Appendix B provides more details.

4.2 Results and Analysis

Evaluation of DreamShard against baselines (RQ1). We perform qualitative and quantitative comparisons of DreamShard against the baselines. **Qualitatively,** Figure 1 visualizes the traces of DreamShard and the baselines on one of the tasks from DLRM-50 (4). DreamShard achieves significant better overall cost than the best baseline (35.95 vs. 42.8) with **1)** a better balance of forward and backward commutation workloads, and **2)** less communication time, possibly due to a better balance of table dimensions. **Quantitatively,** Table 1 presents comprehensive evaluations on tasks with different numbers of tables and devices on the DLRM and the Prod datasets. **Observations: 1)** DreamShard outperforms the baselines on *all* the tasks. **2)** DreamShard shows strong generalizability on unseen tables, achieving the same level of performance on *all* the testing and training tasks. **3)** DreamShard appears to be more advantageous on harder tasks. Specifically, DreamShard achieves more improvement over the baselines on tasks with more tables/devices on the Prod dataset. In particular, DreamShard achieves 19% improvment over the strongest baseline on Prod-80 (8). **4)**

[2]`https://github.com/facebookresearch/dlrm_datasets`

Table 1: Overall cost comparison in milliseconds and relative speedups over random placement, averaged over 50 different randomly sampled tasks. The placement tasks are denoted as `dataset-num_tables` (`num_devices`). For example, DLRM-30 (4) suggests that 30 tables are sampled from the DLRM dataset for each task with 4 GPUs. More results are provided in Appendix F.

