A Scalable Deep Reinforcement Learning Model for Online Scheduling Coflows of Multi-Stage Jobs for High Performance Computing

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Abstract—Coflow is a recently proposed networking abstraction to help improve the communication performance of data-parallel computing jobs. In multi-stage jobs, each job consists of multiple coflows and is represented by a Directed Acyclic Graph (DAG). Efficiently scheduling coflows is critical to improve the data-parallel computing performance in data centers. Compared with hand-tuned scheduling heuristics, existing work DeepWeave [1] utilizes Reinforcement Learning (RL) framework to generate highly-efficient coflow scheduling policies automatically. It employs a graph neural network (GNN) to encode the job information in a set of embedding vectors, and feeds a flat embedding vector containing the whole job information to the policy network. However, this method has poor scalability as it is unable to cope with jobs represented by DAGs of arbitrary sizes and shapes, which requires a large policy network for processing a high-dimensional embedding vector that is difficult to train. In this paper, we first utilize a directed acyclic graph neural network (DAGNN) to process the input and propose a novel Pipelined-DAGNN, which can effectively speed up the feature extraction process of the DAGNN. Next, we feed the embedding sequence composed of schedulable coflows instead of a flat embedding of all coflows to the policy network, and output a priority sequence, which makes the size of the policy network depend on only the dimension of features instead of the product of dimension and number of nodes in the job’s DAG. Furthermore, to improve the accuracy of the priority scheduling policy, we incorporate the Self-Attention Mechanism into a deep RL model to capture the interaction between different parts of the embedding sequence to make the output priority scores relevant. Based on this model, we then develop a coflow scheduling algorithm for online multi-stage jobs. Our simulation results are based on the real trace of Facebook. Compared with a state-of-the-art approach, our model can shorten the average weighted job completion time by up to 40.42% and complete jobs at least 1.68 times faster. It also has better scalability and robustness.

Index Terms—coflow scheduling, reinforcement learning, graph neural network, attention mechanism, parallel processing.

1 INTRODUCTION

Data parallel frameworks, such as MapReduce [2], Hadoop [3] and Spark [4] are very popular in cloud applications. In typical data center applications, the execution process is an application consisting of multiple consecutive stages. Each stage relies on several parallel flows, and the next stage cannot begin until all flows in the current stage have been transmitted. Therefore, the traditional network metrics, such as minimizing the average flow completion time (FCT), though can guarantee the performance at the flow level, is unable to effectively improve the transmission performance of the application.

The coflow abstraction was first proposed in [5] to improve the application-level communication performance, which is defined as a collection of parallel flows with the same application semantic, usually appearing between two stages of a job, (e.g. shuffle flows in MapReduce). Fig. 1 shows the shuffle process in MapReduce, where flows in one shuffle phase are termed a coflow. The MapReduce shuffle phase will not complete until all parallel flows have finished transmission. Obviously, the slowest flow in a coflow critically affects the completion time of reducer tasks. Hence, coflow completion time (CCT) is the completion time of the slowest flow within a coflow and minimizing CCT will speed up the completion of the corresponding job [5].

Fig. 1: Coflow abstraction in parallel computing

To improve the communication performance of data-parallel computing jobs, many scheduling methods [6], [7], [8], [9], [10], [11] have been proposed to minimize CCT. These researches have greatly accelerated the execution of a single-stage job containing only one coflow, where minimizing CCT implies minimizing job completion time (JCT). However, in the data-parallel computing framework, multi-stage jobs are common. The structure of a multi-stage job is shown in Fig. 2, where the nodes represent the coflows and the directed edges represent the dependencies between them. Each multi-stage job contains multiple coflows with dependencies, and each coflow is composed of...
multiple parallel flows. There are two types of dependencies: \textit{starts-after} dependency and \textit{finishes-before} dependency [12], where \textit{starts-after} indicates that $C_2$ cannot start until $C_1$ has finished and \textit{finishes-before} indicates that $C_2$ can coexist with $C_1$ but it cannot finish until $C_1$ has finished.

In the multi-stage job scenarios, minimizing the average CCT does not necessarily lead to minimizing jobs completion time because the dependencies in a job should be considered. To tackle this problem, several heuristics [12] and approximation solutions [13], [14] have recently been proposed to minimize CCT. However, they simplified the problem with some relaxation and ignored the workflow characteristics. In recent years, with the development of artificial intelligence, machine learning methods have been increasingly applied to task scheduling problems in cloud data centers. Reinforcement learning (RL), as a current research hotspot in the field of machine learning, is used by many researchers to solve task scheduling problems in complex data center environments. [15], [16], [17]. RL can learn directly from the actual working environment without relying on inaccurate empirical summaries. Compared with traditional reinforcement learning, Deep Reinforcement Learning (DRL) [18] has powerful representation capabilities of neural networks and decision-making capabilities in the field of control.

DeepWeave [1] is the first to use the RL framework to generate efficient coflow scheduling strategies in job DAGs automatically. In DeepWeave, the node embeddings obtained after GNN processing is directly flattened into a high-dimensional embedding vector containing all the information as the input of the policy network. However, this intuitive approach cannot scale to the job DAG of arbitrary size and shape, particularly because neural networks usually require fixed-sized vectors as inputs and processing a high-dimensional feature vector would require a large policy network that is difficult to train [19]. In addition, DeepWeave considers the scheduling problem of a single job DAG while ignoring the online situation where multiple multi-stage jobs coexist, i.e., there is the newly coming job DAG in addition to the existing ones that have not finished their transmission in the network.

