Pipeline Parallelism for Inference on Heterogeneous Edge Computing

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Abstract

Deep neural networks with large model sizes achieve state-of-the-art results for tasks in computer vision (CV) and natural language processing (NLP). However, these large-scale models are too compute- or memory-intensive for resource-constrained edge devices. Prior works on parallel and distributed execution primarily focus on training—rather than inference—using homogeneous accelerators in data centers. We propose EdgePipe, a distributed framework for edge systems that uses pipeline parallelism to both speed up inference and enable running larger (and more accurate) models that otherwise cannot fit on single edge devices. EdgePipe achieves these results by using an optimal partition strategy that considers heterogeneity in compute, memory, and network bandwidth. Our empirical evaluation demonstrates that EdgePipe achieves 10.59× and 11.88× speedup using 16 edge devices for the ViT-Large and ViT-Huge models, respectively, with no accuracy loss. Similarly, EdgePipe improves ViT-Huge throughput by 3.93× over a 4-node baseline using 16 edge devices, which independently cannot fit the model in memory. Finally, we show up to 4.16× throughput improvement over the state-of-the-art PipeDream when using a heterogeneous set of devices.

1 Introduction

In recent years, deep neural network (DNN) model sizes have increased exponentially to provide better accuracy [Krizhevsky and others, 2012; Redmon and Farhadi, 2017; Tao \textit{et al}., 2018]. In particular, large transformer-based models have achieved state-of-the-art accuracy in various computer vision (CV) [Dosovitskiy \textit{et al}., 2020; Yuan \textit{et al}., 2021] and natural language processing (NLP) tasks [Vaswani \textit{et al}., 2017; Dosovitskiy \textit{et al}., 2020; Carion \textit{et al}., 2020]. However, these large models cause significant challenges for training and inference in all environments, especially at the edge, which consists of resource-constrained devices in close proximity to a data source [Satyanarayan, 2017]. For example, the base vision transformer model (ViT-Base) [Dosovitskiy \textit{et al}., 2020] has 86.6M parameters and requires about 110B FLOPs to perform inference on one image [Narayanan \textit{et al}., 2021b], resulting in limited throughput on a MinnowBoard edge device, as shown in Figure 1. The ViT-Large and ViT-Huge models have considerably more parameters, which makes their deployment on resource-constrained edge devices more difficult, e.g., they do not even fit in memory on the MinnowBoard.

Various methods have been proposed to address large model inference challenges on edge devices, including model compression [Hinton \textit{et al}., 2015; Han \textit{et al}., 2015; Yao \textit{et al}., 2021; Kundu and Sundaresan, 2021], adaptive inference [Tambe \textit{et al}., 2020], and neural architecture search [Wang \textit{et al}., 2020]. These approaches reduce the number of required computation operations, but at the cost of reduced accuracy. Moreover, most of these approaches are limited to a single device, and do not take advantage of idle devices that may be available to assist and improve performance in distributed settings.

Pipeline parallelism partitions models into multiple stages, which can accelerate processing without accuracy loss by utilizing additional resources. Pipelining is complementary to compression methods, providing additional opportunities to mitigate model complexity. Research on pipeline parallelism has focused on data center scenarios with high interconnect bandwidth and homogeneous accelerators like graphics processing units (GPUs) and tensor processing units (TPUs) [Yang \textit{et al}., 2021; Huang \textit{et al}., 2019; Li \textit{et al}., 2021; He \textit{et al}., 2021]. In contrast, edge environments are more resource-constrained, with heterogeneous communication and computation characteristics.

Several other frameworks consider pipeline parallelism for limited heterogeneity in data centers, e.g., heterogeneous com-
munication topologies with homogeneous GPUs [Narayanan et al., 2019; Narayanan et al., 2021a], or heterogeneous GPU clusters with homogeneous networks [Park et al., 2020a]. Torchpipe [Kim et al., 2020] provides an automatic balancing strategy for large models, but only for the single-node scenario and does not claim optimality. Finding an optimal partition strategy under fully heterogeneous conditions (heterogeneous devices and network), which is critical to edge scenarios, remains a largely open problem.