Task		No strategy	Human Experts				RL	
		Random	Size-based	Dim-based	Lookup-based	Size-lookup-based	RNN-based	DreamShard
DLRM-20 (4)	Train	24.0±0.6	22.7±0.0 (+5.7%)	21.3±0.0 (+12.7%)	19.1±0.0 (+25.7%)	19.1±0.0 (+25.7%)	22.4±0.5 (+7.1%)	**18.6±0.2 (+29.0%)**
	Test	23.0±0.5	21.7±0.0 (+6.0%)	19.9±0.0 (+15.6%)	18.3±0.0 (+25.7%)	18.4±0.0 (+25.0%)	20.9±0.3 (+10.0%)	**17.6±0.2 (+30.7%)**
DLRM-40 (4)	Train	41.3±0.2	39.6±0.0 (+4.3%)	37.4±0.1 (+10.4%)	33.6±0.0 (+22.9%)	33.6±0.1 (+22.9%)	39.2±0.7 (+5.4%)	**32.8±0.3 (+25.9%)**
	Test	41.1±0.5	40.3±0.0 (+2.0%)	37.3±0.0 (+10.2%)	33.0±0.1 (+24.5%)	33.2±0.0 (+23.8%)	39.2±1.1 (+4.8%)	**32.4±0.3 (+26.9%)**
DLRM-60 (4)	Train	57.7±0.8	56.6±0.1 (+1.9%)	52.9±0.0 (+9.1%)	49.2±0.1 (+17.3%)	49.3±0.0 (+17.0%)	55.5±0.9 (+4.0%)	**47.6±0.4 (+21.2%)**
	Test	58.1±0.6	59.6±0.1 (-2.5%)	53.7±0.0 (+8.2%)	48.7±0.2 (+19.3%)	49.1±0.1 (+18.3%)	56.0±0.7 (+3.8%)	**47.9±0.7 (+21.3%)**
DLRM-80 (4)	Train	75.7±1.0	76.0±0.0 (-0.4%)	70.0±0.3 (+8.1%)	64.8±0.0 (+16.8%)	65.3±0.1 (+15.9%)	73.2±2.7 (+3.4%)	**62.2±0.2 (+21.7%)**
	Test	74.5±0.8	77.7±0.2 (-4.1%)	69.9±0.4 (+6.6%)	64.1±0.2 (+16.2%)	65.1±0.0 (+14.4%)	72.9±2.4 (+2.2%)	**62.7±0.3 (+18.8%)**
DLRM-100 (4)	Train	91.8±1.7	94.1±0.3 (-2.4%)	86.7±0.3 (+5.9%)	81.2±0.4 (+13.1%)	82.2±0.2 (+11.7%)	94.5±10.7 (-2.9%)	**78.4±0.6 (+17.1%)**
	Test	94.5±6.5	95.4±0.0 (-0.9%)	84.7±0.4 (+11.6%)	79.5±0.3 (+18.9%)	80.8±0.3 (+17.0%)	94.8±13.0 (-0.3%)	**77.8±0.8 (+21.5%)**
DLRM-40 (8)	Train	15.6±0.4	14.1±0.0 (+10.6%)	13.4±0.1 (+16.4%)	**9.8±0.0 (+59.2%)**	9.9±0.0 (+57.6%)	16.2±0.8 (-3.7%)	**9.8±0.6 (+59.2%)**
	Test	15.2±0.2	14.5±0.0 (+4.8%)	13.2±0.0 (+15.2%)	9.5±0.0 (+60.0%)	9.5±0.0 (+60.0%)	16.0±1.1 (-5.0%)	**9.4±0.5 (+61.7%)**
DLRM-80 (8)	Train	25.0±0.2	24.0±0.0 (+4.2%)	21.7±0.0 (+15.2%)	17.1±0.0 (+46.2%)	17.5±0.0 (+42.9%)	51.4±3.9 (-51.4%)	**16.1±0.3 (+55.3%)**
	Test	25.2±1.3	25.6±0.5 (-1.6%)	20.8±0.0 (+21.2%)	16.7±0.2 (+50.9%)	16.9±0.1 (+49.1%)	53.4±4.6 (-52.8%)	**16.1±0.4 (+56.5%)**
DLRM-120 (8)	Train	34.0±0.3	32.3±0.0 (+5.3%)	29.8±0.0 (+14.1%)	24.5±0.0 (+38.8%)	25.3±0.0 (+34.4%)	58.6±2.7 (-42.0%)	**23.3±0.2 (+45.9%)**
	Test	33.5±0.5	35.0±0.0 (-4.3%)	29.2±0.0 (+14.7%)	23.7±0.0 (+41.4%)	24.5±0.0 (+36.7%)	58.7±3.1 (-42.9%)	**22.8±0.2 (+46.9%)**
DLRM-160 (8)	Train	42.8±0.3	41.6±0.0 (+2.9%)	39.0±0.0 (+9.7%)	32.0±0.0 (+33.7%)	32.7±0.0 (+30.9%)	58.3±3.5 (-26.6%)	**30.3±0.2 (+41.3%)**
	Test	41.1±0.0	42.4±0.0 (-3.1%)	36.4±0.0 (+12.9%)	30.8±0.0 (+33.4%)	31.6±0.0 (+30.1%)	59.3±5.4 (-30.7%)	**29.6±0.2 (+38.9%)**
DLRM-200 (8)	Train	51.5±1.2	48.2±0.0 (+6.8%)	48.0±0.0 (+7.3%)	38.9±0.0 (+32.4%)	39.9±0.0 (+29.1%)	68.7±2.4 (-25.0%)	**37.2±0.2 (+38.4%)**
	Test	50.7±0.2	50.8±0.0 (-0.2%)	44.8±0.0 (+13.2%)	38.0±0.0 (+33.4%)	38.6±0.0 (+31.3%)	70.4±2.8 (-28.0%)	**36.4±0.3 (+39.3%)**
Prod-20 (2)	Train	41.3±0.7	43.4±0.0 (-4.8%)	37.0±0.0 (+11.6%)	44.2±0.0 (-6.6%)	45.8±0.0 (-9.8%)	38.0±0.3 (+8.7%)	**36.3±0.3 (+13.8%)**
	Test	42.8±0.4	46.1±0.0 (-7.2%)	39.5±0.0 (+8.4%)	45.9±0.0 (-6.8%)	45.7±0.0 (-6.3%)	39.3±0.6 (+8.9%)	**37.5±0.2 (+14.1%)**
Prod-40 (4)	Train	35.1±0.3	39.4±0.0 (-10.9%)	31.3±0.0 (+12.1%)	36.4±0.0 (-3.6%)	38.8±0.0 (-9.5%)	33.9±2.5 (+3.5%)	**28.3±0.3 (+24.0%)**
	Test	38.3±0.3	43.6±0.0 (-12.2%)	33.5±0.0 (+14.3%)	37.4±0.0 (+2.4%)	40.1±0.0 (-4.5%)	36.7±2.8 (+4.4%)	**30.4±0.7 (+26.0%)**
Prod-80 (8)	Train	43.2±0.2	44.3±0.0 (-2.5%)	39.0±0.0 (+10.8%)	43.7±0.0 (-1.1%)	49.3±0.0 (-12.4%)	56.6±6.8 (-23.7%)	**33.6±0.9 (+28.6%)**
	Test	47.7±0.4	53.9±0.0 (-11.5%)	41.9±0.0 (+13.8%)	46.1±0.0 (+3.5%)	49.6±0.0 (-3.8%)	62.5±4.2 (-23.7%)	**35.2±0.8 (+35.5%)**

Table 2: Generalization performance of DreamShard on target tasks w.r.t. to different numbers of tables (**top**) and devices (**bottom**), averaged over 50 randomly sampled tasks. Appendix G provides the results of more challenging tasks, such as mixed table-wise and device-wise transferring scenarios.