The contributions of this paper can be summarized as follows:

- We propose a novel Pipelined-DAGNN that can effectively speed up the feature extraction process of DAGNN [20] and encode the job information in a set of embedding vectors.
- We present a novel scalable deep RL model that feeds an embedding sequence of vectors to the policy network instead of creating a high-dimensional flat embedding vector as DeepWeave [1], which significantly reduces the size of the policy network and hence can process DAGs of arbitrary sizes and shapes.
- We propose a novel scheme of incorporating the self-attention mechanism into the deep RL model to capture the interaction between schedulable coflows encoded as the embedding sequence, and thus remedy the accuracy loss in our output policy without packing individual embedding vectors into a long flat vector.
- We evaluate the model’s performance using real-life traces and generated traces. Simulation results show our model outperforms state-of-the-art solutions in terms of the total weighted JCT.

The remainder of the paper is organized as follows: Section 2 discusses the related work in recent years. Section 3 mathematically formulates the problem we study. Section 4 and Section 5 describe the proposed model and online scheduling algorithm, respectively. Section 6 presents the experimental results of our algorithm on real-world data collected from Facebook and performance comparison with

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**Fig. 2: Multi-stage job structure**

It has been shown that even if all coflows arrive simultaneously and their sizes are known in advance, the coflow scheduling problem of single-stage jobs is NP-hard [6]. Therefore, the coflow scheduling problem of online multi-stage jobs is more challenging. In this paper, we propose an Attention-based Reinforcement Learning Model to generate coflow scheduling policies for multi-stage jobs, which can process DAGs of arbitrary sizes and shape while ensuring the accuracy of the scheduling strategy. Considering that jobs from different applications have different importance, jobs with larger weights should be given priority. In this paper, we take average/total weighted JCT as the main optimization goal.
the state-of-the-art work. Finally, Section 7 concludes the paper.

2 Related Work

Coflow abstraction can better capture application-level semantics, thereby improving the communication performance of distributed data-parallel jobs. Existing work mostly focuses on scheduling coflows in single-stage jobs and minimizing coflow completion time (CCT) as the optimization goal. However, only a few works consider multi-stage scenarios, which concentrate on minimizing job completion time (JCT). Next, we introduce related work from these two aspects.

Single-Stage Scheduling: For the single-stage job scheduling problem, many heuristic algorithms have been proposed to minimize CCT, including heuristic algorithms [21], [6], [7], [8]. Orchestra [21] is perhaps the first work to mention the concept of coflow and shows that even a simple FIFO algorithm can significantly improve coflow performance. Coflow abstraction is later formally defined in [5]. Varys [6] proposes the smallest-effective-bottleneck-first (SEBF) and minimum-allocation-for-desired-duration (MADD) heuristic algorithms to greedily schedule coflows according to the bottleneck completion time of coflow to minimize CCT and meet the deadline of coflow at the same time. Barrat [7] and Stream [8] both aim at decentralized coflow scheduling, and Barrat [7] exploits multiplexing to prevent head-of-line blocking to small coflows. There is also some theoretical work [9], [10], [11] aimed at minimizing the approximate algorithm of the total weighted CCT. [9] provided the first deterministic algorithm with a constant approximation ratio of \( \frac{8}{7} \) to minimize the total weighted CCT. [10] presented a 12-approximation ratio algorithm by reducing to concurrent open shop problem, and [11] further proposed a 5-approximation ratio algorithm by relaxing the problem to linear programming (LP). The work as mentioned above abstracts the network topology as a big non-blocking switch fabric, with no consideration of the constraints of network resources. Now, several research works have considered network resource constraints and combined routing and resource scheduling to minimize CCT [22], [23]. Rapier [22] is the first algorithm that considers routing and scheduling jointly to minimize CCT. However, it is a heuristic solution and cannot provide theoretical performance guarantees. Next, Tian et al. [23] proposed a rounding-based randomization algorithm for single coflow and online algorithms to provide performance guarantees for multiple coflow routing and scheduling. Recently, a distributed bottleneck aware coflow scheduling algorithm [24] was proposed to minimize CCT by reducing network bottlenecks and improving link capacity utilization. However, these algorithms focus on minimizing CCT without considering the dependencies among coflows of multi-stage jobs.

Multi-Stage Scheduling: Among the above methods, some have been proven to be effective for single-stage job scheduling problems, they may not be suitable for solving coflow scheduling problems in multi-stage jobs. In a multi-stage job scenario, due to the dependency between coflows, minimizing CCT may not minimize JCT. To the best of our knowledge, only a few works [12], [13], [1], [25] considered the coflow scheduling problem in the case of multi-stage jobs. Aalo [12] is the first effective heuristic algorithm with the objective of minimizing JCT, which discusses coflow scheduling in multi-stage jobs, and proposes to prioritize coflows according to dependency orders to schedule coflow. However, it only takes a short section to discuss the heuristic algorithm without neither formal formulation and analysis. Tian et al. [13] proposed a deterministic algorithm with an M-approximation ratio by relaxing the multi-stage job scheduling problem to LP, where M represents the number of machines. Unfortunately, it cannot be used in online cases as all job statistics are required to be known in advance to solve the relevant LP. DeepWeave [1] is the first to propose a reinforcement learning model to solve the coflow scheduling problem, which can adaptively generate an efficient coflow scheduling policy without human expertise. However, this approach cannot scale to job DAGs of arbitrary sizes and shapes, and ignores the online situation where multiple multi-stage jobs coexist in the network. Similarly, [25] is the first to study how to schedule multi-stage jobs under taking network resource constraints into account so as to minimize the total weighted JCT.

In this paper, we ignore network resource constraints and only consider the problem of minimizing the total weighted JCT of multi-stage jobs in a large non-blocking switch.

3 Formulation

In this section, we first introduce the model of datacenter networks and multi-stage jobs, and then formulate the coflow scheduling problem in multi-stage jobs. The notations to be used are listed in Tables 1 and 2.