We address these challenges with EdgePipe, a distributed inference framework that exploits pipeline parallelism to improve inference performance on heterogeneous edge devices and networks. In particular, this paper makes the following contributions:

- A distributed pipeline parallelism framework to accelerate large-scale model inference on heterogeneous edge computing without accuracy loss.
- A dynamic programming (DP) algorithm to determine the optimal partition mapping of pipeline parallelism to heterogeneous devices and communication channels.
- A detailed experimental evaluation on a real edge testbed, demonstrating throughput performance improvements up to 11.88× speedup in a 16-device homogeneous cluster and 4.16× speedup over the state-of-the-art PipeDream in a heterogeneous cluster.

2 Background and Motivation

2.1 Background

Pipeline Parallelism. Pipeline parallelism partitions a neural network model into multiple stages, where each stage consists of a consecutive set of layers in the original model [Yang et al., 2021; Narayanan et al., 2019]. Each stage in the pipeline is assigned to a worker to achieve the parallel execution of model training or inference. The input minibatch is split into multiple chunks of equal size, which are called microbatches [Huang et al., 2019]. The microbatch size affects the pipeline performance, with the optimal size depending on multiple factors including the characteristics of the model and the number of pipeline stages [Narayanan et al., 2021b]. A worker in a system that has pipeline parallelism need only send its output data to a single worker, which avoids the collective communication to synchronize results with all workers. Pipelining can also overlap computation and communication to improve the performance [Narayanan et al., 2019].

Transformer-based Models. The transformer model was proposed to improve the effectiveness in learning dependencies between distant positions for sequence modeling tasks [Vaswani et al., 2017]. A transformer encoder includes multiple transformer layers with identical structures. Every transformer layer is composed of a multi-head self-attention layer, a multi-layer perceptron (MLP), two layer normalization operations, and residual connections. The multi-head self-attention layer calculates the attention score of the input sequence $A = (a_1,..., a_n)$ through dot product operations and generates the output representation $B = (b_1,..., b_n)$ with the same dimension. Outputs $b_i$ and $b_j$ (where $i \neq j$) are operationally independent, which provides the possibility of parallel execution for both training and inference [Park et al., 2020b]. Attention-based models have recently been extended to replace conventional convolutional neural networks (CNNs) [Dosovitskiy et al., 2020; Kundu and Sundaresan, 2021] in performing complex CV tasks. In particular, the ViT models enjoy superior representation ability [d’Ascoli et al., 2021], and also suffer less from positional invariance issues which are prevalent in conventional CNNs [Su et al., 2019].

2.2 Motivation

Large-scale model inference is a challenging task for resource-limited devices. Classical model compression techniques, including pruning [Zhang et al., 2018; Kundu et al., 2021], quantization [Yao et al., 2021], low-rank approximation [Chin et al., 2020], and knowledge distillation [Hinton et al., 2015] can shrink neural network model sizes to potentially accelerate deep neural networks. However, these techniques often require iterative retraining and a full-precision pre-trained model to avoid significant accuracy-drop. More importantly, these methods generally focus on a single compute node. Distributed edge computing scenarios, in contrast, often include a large number of resource-limited devices, e.g., in vehicular edge computing (VEC) for internet of vehicles [Liu et al., 2021], wireless-connected AI-enabled sensors [Sharma et al., 2021], and smart home systems [Isyanto et al., 2020; Cheng and Kunz, 2009].

Pipeline parallelism has proven to be effective for distributed training on accelerators in data centers where devices are relatively homogeneous and the network bandwidth is generally high [Huang et al., 2019; Yang et al., 2021; He et al., 2021]. However, edge computing has unique characteristics:

- **Small Memory Capacity.** Compared with data-center servers, edge devices usually have smaller memory capacities, ranging from tens of MB to several GB.
- **Heterogeneous Devices.** Edge devices have diverse computational performance and memory capacities.
- **Limited Bandwidth.** Unlike communication within data centers, edge computing systems often rely on wireless communication with limited bandwidth.
- **Heterogeneous Network Link Capacities.** The bandwidth between different pairs of devices depends on physical distance and channel interference, and could range from tens of Kbps to hundreds of Mbps.