Source Task $\rightarrow$ Target Task	Random	Best baseline strategy	DreamShard (trained on target task)	DreamShard (trained on source task)
DLRM-20 (4) $\rightarrow$ DLRM-100 (4)	94.5±6.5	79.5±0.3 (+18.9%)	**77.8±0.8 (+21.5%)**	77.9±0.4 (+21.3%)
DLRM-40 (4) $\rightarrow$ DLRM-80 (4)	74.5±0.8	64.1±0.2 (+16.2%)	**62.7±0.3 (+18.8%)**	**62.7±0.5 (+18.8%)**
DLRM-80 (4) $\rightarrow$ DLRM-40 (4)	41.1±0.5	33.0±0.1 (+24.5%)	**32.4±0.3 (+26.9%)**	**32.4±0.2 (+26.9%)**
DLRM-100 (4) $\rightarrow$ DLRM-20 (4)	23.0±0.5	18.3±0.0 (+25.7%)	**17.6±0.2 (+30.7%)**	17.7±0.3 (+29.9%)
DLRM-20 (4) $\rightarrow$ DLRM-20 (2)	29.9±0.4	26.0±0.0 (+15.0%)	**25.8±0.2 (+15.9%)**	**25.8±0.1 (+15.9%)**
DLRM-40 (4) $\rightarrow$ DLRM-40 (2)	58.6±0.7	52.4±0.0 (+11.8%)	**51.9±0.1 (+12.9%)**	**52.0±0.3 (+12.7%)**
DLRM-20 (2) $\rightarrow$ DLRM-20 (4)	23.0±0.5	18.3±0.0 (+25.7%)	**17.6±0.2 (+30.7%)**	17.8±0.3 (+29.2%)
DLRM-40 (2) $\rightarrow$ DLRM-40 (4)	41.1±0.5	33.0±0.1 (+24.5%)	**32.4±0.3 (+26.9%)**	32.6±0.3 (+26.1%)

RNN-based method is only better than the random strategy on tasks with few tables/devices, but is worse on harder tasks. A possible reason is that RNN-based algorithm does not have a cost network, and using RL alone could lead to unstable performance. **5)** Lookup-based strategy is the best baseline on the DLRM dataset, while dim-based strategy is better on the Prod dataset. A potential reason is that the tables in the Prob dataset have very diverse table dimensions, while the tables in the DLRM dataset have the same dimension. As such, the dimensions on Prod tasks can more easily become imbalanced, leading to poor communication efficiency. Dim-based strategy can better balance the dimensions, which leads to a better overall performance. DreamShard outperforms the baselines on both the DLRM and the Prod datasets, showing its flexibility in dealing with different scenarios.

Analysis of generalizability (RQ2). In Table 2, we directly apply a DreamShard model trained from one task to another task *without any fine-tuning* (the rightmost column), where the source and the target tasks have different numbers of tables and/or devices. DreamShard shows neglectable performance drop, suggesting that it is generalizable across different numbers of tables and/or devices.

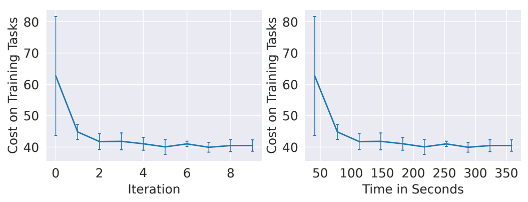


Figure 5: Performance (↓) of DreamShard on the DLRM-50 (4) datasets w.r.t. the numbers of iterations (**left**) and running time (**right**). Curves for other tasks are in Appendix H.

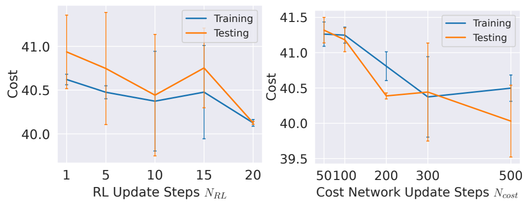


Figure 6: Impacts of the number of RL update steps N_{RL} (**left**) and cost network update steps N_{cost} (**right**) on the DLRM-50 (4) dataset. Curves for other tasks are in Appendix I.

Table 3: Ablation study of DreamShard. Results on other tasks are in Appendix J.