TABLE 1: Notations of constants.

| Symbol | Definition |
|--------|------------|
| \( N \) | The number of jobs |
| \( K_n \) | The number of coflows in job \( j_n \) |
| \( P \) | The size of network |
| \( M_{n,k} \) | The number of flows in coflow \( c_{n,k} \) |
| \( X_{n,k,k'} \) | The binary constant indicates whether there is a dependency: coflow \( c_{n,k} \) starts after coflow \( c_{n,k'} \) |
| \( a_n \) | The arrival time of job \( j_n \) |
| \( w_n \) | The weight of job \( j_n \) |
| \( b_{n,k,m} \) | The total bytes of flow \( f_{n,k,m} \) |

TABLE 2: Notations of variables.

| Symbol | Definition |
|--------|------------|
| \( J_n \) | The completion time of job \( j_n \) |
| \( C_{n,k} \) | The completion time of coflow \( c_{n,k} \) |
| \( F_{n,k,m} \) | The completion time of flow \( f_{n,k,m} \) |
| \( T_{n,k,m} \) | The starting transmission time of flow \( f_{n,k,m} \) |
| \( r_n \) | The release time of job \( j_n \) |

3.1 Model

Network Model: We extract the network topology as a \( P \times P \) non-blocking switch fabric, with \( P \) ingress ports connected to \( P \) source servers and \( P \) egress ports connected to \( P \) destination servers. Without loss of generality, we assume that each ingress/egress port has a capacity of 1Gbps, equivalently 128MBps. In the online simulation, we choose
the time unit as $1/128$ second accordingly so that each port has a capacity of 1MB per time unit. Fig. 3 shows the scheduling of coflows through a $3 \times 3$ datacenter fabric. Under this model, each ingress port has flows from one or more coflows to various egress ports, port-sharing is allowed, and it is assumed that congestion occurs only at the ingress and egress ports. Coflows 1 and 2 can share the network resources at the same time because they are independent. Once all their flows are transmitted, coflow 3 will be ready to be transmitted. According to the starts-after dependency, only when all flows in coflow 1 and coflow 2 are completed, coflow 3 can be released.

![Diagram of coflow scheduling over a $3 \times 3$ data center fabric](image)

Fig. 3: Coflow scheduling over a $3 \times 3$ data center fabric

**Job Model:** Considering $N$ jobs in the network, denoted by $j_1, j_2, \ldots, j_N$, arriving at $a_1, a_2, \ldots, a_N$ respectively, and the arrival time of each job obeys Poisson distribution. In the context of our multi-stage jobs, information about future jobs is not known. The information of each job $j_n$ containing $K_n$ coflows, denoted by $c_{n,1}, c_{n,2}, \ldots, c_{n,K_n}$ is given at arrival. Each coflow $c_{n,k}$ contains $M_{n,k}$ parallel flows, denoted by $f_{n,k,1}, f_{n,k,2}, \ldots, f_{n,k,M_{n,k}}$, and the total bytes of flow $f_{n,k,m}$ is $b_{n,k,m}$.

### 3.2 Problem formulation

In the scenario of multi-stage jobs, we want to optimize the overall performance of weighted jobs by minimizing the total weighted JCT.

$$\min \sum_{n=1}^{N} w_n J_n$$

(1)

where $J_n$ denotes the completion time of job $j_n$, the weights capture different priorities for different jobs and important jobs are prioritized by assigning higher weights. Therefore, minimizing the average JCT is a special case of our goal when all weights are equal.

The completion time of a multi-stage job depends on the completion time of the latest coflow that completes it. So

$$J_n = \max_{k \in \{1, 2, \ldots, K_n\}} C_{n,k}, \forall n \in \{1, 2, \ldots, N\}$$

(2)

where $C_{n,k}$ represents the completion time of coflow $c_{n,k}$.

Similarly, the completion time of a coflow depends on the completion time of the latest flow that completes it. Hence,

$$C_{n,k} = \max_{m \in \{1, 2, \ldots, M_{n,k}\}} F_{n,k,m}, \forall n \in \{1, 2, \ldots, N\},$$

$$k \in \{1, 2, \ldots, K_n\}$$

(3)

where $F_{n,k,m}$ represents the completion time of flow $f_{n,k,m}$.

**Start time constraints:** Flows in a job can start its transmission only after the job is released. So

$$\forall n \in \{1, 2, \ldots, N\}, k \in \{1, 2, \ldots, K_n\},$$

$$m \in \{1, 2, \ldots, M_{n,k}\}$$

$$F_{n,k,m} \geq r_n,$$

$$r_n \in \{1, 2, \ldots, \}$$

(4)

where $F_{n,k,m}$ denotes the starting transmission time of flow $f_{n,k,m}$ and $r_n$ denotes the release time of job $j_n$. Obviously, $a_n \leq r_n$, $a_n$ denotes the arrival time of job $j_n$.

**Dependency constraints:** In this paper, we only consider scheduling multi-stage jobs with starts-after dependencies. The flows in a coflow cannot start their transmission until the coflows on which they depend have completed their transmission. Consequently, the dependency constraint can be expressed as follows

$$\forall n \in \{1, 2, \ldots, N\}, k', k \in \{1, 2, \ldots, K_n\},$$

$$m \in \{1, 2, \ldots, M_{n,k}\}$$

$$F_{n,k,m} \geq X_{n,k,k'}C_{n,k'},$$

(5)

where $X_{n,k,k'}$ is a binary indicator which is equal to 1 if there is a dependency that coflow $c_{n,k}$ starts after coflow $c_{n,k'}$ or 0 otherwise [1].

### 4 The Framework

In this section, we introduce the framework of the proposed model. First, we overview the architecture of the model. Second, we introduce the processing mechanism of DAGNN, and present our Pipelined-DAGNN to speed up the feature extraction process. Then, we give the Self-Attention Mechanism which is the key for ensuring the performance of the coflow scheduling strategy. Finally, we describe the training framework of the DRL model.