Model partition methods for homogeneous clusters will therefore perform poorly in heterogeneous edge environments. A new pipeline parallelism framework is needed to overcome these challenges. In the next section, we introduce a framework for distributed edge clusters that uses heterogeneity-aware pipeline parallelism to improve inference performance and enable running larger—and more accurate—models.
3 Parallelism for Edge Devices

In this section, we present our system design and discuss the problem of partitioning a transformer model for a fully heterogeneous cluster. We introduce the DP-based optimal partition algorithm in Section 3.3.

3.1 EdgePipe System Design

Figure 2 presents the EdgePipe system design, which consists of three major components: the partitioning algorithm for heterogeneous clusters, the data loader, and the runtime framework that implements pipeline parallelism. First, the configuration of the original transformer model and partition constraints are sent to the partition algorithm to generate an optimal partition method. The partition constraints include available edge devices, computation and memory capabilities of these devices, and the bandwidth between devices. The specific partition problem will be introduced in Section 3.2. To fit into every edge device and improve the throughput, input data should be split into small chunks, called a microbatch. At runtime, selected devices are only responsible for the inference of one part of the original model. After finishing the inference of one microbatch, the edge device transmits intermediate outputs to the device in the next pipeline stage. The device in the final stage produces the final result, which could be transmitted to another host or stored locally.

To construct a pipeline with \( k \) stages, the transformer model should be partitioned into \( k \) parts \( T_1, T_2, \ldots, T_k \). Part \( T_i \) includes \( l_i \) layers, and \( \sum_{i=1}^{k} l_i = L \), where \( L \) is the number of layers. Part \( T_i \) is assigned to the \( i \)-th device to construct the \( i \)-th pipeline stage. For one microbatch input \( \mathcal{X} \), the process of inference may be denoted as \( \hat{Y} = T_k(T_{k-1}(...(T_2(T_1(\mathcal{X}))))), \) where \( \hat{Y} \) is the final output of the inference. The intermediate output of the \( i \)-th device is sent to the \((i + 1)\)-th device to continue the computation. The number of pipeline inference stages in EdgePipe is equal to the number of devices participating in inference.

3.2 Partition Problem Formulation

Fully heterogeneous clusters include heterogeneity in both the devices and the communication networks. It is common in edge computing for devices have different computation and memory capabilities. In addition, the network bandwidth between devices may be different. It is therefore challenging to decide the partition method for the cluster.

We define a transformer model \( T \) with \( L \) layers, inter-layer transmission data size \( P_j \) for the \( j \)-th layer, and a list of heterogeneous devices \( \mathcal{D} (|\mathcal{D}| = D) \) with different memory, computation, and communication capabilities. In heterogeneous communication, the bandwidth between a pair of devices \( u \) and \( v \) may be different than the bandwidth between a different pair of devices \( u' \) and \( v' \): \( b_{u,v} \neq b_{u',v'} \). The optimal strategy \( \mathbb{R} \) partitions the model \( T \) into \( S \) parts and allocates them to the selected devices \( \mathcal{S} \subseteq \mathcal{D}, |\mathcal{S}| = S \leq D \) to achieve maximal throughput and conform to the memory limitations of the selected devices.