Task		w/o dim	w/o hash size	w/o pooling factor	w/o table size	w/o distribution	w/o cost	w/ RNN	DreamShard
DLRM-50 (4)	Train	40.8±0.4	40.7±0.1	46.3±0.3	40.8±0.4	40.6±0.2	47.5±1.2	40.5±0.2	**40.4±0.5**
	Test	40.9±0.6	40.6±0.3	47.2±0.1	40.6±0.7	40.5±0.2	46.3±0.1	40.5±0.1	**40.4±0.6**

Analysis of training efficiency (RQ3). Figure 5 plots the performance of DreamShard w.r.t. the number of iterations and running time in seconds on four 1080Ti GPUs. The training of DreamShard is highly efficient. On DLRM-50 (4), it can achieve strong performance in less than 5 iterations or 200 seconds. Note that we only need to re-train or fine-tune DreamShard when the table pools have significant changes. Once trained, it only needs a forward pass for inference.

Hyperparameter study (RQ4). We study the impacts of two key hyperparameters: **1)** N_{RL}, which controls the RL update frequency, and **2)** N_{cost}, which determines the cost network update frequency. We vary one of them with the other fixed, shown in Figure 6. Increasing N_{RL} or N_{cost} will both lead to improvement, suggesting that both the cost network and the policy network need to be sufficiently trained. However, when N_{RL} and N_{cost} are large enough, increasing them will not bring more improvement. Considering that larger values will lead to more computational costs, we set $N_{\text{RL}} = 10$ or $N_{\text{cost}} = 300$ as a trade-off between the performance and the training efficiency.

Ablation study (RQ5). We study the importance of each table feature and check whether the RNN architecture helps, with the following ablations. **1)** We remove each of the features in the state. **2)** We add an RNN upon the device representation in the policy network. We makes several observations from the results in Table 3. **1)** Cost features play a significant role, which demonstrates the effectiveness of our proposed augmented state. **2)** The most contributing table features are the pooling factor and the dimension, which aligns with our intuitions since these two feature are the determining factors of computation and communication workloads. **3)** Using more features leads to consistently good performance. **4)** While the policy makes decisions sequentially, RNN does not provide clear benefits. This is why we have kept the architecture simple with only MLP in DreamShard.

Study of the estimated MDP (RQ6). First, we study how many data points are required to train an accurate cost network, and how accurate the cost network needs to be to enable a strong policy. Specifically, we randomly sample 10,000 cost data points from the DLRM-50 (4) dataset. Then we use 20% for testing, and vary the size of the training data to train the cost network. Further, we fully train a policy network with 100 iterations based on each of the trained cost networks. We make two observations from the results in Figure 7. **1)** As expected, more data points lead to a more accurate cost network. **2)** Interestingly, after around 100 data points, the policy network does not keep improving even though the cost network becomes more accurate. Thus, we only need a sufficiently (but not perfectly) accurate cost estimation to achieve the best performance. This also partially explains why DreamShard can generalize: even though the cost network could be not very accurate on unseen tables, DreamShard can still find strong placements with the policy network. **Second,** we study the necessity of the estimated MDP. We consider a variant that obtains the cost features and rewards directly from GPUs, shown in Figure 8. Using the estimated MDP can make the training and the inference orders of magnitudes faster, while achieving the same level of performance. In particular, the inference time is less than one second even with a hundred tables.

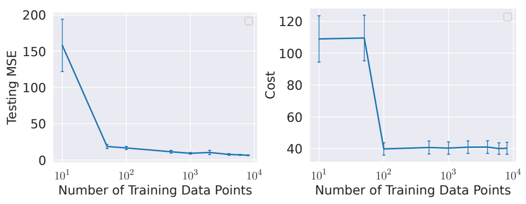


Figure 7: MSE of the cost network w.r.t. the number of training data points collected from GPUs (**left**), and the corresponding performance of a fully trained policy network based on the trained cost network (**right**) on the DLRM-50 (4) dataset.

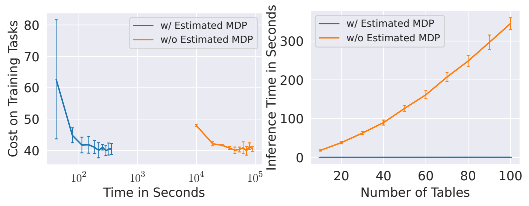


Figure 8: Training curves w/ or w/o the estimated MDP on DLRM-50 (4) dataset (**left**), and their inference times w.r.t. the number of tables (**right**). Using cost network to estimate the MDP leads orders of magnitudes faster training and inference.