#### 4.1 Overview of the Framework

The proposed model is designed based on the framework of DRL and can automatically generate efficient coflow scheduling policies for the network. Fig. 4 is a complete learning framework of the proposed model, where the agent plays the role of the coflow scheduler, which is composed of three modules, Pipelined-DAGNN, Self-Attention Layer and Policy Network. (See Section 4.2.1, Section 4.2.2 and Section 4.2.3 for details).

When the model is running, the agent collects the job DAGs information and converts the information to a feature map as the input of Pipelined-DAGNN, which encodes the features of the job DAGs in a set of embeddings and passes the embedding sequence composed of schedulable coflows to a Self-Attention Layer. Finally, the generated self-attentive sequence serves as the input to the Policy Network and outputs a priority list for scheduling coflows and the flows in coflows. The active queue stores coflows that have been released but not yet completed; the coflows in the waiting queue need to wait for higher priority coflows to release the required port resources. All currently schedulable coflows are placed in the active queue and waiting queue, respectively. With the release of resources, the coflows that have finished transmission are placed in finished queue, the
4.2 Neural Network Implementation

As shown in Fig. 5, the neural network implementation in our model includes three stages: Pipelined-DAGNN processing, self-attention processing, and policy network processing. Next, we describe the three stages in detail.

4.2.1 Pipelined-DAGNN Processing

In multi-stage jobs, each job consists of multiple coflows and is represented by a Directed Acyclic Graph (DAG). Compared with the most common GNN architecture that aggregates information from neighbouring nodes at the previous layer based on message passing, DAGNN is driven by the partial order induced by the DAG and aggregates neighbourhood information in the current layer [20]. Note that DAGNN exploits an inductive bias that relies on the assumption that the input graph is a DAG. To facilitate subsequent understanding, we first briefly describe the DAGNN framework:

$$H_v^\ell = F^\ell \left( G^\ell \left( \{ H_u^\ell \mid u \in P(v) \} , H_v^{\ell-1} \right) , H_v^{\ell-1} \right),$$

$$H_G = R \left( \{ H_v^\ell \mid \ell = 1, \ldots, L, v \in T \} \right) \tag{6}$$

It can be seen from the above formula, DAGNN uses only direct predecessors for aggregation and the pooling on only nodes without successors. In addition, as shown in Fig. 6, DAGNN considers topological batching, which divides all nodes in job DAG into sequential batches $B_i$ that nodes without dependency may be grouped together and processed concurrently if their predecessors have all been processed [20]. Obviously, sequential batch $B_i$ of the same $i$ in different DAGs can be combined and processed simultaneously, which achieves better parallel concurrency.

It can be seen from Fig. 5 that nodes 0, 1, 4, and 5 come from different jobs in the same sequential batch $B_0$, which can be processed concurrently by DAGNN.

Inspired by [20], we employ DAGNN to encode the job DAGs information in a set of embeddings, which contain per-node embedding $e_i^v$, and per-job embedding $y^i$. The former captures information about the node and its predecessor nodes, and the latter aggregates information across the set of nodes without successors $T$. Given the feature vectors $x_i^v$ of node $v$ in job DAG $G_i$, we build a per-node embedding $(G_i, x_i^v) \rightarrow e_i^v$, and compute a per-job embedding for each DAG $G_i$, $(x_i^v, e_i^v), v \in T \rightarrow y^i$.

Table 3 defines our notation. However, DAGNN is still computationally expensive since it uses an iterative message passing scheme. Hence, we propose a novel Pipelined-DAGNN that can effectively speed up the feature extraction process of DAGNN.

To demonstrate this, let us consider a simple example in Fig. 7. Using topological batching to update the two job DAG in the figure at the same time, and assuming that the average time required for $B_j$ to be updated once is $T_0$. $L = 2$, is the number of iterations. $N = 3$, is the maximum number of sequential batches in job DAGs. Because Pipelined-DAGNN use the current-layer, rather than the past-layer, information to compute the current-layer representation of $v$ and aggregates from the direct-predecessor set $P(v)$ only, rather than the entire neighborhood [20]. As shown in Fig. 6, $B_1^j$ and $B_2^j$ respectively represent the first iteration update and the second iteration update of the sequential batch $B_j$. The time required for sequential batch $B_j$ to iteratively update twice is $2T_0$, and considering the pipeline mechanism, when $B_1^j$ ends, $B_0^2$ and $B_1^1$ can be performed simultaneously, the time spent is $4T_0$. It can be inferred...
from the figure that the time spent without considering the pipeline mechanism is $N \times L \times T_0$. On the contrary, the time spent is $(N-1) \times T_0 + L \times T_0$. The acceleration ratio is $\frac{L \times N}{L+N-1}$.

Fig. 5: Neural Network Implementation

4.2.2 Self-Attention Processing

After Pipelined-DAGNN processing, the embedding of each node and each job in DAGs can be obtained. However, for job DAGs, there is a dependency relationship between nodes, and only those that have no predecessor dependencies or all predecessor dependencies that have finished scheduling can be scheduled. As shown in Fig. 5, node 1 has no predecessor dependency, and the predecessor node 0 of node 4 has completed scheduling. Therefore, the current schedulable nodes are 1, 5, 6. Next, we consider feeding the embedding sequence of current schedulable nodes to the policy network to output a priority sequence. In this way, the scale of the policy network has nothing to do with the number of jobs or nodes, only the feature dimension of node embedding, so as to reduce the size of the policy network and achieve scalability. But no matter from the same job DAG or different job DAGs, there is no directed edge connection between the current schedulable nodes. Each schedulable node embedding only contains its own information and information aggregated from direct-predecessor nodes after Pipelined-DAGNN processing. Therefore, the priority scores output by the policy network in parallel are independent, and the generated priority sequence cannot be used as an effective strategy to guide the agent, resulting in the low accuracy of the coflow scheduling algorithm.