3.3 Target Optimization

We denote \( T_{\text{comp}}(l, u) \) as the execution time for the set of layers \( l \) on a device \( u \). \( T_{\text{comm}}(u, v, P_j) \) is the time to communicate data \( P_j \) between devices \( u \) and \( v \), which is computed by Equation (1), where \( b_{u,v} \) is the bandwidth between devices \( u \) and \( v \).

\[
T_{\text{comm}}(u, v, P_j) = \frac{P_j}{b_{u,v}} \tag{1}
\]

We assume the pipeline system supports asynchronous communication, and the computation time and communication time are perfectly overlapped. Thus, the maximum latency for the single device \( u \) can be calculated as:

\[
T_{\text{period}}(l, u, v, P_j) = \max \left\{ \frac{T_{\text{comp}}(l, u)}{T_{\text{comm}}(u, v, P_j)} \right\} \tag{2}
\]

For the selected devices, achieving the maximal throughput is equivalent to minimizing the execution time \( T_{\text{opt}} \), which
is determined by the slowest stage under the given strategy and is equal to the largest $T_{\text{period}}(i, u, v, P_j)$. The problem of pipeline partitioning can itself be partitioned. The optimal solution for partitioning the whole pipeline on given set of devices can be constructed from the optimal partitioning result for the sub-problem, which could be solved by DP methods.

To tackle this partition problem for fully heterogeneous clusters, we design a three-dimensional DP algorithm recording the state of processed layers, used devices, and the device in the last pipeline stage. Let $h(i, S, u)$ denote the minimum time to process the first $i$ layers with the set of used devices $S$, and the device $u$ is the next device to be used. $h(i, S, u)$ is the optimal solution of the subproblem for $i$ layers and $S$ devices. The final optimal solution of this partition problem is the minimum $T_{\text{opt}} = h(L, S, \emptyset)$ with $S \subseteq D$.

The calculation of $h(j, S \cup \{u\}, v)$ needs to use the optimal subproblem property: it is determined by the previous state $h(i, S, u), 0 \leq i < j \leq L$, or the calculation time $T_{\text{period}}(\{i \to j\}, u, v, P_j)$ from $i$-th layer to $j$-th layer on the current device $u$. We further analyze these two situations:

- $h(j, S \cup \{u\}, v) \leftarrow h(i, S, u)$, the slowest pipeline stage for $j$ transformer layers is determined by the previous stage $h(i, S, u)$. Since device $u$ implements the current stage from the $i$-th to the $j$-th layer in the current pipeline, the used devices set for the next state $h(j, S \cup \{u\}, v)$ should include the device $u$, noted as $S \cup \{u\}$. Parameters $i$ and $u \in D \setminus S$ will be enumerated to find the optimal solution of the subproblem.
- $h(j, S \cup \{u\}, v) \leftarrow T_{\text{period}}(\{i \to j\}, u, v, P_j)$, the device $u$ that constitutes the slowest stage of the current pipeline and limits the performance of the system. The $T_{\text{period}}(\{i \to j\}, u, v, P_j)$ is calculated from Equation 2. Similarly, device $u$ and first $i$ layers are enumerated to obtain the minimum value.

Thus, the state transition equation can be formulated as:

$$h(j, S', v) = \min_{0 \leq i < j \leq L} \max_{u, v \in D \setminus S} \left\{ h(i, S, u), T_{\text{period}}(\{i \to j\}, u, v, P_j) \right\}$$

$$= \min_{0 \leq i < j \leq L} \max_{u, v \in D \setminus S} \left\{ h(i, S, u), T_{\text{comm}}(u, v, P_j), T_{\text{opt}}(\{i \to j\}, u) \right\}$$

(3)

where the first term inside the max is the maximum time for the first $i$ layers with the set of devices $S$ and the next used devices $u$; the second term is communication time of transferring $P_j$ data from device $u$ to device $v$; the third term is the computation time for the last $j-i$ layers on the device $u$. For initialization, $h(0, \emptyset, \emptyset)$ is set to 0.

Equation 3 calculates the optimal pipeline execution time. However, we need to obtain the selected devices and their order in the pipeline for the optimal strategy. Algorithm 1 describes the memoization technique pseudo-code to find the optimal time $T_{\text{opt}}$ and the corresponding pipelining strategy.