5 Related Work

Embedding tables. Embedding tables are commonly used to deal with sparse features in recommendation models [1, 2, 3, 4, 5, 29, 30, 31]. However, the extremely large embedding tables are often the storage and efficiency bottlenecks [6, 7, 8, 3, 6, 9, 10, 11, 32]. To our knowledge, the only two studies that target the embedding table placement problem are RecShard [27] and our previous work AutoShard [33]. RecShard approaches table placement at a per-row granularity through exploitation of the underlying feature distributions. RecShard leverages these distributions, along with characteristics of the training system, to shard embedding tables across a tiered memory hierarchy using a mixed integer linear program, with more frequent rows placed in GPU HBM and the remaining placed in CPU DRAM. In contrast, our work develops a neural cost network for cost estimation and an RL-based optimization algorithm, and focuses on sharding across a single memory layer as opposed to a tiered memory hierarchy. AutoShard also leverages RL for embedding table sharding. However, it only balances the computational costs, which will lead to sub-optimal solutions since communication also account for significant costs. In addition, our DreamShard is more efficient in training than AutoShard due to the design of the estimated MDP. Another line of work focuses on reducing the embedding table sizes [34, 35, 36, 37, 38, 39, 40], which is orthogonal to our work since DreamShard is also applicable to compressed tables.

Device placement optimization. The existing device placement techniques can be mainly grouped into two categories: RL-based algorithms, and cost modeling methods. **1)** RL-based algorithms treat the device placement as a black box and optimize the cost objective in a trial-and-error fashion [13, 14, 15, 16, 17, 18, 19, 20]. Unfortunately, these methods are computationally expensive and often require training from scratch on unseen tasks. While Placeto [16] shows generalizabily on computational graphs with graph embeddings, it can not deal with various table combinations since there is no graph structure, and it can not handle different numbers of devices. **2)** Cost modeling methods build a cost model to reflect the real performance and adopt offline algorithms (e.g., scheduling, and dynamic programming) to optimize the placement [41, 42, 43, 44, 45]. However, the cost model could be inaccurate. In particular, they can not deal with the operation fusion of embedding tables. Whereas, DreamShard combines the advances of RL with a neural cost model for accurate cost prediction.

Deep RL. Deep RL has recently made significant progress in games [46, 47, 48, 49, 50, 51, 52, 53, 54]. Our work is related to using RL to optimize machine learning model designs, such as neural architecture search [55, 56, 57, 58, 59], data augmentation [60], data sampling [61, 62], pipeline search [63, 64, 65]. However, these methods often only focus on one task and can not generalize to unseen tasks. Our work is related to meta-learning [66, 67, 68]. Instead of performing meta-learning for machine learning tasks, we focus on machine learning system design. Our work is also related to solving combinational optimization problems with RL [24, 69]. Unlike the above studies, we show that RL can tackle a practical problem of embedding table placement and the learned policy is generalizable.

6 Conclusions and Future Work

We present DreamShard for embedding table placement in recommender systems. We formulate the problem as an MDP which places the tables one by one at each step. Then we leverage RL to solve the MDP. To accelerate the training and the inference, we build an estimated MDP by training a cost network to approximate the state features (i.e., computation and communication times) and the reward (i.e., the overall cost), leading to orders of magnitudes faster training and inference speeds. Extensive experiments on the open-sourced DLRM dataset and our production dataset demonstrate the superiority of DreamShard over the existing algorithms. Moreover, DreamShard shows strong generalizability, making it a desirable choice in real-world applications. In the future, we will extend DreamShard to tiered memory hierarchy and large-scale training clusters with complex topologies.

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References

[1] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys (CSUR)*, 52(1):1–38, 2019.

[2] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. Wide & deep learning for recommender systems. In *DLRS Workshop*, 2016.

[3] Maxim Naumov, Dheevatsa Mudigere, Hao-Jun Michael Shi, Jianyu Huang, Narayanan Sundaraman, Jongsoo Park, Xiaodong Wang, Udit Gupta, Carole-Jean Wu, Alisson G Azzolini, et al. Deep learning recommendation model for personalization and recommendation systems. *arXiv preprint arXiv:1906.00091*, 2019.

[4] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. In *WWW*, 2017.

[5] Weiping Song, Chence Shi, Zhiping Xiao, Zhijian Duan, Yewen Xu, Ming Zhang, and Jian Tang. Autoint: Automatic feature interaction learning via self-attentive neural networks. In *CIKM*, 2019.

[6] Weijie Zhao, Deping Xie, Ronglai Jia, Yulei Qian, Ruiquan Ding, Mingming Sun, and Ping Li. Distributed hierarchical gpu parameter server for massive scale deep learning ads systems. In *MLSys*, 2020.

[7] Paul Covington, Jay Adams, and Emre Sargin. Deep neural networks for youtube recommendations. In *RecSys*, 2016.

[8] Bilge Acun, Matthew Murphy, Xiaodong Wang, Jade Nie, Carole-Jean Wu, and Kim Hazelwood. Understanding training efficiency of deep learning recommendation models at scale. In *HPCA*, 2021.

[9] Amazon dsstne: Deep scalable sparse tensor network engine. `https://github.com/amazon-archives/amazon-dsstne`.