To solve it, we utilize the self-attention mechanism as an operation to calculate the relevance between different parts of the embedding sequence.

Intuitively, the attention mechanism is similar to the human attention distribution process, that is, in the information processing process, different content is assigned different attention weights. The essence of Attention can be described as a query $Q$ to a series of key-value ($K$-$V$) pairs of mapping. Self-Attention [26] is a special form of Attention Mechanism. The self-attention model is actually to make $Q$, $K$ and $V$ equal, and do attention inside the sequence to find the connections within the sequence. Essentially, for each input vector, Self-Attention generates a vector that is weighted and summed on its neighboring vectors, where the weight is determined by the relationship between inputs. For example, if we enter a sentence, each word in it must be calculated with all the words in the sentence. The purpose is to learn the word relevance within the sentence and capture the internal structure of the sentence.

Feeding the embedding sequence $Z_{\text{embed}}$ of currently schedulable nodes to the self-attention layer is achieved as follows: First, perform a linear projection on $Z_{\text{embed}}$ that is, assign three weight matrices $W_Q, W_K, W_V \in \mathbb{R}^{\text{embed}\_\text{dim}\times\text{embed}\_\text{dim}}$ to $Z_{\text{embed}}$ to obtain three matrices $Q, K, V$ representing queries, keys, and values respectively, with the same dimensions. Then the similarity is calculated by $\sqrt{d_k}$-regulated dot-product to obtain the weights $(QK^T) / \sqrt{d_k}$, where $d_k$ is the dimension of the key vectors serving as a scaling factor [26], and the softmax function is applied to normalize these weights; Finally, the weights and corresponding value (matrix) $V$ are multiplied to obtain the attention. This process can be done via matrix multiplications:

$$Q = \text{Linear}(Z_{\text{embed}}) = Z_{\text{embed}}W_Q$$
$$K = \text{Linear}(Z_{\text{embed}}) = Z_{\text{embed}}W_K$$
$$V = \text{Linear}(Z_{\text{embed}}) = Z_{\text{embed}}W_V$$

$$\text{Attention}(Q, K, V) = \text{soft max} \left( \frac{QK^T}{\sqrt{d_k}} \right) V. \quad (8)$$

4.2.3 Policy Network Processing

After the self-attention processing stage, the self-attentive sequence of schedulable node embeddings and their job level information (per-job embeddings) are sent to the policy

Fig. 6: Topological Batching for Multiple Job DAGs

Fig. 7: Pipeline Mechanism Acceleration

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network. For a node \( v \) in job DAG \( G_j \), the policy network computes a score \( q_i^v \equiv q(s_i^v, y^v) \), where \( q(\cdot) \) is a score function that maps the embedding (per-node self-attentive embedding and per-job embedding) to a scalar value. The scalar value is the priority value when the jobs are of equal weight.

### 4.3 DRL Neural Network Training

Another key task in our model is to train the neural networks in the framework of DRL comprising of three stages of Pipelined-DAGNN processing, self-attention processing, and policy network processing, as illustrated in Fig. 5. These three stages, collectively representing the scheduling agent in our DRL model, are realized by their respective neural networks and updated in the end-to-end online training process, with the output of one stage being the input of another stage. Deep Reinforcement Learning (DRL) combines the perception ability of deep learning with the decision-making ability of reinforcement learning and realizes the end-to-end process from perception to decision-making, which is an artificial intelligence method closer to human thinking. Consider the general setting in Fig. 8, where a DRL Agent interacts with an Environment. The DRL agent gets trained through the interaction with the network environment step by step. At each step \( k \), the agent observes a state \( s_k \) as the input of the parameterized neural network, and the output policy \( \pi_\theta(s_k, a_k) \) is defined as the probability of taking action \( a_k \) in the state \( s_k \). The agent selects action \( a_k \) according to the strategy \( \pi_\theta(s_k, a_k) \) to act on the environment and change the state of the environment. The environment state is converted to \( s_{k+1} \), and the agent receives an instant reward \( r_k \) as feedback to evaluate the quality of the action \( a_k \).

![Fig. 8: The general framework of DRL](image)

In our DRL model, the scheduling agent observes the state of the environment, including the shape of the job DAGs, flows in each coflow and their occupation of network resources, and outputs the priority list of the current schedulable nodes. To guide the movement of the agent’s action towards the goal (minimizing the average/total weighted JCT), the environment will give the agent a reward \( r_k \) after each action (ordering). We penalize the agent with a reward \( r_k = \sum_{k'=i}^l w_{i}^{-} \) after the \( k^{th} \) action, where \( l_k \) is the wall-clock time of the \( k^{th} \) action and \( n_k \) is the number of jobs that left in the system during the interval \([l_k, l_{k+1})\), \( w_i \) is the weight of the corresponding job \( i \). RL training proceeds in episodes. Each episode consists of multiple coflow ordering (action) and scheduling events. In each episode, the target of the training is to maximize the cumulated reward \( \sum_{k=0}^{T} r_k \), where \( T \) denotes the total number of actions performed in this episode.

In our model, we use a policy gradient algorithm [27] for training. In the training process, the policy gradient algorithm uses the reward of environmental feedback to perform gradient descent on the neural network parameters to learn. Consider an episode of length \( T \), the agent collects \((s_k, a_k, r_k)\) at each step \( k \). The parameters \( \theta \) of its policy \( \pi_\theta(s_k, a_k) \) is updated as follows

\[
\theta \leftarrow \theta + \alpha \sum_{k=1}^{T} \nabla_\theta \log \pi_\theta(s_k, a_k) \left( \sum_{k'=k}^{T} r_{k'} - b_k \right) \tag{9}
\]

where \( \alpha \) is the learning rate and \( b_k \) is a baseline used to reduce the variance of the policy gradient [28]. The entire training process is shown in Algorithm 4, using the REINFORCE policy gradient algorithm [27] to minimize the parameters of the neural network and output an effective coflow scheduling strategy. The key idea of the policy gradient algorithm is to estimate the gradient using the trajectories of execution with the current policy.