[10] Udit Gupta, Carole-Jean Wu, Xiaodong Wang, Maxim Naumov, Brandon Reagen, David Brooks, Bradford Cottel, Kim Hazelwood, Mark Hempstead, Bill Jia, et al. The architectural implications of facebook's dnn-based personalized recommendation. In *HPCA*, 2020.

[11] Maxim Naumov, John Kim, Dheevatsa Mudigere, Srinivas Sridharan, Xiaodong Wang, Whitney Zhao, Serhat Yilmaz, Changkyu Kim, Hector Yuen, Mustafa Ozdal, et al. Deep learning training in facebook data centers: Design of scale-up and scale-out systems. *arXiv preprint arXiv:2003.09518*, 2020.

[12] Wikipedia. Partition problem — Wikipedia, the free encyclopedia. `http://en.wikipedia.org/w/index.php?title=Partition%20problem&oldid=1085673119`, 2022. [Online; accessed 05-May-2022].

[13] Azalia Mirhoseini, Hieu Pham, Quoc V Le, Benoit Steiner, Rasmus Larsen, Yuefeng Zhou, Naveen Kumar, Mohammad Norouzi, Samy Bengio, and Jeff Dean. Device placement optimization with reinforcement learning. In *ICML*, 2017.

[14] Azalia Mirhoseini, Anna Goldie, Hieu Pham, Benoit Steiner, Quoc V Le, and Jeff Dean. A hierarchical model for device placement. In *ICLR*, 2018.

[15] Yuanxiang Gao, Li Chen, and Baochun Li. Spotlight: Optimizing device placement for training deep neural networks. In *ICML*, 2018.

[16] Ravichandra Addanki, Shaileshh Bojja Venkatakrishnan, Shreyan Gupta, Hongzi Mao, and Mohammad Alizadeh. Placeto: learning generalizable device placement algorithms for distributed machine learning. In *NeurIPS*, 2019.

[17] Yanqi Zhou, Sudip Roy, Amirali Abdolrashidi, Daniel Wong, Peter C Ma, Qiumin Xu, Ming Zhong, Hanxiao Liu, Anna Goldie, Azalia Mirhoseini, et al. Gdp: Generalized device placement for dataflow graphs. *arXiv preprint arXiv:1910.01578*, 2019.

[18] Aditya Paliwal, Felix Gimeno, Vinod Nair, Yujia Li, Miles Lubin, Pushmeet Kohli, and Oriol Vinyals. Reinforced genetic algorithm learning for optimizing computation graphs. In *ICLR*, 2019.

[19] Yuanxiang Gao, Li Chen, and Baochun Li. Post: Device placement with cross-entropy minimization and proximal policy optimization. In *NeurIPS*, 2018.

[20] Anna Goldie and Azalia Mirhoseini. Placement optimization with deep reinforcement learning. In *ISPD*, 2020.

[21] Wei Niu, Jiexiong Guan, Yanzhi Wang, Gagan Agrawal, and Bin Ren. Dnnfusion: accelerating deep neural networks execution with advanced operator fusion. In *PLDI*, 2021.

[22] Daya Khudia, Jianyu Huang, Protonu Basu, Summer Deng, Haixin Liu, Jongsoo Park, and Mikhail Smelyanskiy. Fbgemm: Enabling high-performance low-precision deep learning inference. *arXiv preprint arXiv:2101.05615*, 2021.

[23] github. Embedding lookup synthetic dataset, 2021.

[24] Irwan Bello, Hieu Pham, Quoc V Le, Mohammad Norouzi, and Samy Bengio. Neural combinatorial optimization with reinforcement learning. *arXiv preprint arXiv:1611.09940*, 2016.

[25] David Ha and Jürgen Schmidhuber. World models. *arXiv preprint arXiv:1803.10122*, 2018.

[26] Danijar Hafner, Timothy Lillicrap, Jimmy Ba, and Mohammad Norouzi. Dream to control: Learning behaviors by latent imagination. In *ICLR*, 2019.

[27] Geet Sethi, Bilge Acun, Niket Agarwal, Christos Kozyrakis, Caroline Trippel, and Carole-Jean Wu. Recshard: Statistical feature-based memory optimization for industry-scale neural recommendation. In *ASPLOS*, 2022.

[28] Michael Lui, Yavuz Yetim, Özgür Özkan, Zhuoran Zhao, Shin-Yeh Tsai, Carole-Jean Wu, and Mark Hempstead. Understanding capacity-driven scale-out neural recommendation inference. In *ISPASS*, 2021.

[29] Jizhe Wang, Pipei Huang, Huan Zhao, Zhibo Zhang, Binqiang Zhao, and Dik Lun Lee. Billion-scale commodity embedding for e-commerce recommendation in alibaba. In *KDD*, 2018.

[30] Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian, Xing Xie, and Wei-Ying Ma. Collaborative knowledge base embedding for recommender systems. In *KDD*, 2016.

[31] Weijie Zhao, Jingyuan Zhang, Deping Xie, Yulei Qian, Ronglai Jia, and Ping Li. Aibox: Ctr prediction model training on a single node. In *CIKM*, 2019.

[32] Xiangru Lian, Binhang Yuan, Xuefeng Zhu, Yulong Wang, Yongjun He, Honghuan Wu, Lei Sun, Haodong Lyu, Chengjun Liu, Xing Dong, et al. Persia: A hybrid system scaling deep learning based recommenders up to 100 trillion parameters. *arXiv preprint arXiv:2111.05897*, 2021.

[33] Daochen Zha, Louis Feng, Bhargav Bhushanam, Dhruv Choudhary, Jade Nie, Yuandong Tian, Jay Chae, Yinbin Ma, Arun Kejariwal, and Xia Hu. Autoshard: Automated embedding table sharding for recommender systems. In *KDD*, 2022.

[34] Caojin Zhang, Yicun Liu, Yuanpu Xie, Sofia Ira Ktena, Alykhan Tejani, Akshay Gupta, Pranay Kumar Myana, Deepak Dilipkumar, Suvadip Paul, Ikuhiro Ihara, et al. Model size reduction using frequency based double hashing for recommender systems. In *RecSys*, 2020.

[35] Hao-Jun Michael Shi, Dheevatsa Mudigere, Maxim Naumov, and Jiyan Yang. Compositional embeddings using complementary partitions for memory-efficient recommendation systems. In *KDD*, 2020.

[36] Xiangyu Zhao, Chong Wang, Ming Chen, Xudong Zheng, Xiaobing Liu, and Jiliang Tang. Autoemb: Automated embedding dimensionality search in streaming recommendations. In *SIGIR*, 2020.

[37] Manas R Joglekar, Cong Li, Mei Chen, Taibai Xu, Xiaoming Wang, Jay K Adams, Pranav Khaitan, Jiahui Liu, and Quoc V Le. Neural input search for large scale recommendation models. In *KDD*, 2020.

[38] Siyi Liu, Chen Gao, Yihong Chen, Depeng Jin, and Yong Li. Learnable embedding sizes for recommender systems. In *ICLR*, 2021.

[39] Wang-Cheng Kang, Derek Zhiyuan Cheng, Ting Chen, Xinyang Yi, Dong Lin, Lichan Hong, and Ed H Chi. Learning multi-granular quantized embeddings for large-vocab categorical features in recommender systems. In *WWW*, 2020.

[40] Wang-Cheng Kang, Derek Zhiyuan Cheng, Tiansheng Yao, Xinyang Yi, Ting Chen, Lichan Hong, and Ed H Chi. Learning to embed categorical features without embedding tables for recommendation. In *KDD*, 2021.

[41] Eugene L Lawler, Jan Karel Lenstra, Alexander HG Rinnooy Kan, and David B Shmoys. Sequencing and scheduling: Algorithms and complexity. *Handbooks in operations research and management science*, 4:445–522, 1993.

[42] Zhihao Jia, Matei Zaharia, and Alex Aiken. Beyond data and model parallelism for deep neural networks. In *MLSys*, 2019.

[43] Zhihao Jia, Sina Lin, Charles R Qi, and Alex Aiken. Exploring hidden dimensions in parallelizing convolutional neural networks. In *ICML*, 2018.

[44] Deepak Narayanan, Aaron Harlap, Amar Phanishayee, Vivek Seshadri, Nikhil R Devanur, Gregory R Ganger, Phillip B Gibbons, and Matei Zaharia. Pipedream: generalized pipeline parallelism for dnn training. In *SOSP*, 2019.

[45] Jakub M Tarnawski, Amar Phanishayee, Nikhil Devanur, Divya Mahajan, and Fanny Nina Paravecino. Efficient algorithms for device placement of dnn graph operators. In *NeurIPS*, 2020.

[46] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*, 2013.

[47] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge. *nature*, 550(7676):354–359, 2017.

[48] Daochen Zha, Jingru Xie, Wenye Ma, Sheng Zhang, Xiangru Lian, Xia Hu, and Ji Liu. Douzero: Mastering doudizhu with self-play deep reinforcement learning. In *ICML*, 2021.

[49] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

[50] Daochen Zha, Kwei-Herng Lai, Kaixiong Zhou, and Xia Hu. Simplifying deep reinforcement learning via self-supervision. *arXiv preprint arXiv:2106.05526*, 2021.

[51] Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. In *ICLR*, 2016.

[52] Marcin Andrychowicz, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, OpenAI Pieter Abbeel, and Wojciech Zaremba. Hindsight experience replay. *NeurIPS*, 2017.