Next, we describe how we implement the algorithm to train our model in practice. At the beginning of training, the neural network parameters are initialized randomly, resulting in a poor output policy in the early stage. With the arrival of jobs, there will be a large number of queued coflows in almost every training episode. Allowing the agent to explore beyond a few steps in these early stages wastes training time. Hence, we can use the method of sampling the episode length from an exponential distribution with a small initial mean \( l_{\text{mean}} \) to terminate the initial episodes early to avoid wasting training time and hence accelerate the training process. Then, with the multiple-stage jobs’ arrival, the agent follows the Monte Carlo Method to collect the online experience episodes for training (line 5). Line 12 is the REINFORCE policy gradient algorithm described in (9). Line 15 is to increase the average episode length. Finally, we update the policy parameter \( \theta \) on line 16. Our policy network is implemented using a neural network of two hidden layers with 32 and 16 hidden units, respectively. We set the learning rate \( \alpha \) at \( 1 \times 10^{-3} \) and use Adam optimizer for gradient descent. We train our model for at least 40,000 iterations.

## 5 The Algorithm

In this section, we present an efficient coflow scheduling algorithm for online multi-stage jobs, as shown in Algorithm 1, which consists of two main components: coflow ordering and scheduling, respectively implemented by Algorithm 2 and Algorithm 3. Algorithm 2 is responsible for assigning priorities to currently schedulable coflows based on the DRL framework. Algorithm 3 is responsible for scheduling flows in active coflows, i.e., the coflows that have been released but not yet completed among the scheduled coflows, based on the priority list. The detailed algorithm design block diagram is shown in Fig. 9.

The following first gives an overall description of the online algorithm, and then introduces these two components separately.
5.1 Online Algorithm Design

Our online scheduling algorithm is shown in Algorithm 1. In the coflow scheduling problem of online multi-stage jobs, there may be multiple multi-stage jobs coexisting in the network, thus competing for network resources. Consequently, we need to determine the priority order of schedulable coflows. Next, we need to allocate bandwidth resources to active coflows based on the priority list. In coflow ordering, a higher value the policy network outputs represent the higher priority, and Algorithm 2 is called only when a job is released or a coflow finishes. In coflow scheduling, port-sharing is allowed, and Algorithm 3 is called only when a flow is completed, or a coflow is released. We first initialize all ports states to idle.

Algorithm 1 Online scheduling policy for coflows and flows

Input: Coflows in the job and job DAGs, active coflow set C
Output: flow rate and flow scheduling priority
▷ INITIALIZE
1: Initialize the bandwidth on each ingress and egress port:
   \( I_p = E_p = \text{port physical bandwidth} \)
▷ ORDERING
2: Determining priority list \( \leftarrow \) call Algorithm 2.
▷ SCHEDULING
3: Scheduling active coflows \( \leftarrow \) call Algorithm 3.
4: if a flow \( F \) completes transmission or a coflow \( C \) is released then
   ▷ UPDATE
5: Update active coflow set \( C \)
▷ SCHEDULING
6: Scheduling active coflows \( \leftarrow \) call Algorithm 3.
7: end if
8: if a coflow \( C \) completes transmission or a job \( J \) is released then
   ▷ UPDATE
9: Update active coflow set \( C \)
▷ ORDERING
10: Determining priority list \( \leftarrow \) call Algorithm 2.
11: end if

5.2 Determining Priority List

In this paper, we train the DRL model based on the policy gradient strategy by Algorithm 4. In the initial stage of training, the network parameters are random, and the output strategy is poor, resulting in a large number of job waiting. To avoid wasting training time with useless exploration in the early stage, we sample the episode length \( l \) from an exponential distribution with a small initial mean \( l_{mean} \) [29]. Considering that the optimization goal is to minimize the average/total weighted JCT, the output score \( q^*_v \) of node \( v \) is multiplied by the weight \( w_i \) of the job \( i \) to generate a priority score \( p_v(1 \leq v \leq |V|) \). Finally, a priority list \( P = (p_1, p_2, \ldots, p_{|V|}) \) is generated as the scheduling policy, where \( p_v(1 \leq v \leq |V|) \) corresponds to the priority value of schedulable coflows in the execution of the job DAG, and a higher \( p_v \) stands for a higher priority. A formal description of the determination of the priority order is given in Algorithm 2.

Algorithm 2 Determining priority list

Input: Coflows in the job, job DAGs and importance weights
Output: Priority list \( P \) of schedulable coflows
▷ TRAINING
1: Training based on policy gradient \( \leftarrow \) call Algorithm 4.
2: Multiplied Priority score by job weight
3: Return priority list \( P = (p_1, p_2, \ldots, p_{|V|}) \)

5.3 Scheduling Active Coflows

Algorithm 3 is designed to schedule active coflows based on the priority list. In other words, it is responsible for determining which flows in active coflows are eligible to occupy network resources to be scheduled. Due to a lack of network resources, flows in active coflows may be blocked. Therefore, before scheduling a flow of an active coflow, we need to check whether the ingress port and the egress port have free resources. Finally, when a flow is scheduled, we need to release the occupation of network resources.