[53] Daochen Zha, Wenye Ma, Lei Yuan, Xia Hu, and Ji Liu. Rank the episodes: A simple approach for exploration in procedurally-generated environments. In *ICLR*, 2021.

[54] Daochen Zha, Kwei-Herng Lai, Songyi Huang, Yuanpu Cao, Keerthana Reddy, Juan Vargas, Alex Nguyen, Ruzhe Wei, Junyu Guo, and Xia Hu. Rlcard: a platform for reinforcement learning in card games. In *IJCAI*, 2021.

[55] Barret Zoph and Quoc V Le. Neural architecture search with reinforcement learning. In *ICLR*, 2017.

[56] Yicheng Wang, Xiaotian Han, Chia-Yuan Chang, Daochen Zha, Ulisses Braga-Neto, and Xia Hu. Auto-pinn: Understanding and optimizing physics-informed neural architecture. *arXiv preprint arXiv:2205.13748*, 2022.

[57] Yuening Li, Zhengzhang Chen, Daochen Zha, Kaixiong Zhou, Haifeng Jin, Haifeng Chen, and Xia Hu. Automated anomaly detection via curiosity-guided search and self-imitation learning. *IEEE Transactions on Neural Networks and Learning Systems*, 2021.

[58] Hieu Pham, Melody Guan, Barret Zoph, Quoc Le, and Jeff Dean. Efficient neural architecture search via parameters sharing. In *ICML*, 2018.

[59] Yuening Li, Zhengzhang Chen, Daochen Zha, Kaixiong Zhou, Haifeng Jin, Haifeng Chen, and Xia Hu. Autood: Neural architecture search for outlier detection. In *ICDE*, 2021.

[60] Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation policies from data. *arXiv preprint arXiv:1805.09501*, 2018.

[61] Daochen Zha, Kwei-Herng Lai, Mingyang Wan, and Xia Hu. Meta-aad: Active anomaly detection with deep reinforcement learning. In *ICDM*, 2020.

[62] Daochen Zha, Kwei-Herng Lai, Qiaoyu Tan, Sirui Ding, Na Zou, and Xia Hu. Towards automated imbalanced learning with deep hierarchical reinforcement learning. In *CIKM*, 2022.

[63] Iddo Drori, Yamuna Krishnamurthy, Remi Rampin, Raoni de Paula Lourenco, Jorge Piazentin Ono, Kyunghyun Cho, Claudio Silva, and Juliana Freire. Alphad3m: Machine learning pipeline synthesis. *arXiv preprint arXiv:2111.02508*, 2021.

[64] Daochen Zha, Zaid Pervaiz Bhat, Yi-Wei Chen, Yicheng Wang, Sirui Ding, Anmoll Kumar Jain, Mohammad Qazim Bhat, Kwei-Herng Lai, Jiaben Chen, et al. Autovideo: An automated video action recognition system. In *IJCAI*, 2022.

[65] Kwei-Herng Lai, Daochen Zha, Guanchu Wang, Junjie Xu, Yue Zhao, Devesh Kumar, Yile Chen, Purav Zumkhawaka, Minyang Wan, Diego Martinez, et al. Tods: An automated time series outlier detection system. In *AAAI*, 2021.

[66] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *ICML*, 2017.

[67] Yue Zhao, Ryan Rossi, and Leman Akoglu. Automatic unsupervised outlier model selection. *NeurIPS*, 2021.

[68] Yue Zhao and Leman Akoglu. Towards unsupervised hpo for outlier detection. *arXiv preprint arXiv:2208.11727*, 2022.

[69] Thomas Barrett, William Clements, Jakob Foerster, and Alex Lvovsky. Exploratory combinatorial optimization with reinforcement learning. In *AAAI*, 2020.

[70] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. Deep interest evolution network for click-through rate prediction. In *AAAI*, 2019.

[71] David C Liu, Stephanie Rogers, Raymond Shiau, Dmitry Kislyuk, Kevin C Ma, Zhigang Zhong, Jenny Liu, and Yushi Jing. Related pins at pinterest: The evolution of a real-world recommender system. In *WWW*, 2017.

[72] Carlos A Gomez-Uribe and Neil Hunt. The netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems (TMIS)*, 6(4):1–19, 2015.

[73] Ronald J Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning*, 8(3):229–256, 1992.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] We have described the limitations in the future work.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Our work does have any potential negative societal impacts to our knowledge.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] The datasets are public. All the codes will be open-sourced.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] We provide all the details in the appendix.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We have run all the experiments five times. The mean and the standard deviation are reported.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] We have described the hardware in the appendix.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [No] But it is mentioned in the link we provided.
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]