Algorithm 3 Scheduling active coflows

Input: priority list of schedulable coflows \( P \)
Output: flow rate of each active coflow
▷ SCHEDULING
1: for \( C \) in \( C \) do
2: \( r = \min \{I_p, E_q\} \), subject to \( C \) still need to send flow to port \( p \) or receive flow from port \( q \)
3: for each unfinished flow \( F \) in \( C \) do
4: allocate bandwidth of \( r \) to \( F \)
5: update \( I_p \) and \( E_q \) by deducting \( r \) from them
6: end for
7: for each finished flow \( F \) in \( C \) do
8: release bandwidth of \( r \) to \( F \)
9: update \( I_p \) and \( E_q \) by adding \( r \) from them
10: end for
11: end for
12: allocate remaining bandwidth equally to all flows
13: Return flow rate of each active coflow

6 Experiment and Evaluation

In this section, we use the traces of Facebook [30] to test the performance of the proposed model and provide simulation results and detailed performance analysis.
Algorithm 4 Training based on policy gradient

\begin{algorithm}
\caption{Training based on policy gradient}
\begin{algorithmic}[1]
\STATE \textbf{INITIALIZE}
\STATE 1: Initialize all neural networks
\FOR {each iteration}
\STATE 2: Episode length $l \sim \text{exponential} (l_{\text{mean}})$
\STATE 3: Run episodes $i = 1$ to $N$
\STATE 4: \{$s_i, a_i, r_i^k, \ldots, s_l, a_l, r_l^k\} \sim \pi_\theta$
\STATE 5: Compute total reward: $R_k^l = \sum_{k'=k}^{l} r_k^{k'}$
\FOR {$k = 1$ to $l$}
\STATE 6: Compute baseline value: $b_k = \frac{1}{N} \sum_{i=1}^{N} R_i^l$
\FOR {$i = 1$ to $N$}
\STATE 7: $R_i^l = \sum_{k'=k}^{l} r_i^{k'}$
\ENDFOR
\FOR {$i = 1$ to $N$}
\STATE 8: $\Delta \theta = \Delta \theta + \nabla_{\theta} \log \pi_\theta (s_i^k, a_i^k) (R_i^k - b_k)$
\ENDFOR
\STATE 9: $l_{\text{mean}} = l_{\text{mean}} + \epsilon$
\STATE 10: $\theta = \theta + \alpha \Delta \theta$
\ENDFOR
\ENDFOR
\end{algorithmic}
\end{algorithm}

6.1 Simulation Settings

Environment: For the simulation environment, we create an online coflow scheduling simulator with Python 3.8 and build neural networks based on Pytorch. The simulation runs on the Ubuntu 19.04 operating system [31].

Workload: Our workload is generated based on Facebook trace [30], collected from a 3000-machine, 150-rack MapReduce cluster at Facebook. This trajectory is widely used in simulation [6], [12], [32], which contains 526 coflows that are scaled down to a 150-port fabric with exact inter-arrival times. We divide 526 coflows into training set, validation set, and test set at an approximate ratio of 8:1:1. In each set, we randomly select several coflows, and construct the job DAG by randomly generating an adjacency matrix. For each coflow, the Facebook trace contains sender machines, receiver machines, and transmitting bytes at the receiver level, not the flow level. Thus we partition the bytes in each receiver to each sender pseudo-uniformly to generate flows. In addition, the trace only contains the information of each coflow, not the job DAG. Therefore, to evaluate our algorithms in the scenarios of dependencies, we randomly select coflows to form the job DAGs so that each job contains $n$ coflows in expectation and $n$ dependencies are generated randomly. We randomly selected $P$ machines from the trace as servers. The arrival time of each job obeys a Poisson distribution $P(\lambda)$; the weights of the jobs follow a uniform distribution.

Metrics: Here, we evaluate several metrics of our model, including minimizing the average/total weighted JCT, average JCT. Minimizing the average JCT is just a special case of minimizing the total weighted JCT, where all jobs have equal weight.

Benchmark algorithms:
1. Varys [6] proposes a Smallest-Effective-Bottleneck-First (SEBF) heuristic algorithm to greedily schedule coflows based on its bottleneck flow’s completion time.
2. IAOA (Information-Agnostic Online Algorithm) [33] formulates the weighted coflow completion time minimization problem and proposes a heuristic solution with an approximation factor of $2$ to the optimal solution. However, IAOA did not consider the dependency between coflows in job DAGs.
3. DeepWeave [1] is the first to use a reinforcement learning framework to automatically generate efficient coflow scheduling strategies in job DAGs. However, DeepWeave does not support the goal of total weighted JCT because it considers the scheduling of jobs one by one. Therefore, to compare our model with DeepWeave, we first evaluate our algorithm in a particular case, that is, all jobs have the same weight, that is, a non-weighted scene. In this case, the optimization goal is indeed equivalent to minimizing the average JCT.

Model Evaluation:
We randomly select several batches of jobs (one batch contains 1000 jobs) from the test set to generate their job DAGs, and use the Pickle module in Python to store job data. Under the same input, we compare the average weighted job completion time of the training model with the state-of-the-art baseline algorithms.

6.2 Simulation Results
First, for the online scenario where multiple jobs (DAGs) coexist, we consider how to schedule these jobs with the same weights. In this case, the optimization objective is equivalent to minimizing the average job completion time (JCT). We build a job DAG generator to generate Poisson flow jobs; the time interval of job arrival obeys an exponential distribution. Unless otherwise specified, we choose the number of ports $P = 20$, the average job arrival rate $\lambda = 20$ and the average number of coflows $n = 8$. In the experiment, we compare our algorithm with DeepWeave, both based on DRL and Varys [6] and IAOA [33] that were also used as popular non-ML baselines for comparison with DeepWeave [1]. In addition, we add an ablation experiment to compare the performance of the retrained model under the same settings, removing the self-attention layer. The results of the average JCT is shown in Fig. 10. Compared with DeepWeave, the average JCT of our algorithm is reduced by up to 40.42%, and the completed jobs is at least 1.68 times more. Besides, in the case of removing the self-attention layer, the performance of the model loses 29.36%.

Fig. 10: Comparison of Average JCT

Next, we consider the importance of different jobs and minimize the average weighted job completion time (the
average weighted JCT). For DeepWeave, in the case of online, each arriving job will need to wait until the previous job is completed before it starts to be released. Consequently, the importance weight of the job does not affect its output policy. On contrast, our model can handle the coexistence of multiple jobs, allowing coflows of different arriving jobs to be scheduled simultaneously, without waiting for the completion of the previous job, which can significantly reduce the average JCT. In our model, the output of the policy network contains the priority scores of schedulable nodes from different jobs and generate the final priority scheduling list by multiplying the job’s priority score with its weight. Fig. 11 shows the performance comparison of different schemes in the online situation.

In order to illustrate better scalability of our proposed model, we compare the number of iterations required by the proposed model and DeepWeave as the average number of nodes in the training set increases in Fig. 12. DeepWeave feeds a flat embedding vector containing the information of the whole job to the policy network, making the (input) size of the neural network implementing the policy network proportional to the number of nodes (n) in the job DAG. As n increases, processing a d-dimensional feature vector for the DAG requires a size $O(dn)$ policy network that is difficult to train. In contrast, in our deep RL model, the policy network scale is related only to the feature dimension d, and hence reduced from previously $O(dn)$ to $O(d)$.

As illustrated, because we generate jobs by randomly combining Facebook traces and obtaining coflows with random dependencies, it is necessary to investigate the cumulative distribution function (CDF) of the average JCT and average weighted JCT. As shown in Fig. 13 and Fig. 14, the performance and stability of our model are better than others: for our model, the average JCT varies from about 113 to 155, and the average weighted JCT varies from about 475 to 536.

As a common issue in machine learning models, online coflows scheduling model based on deep reinforcement learning is sensitive to noise, yielding significant variance between runs. To explore the robustness of the proposed model and DeepWeave, we add noise following normal distribution function (CDF) of the average JCT.

The training set and test set of the above experiments are randomly selected from Facebook trajectories and have the same internal distribution. However, in a complex data center network, data transmission is often accompanied by various noises, which are not included in the sampled data. As a common issue in machine learning models, online coflows scheduling model based on deep reinforcement learning is sensitive to noise, yielding significant variance between runs. To explore the robustness of the proposed model and DeepWeave, we add noise following normal distribution to the test data set and compare the changes of the cumulative distribution of job completion time.

When we add a small amount (5%) of noise, the cumulative distribution changes of the two models are shown in Fig. 15. Compared with DeepWeave [1], the variance and mean differences on job completion time of the proposed model are smaller. Furthermore, when the amount of noise in the test set is increased to 30%, both distributions of the two models diverge significantly from the original, as shown in Fig. 16. DeepWeave has a more significant variance than our model, because DeepWeave [1] requires to train a large policy network and is prone to over-fitting.
resulting in poor robustness, as the result of directly feeding a high-dimensional embedding vector containing all the job information as the input of the policy network.

![Fig. 15: CDF of Average Weighted JCT with 5% Noise](image1)

Fig. 15: CDF of Average Weighted JCT with 5% Noise

Then, we investigate the influence of the average job arrival rate, i.e. the parameter $\lambda$ in Poisson process, on the average job completion time (JCT) and average weighted JCT, where a smaller $\lambda$ corresponds to a smaller load, indicating fewer jobs arriving in a unit time. As shown in Fig. 17 and Fig. 18, with the increase of network load, there are a large number of job queues in DeepWeave, resulting in a dramatic rise in both average JCT and average weight JCT.

![Fig. 16: CDF of Average Weighted JCT with 30% Noise](image2)

Fig. 16: CDF of Average Weighted JCT with 30% Noise

![Fig. 17: Influence of Network Loads on Average JCT](image3)

Fig. 17: Influence of Network Loads on Average JCT

![Fig. 18: Influence of Network Loads on Average Weighted JCT](image4)

Fig. 18: Influence of Network Loads on Average Weighted JCT

7 Conclusion

In this paper, we proposed an Attention-based Deep Reinforcement Learning (DRL) Model to generate coflow scheduling policies for multi-stage jobs with a policy network of significantly reduced size, which can process job DAGs of arbitrary sizes and shapes representing jobs with arbitrary coflows while ensuring the accuracy of the scheduling strategy. Based on this model, we consider the coflow scheduling problem for online multi-stage jobs, and developed an effective online algorithm. Our work addresses the main challenge of building a scalable policy network in applying deep reinforcement learning to generate coflow scheduling strategies for arbitrary-size job DAGs, and presents a novel DRL model for online coflow scheduling that is empowered by the pipelined-DAGNN encoding job DAGs and self-attention mechanism capturing the interactions among schedulable coflows. Our model improves the existing work of deploying DRL for coflow scheduling in scheduling quality for the common goal of minimizing job completion time, scalability and robustness (sensitivity to noise).

We notice that most existing machine-learning-based coflow scheduling models, including the state-of-the-art work DeepWeave [1] and our proposed model, have not considered preemptive scheduling, which allows reordering of the coflows in the active coflow set. The non-preemption assumption of the active coflows makes these models more stable and easier to learn effective output strategies. In the future, we will study DRL based models for preemptive scheduling. Direct application of our proposed model requires a larger action space and more frequent decisions to be made by the scheduling agent, which will increase the training difficulty and reduce the stability of the model significantly. Consequently, we will investigate the deployment of multi-agent reinforcement learning techniques [34], [35], [36] to design an effective preemptive scheduling model with the strategy of deploying independent agents to make preemption decisions autonomously.

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