The computational complexity of the proposed algorithm is $O(D^2 \times L^2 \times D^2)$, where $D$ is the number of available devices and $L$ is the number of layers. The $D^2$ factor is due to the assumption that all devices are distinct. As a comparison, for the naive brute force solution, the search space is $\sum_{i=1}^{\min(D,L)} D^D \times (L-1)^D \gg D! \gg 2^D$, which has a much higher complexity. Moreover, in most scenarios, there should exist identical devices with the same computation and communication capabilities. Therefore, the number of devices $D$ could be divided into $N$ categories, where the $i$-th category has $n_i$ devices ($\sum_{i=1}^{N} n_i = D$). The search space of DP can be further reduced, hence the computation complexity could be reduced to $O(\prod_{i=1}^{N} (n_i+1) \times L^2 \times N^2)$. For instance, consider the case where there are three types of devices, $N = 3$, and each type has the same number of devices, i.e., $n_1 = n_2 = n_3 = n$. Then the actual computational complexity is $O((n+1)^3 \times L^2 \times N^2) = O(9 \times (n+1)^3 \times L^2)$. For example, given $N = 3$ device types, where each type has $n = 3$ devices, we measure the execution time for these three methods using the ViT-Base model on a 1.6 GHz Intel Core i5 CPU and present the results in Table 2.

### Table 2: Partitioning method performance.

| Algorithm               | Time     |
|-------------------------|----------|
| Category dynamic programming | 0.01 sec |
| Naive dynamic programming | 18.6 sec |
| Brute force search      | 71 min   |

| Table 1: Symbol definitions |
|-----------------------------|
| Symbol | Description |
|-------|-------------|
| $T, L, P_j, M_j$ | A transformer model with $L$ layers. The $j$-th layer has $P_j$ parameters for transmission and requires $M_j$ runtime memory for execution. |
| $D, D, m_v$ | A list of $D$ available devices. Device $v$ has the memory capacity $m_v$. |
| $S, S$ | The list of $S$ selected devices. Every device should participate in the inference. |
| $b_{u,v}$ | Bandwidth between devices. $b_{u,v}$ is the bandwidth between devices $u$ and $v$. |
| $R$ | The optimal mapping strategy. |
| $T_{\text{comp}}(l, u)$ | Computation time with the set of layers $l$ on the device $u$. |
| $T_{\text{comm}}(u, v, P_j)$ | Communication time for transferring $P_j$ data from devices $u$ to $v$. |
| $T_{\text{period}}(i, u, v, P_j)$ | The maximum latency of executing pipeline stage on device $u$ with transferring $P_j$ data to device $v$. |
| $T_{\text{opt}}$ | The optimal time for the pipeline stage under given conditions. |

This section describes the experimental hardware, software dependencies, and evaluation baselines.

**Testbed.** We conduct experiments on the Dispersed Computing Program Testbed (DCompTB) for edge computing platforms [Goodfellow et al., 2019]. DCompTB exposes the two edge device types described in Table 3: a MinnowBoard and an RCC-VE Network Board. For evaluation, we first configure
Algorithm 1 DP-based Pipeline Partition Strategy

Require:
1: $T_{opt}$: the transformer model with $L$ and $P$;
2: $D$: the list of available devices;
3: $R$: bandwidth between devices;

Ensure:
4: $T_{opt}$: the optimal time for maximum throughput;
5: $R$: the specific strategy for the optimal time;
6: Initial $h(i, S, u) ← +\infty$ for all $i, S, u$;
7: Initial $h(0, \emptyset, \emptyset) ← 0$;
8: Initial $answer ← \infty$;
9: for $i = 0$ to $L - 1$ do
10: for each subset $S \subseteq D$ do
11: for each $u \in D \setminus S$ do
12: for $j = i + 1$ to $L$ do
13: if $\sum_{k=0}^{j} M_k > m_u$ then
14: Break;
15: end if
16: Calculate Eq. (3) and assign its value to $C$;
17: if $j = L$ then
18: if $C < answer$ then
19: $answer = C$;
20: $index = (L, S, u)$;
21: end if
22: end if
23: else
24: for each $v \in D \setminus S \cup \{u\}$ do
25: if $C < h(j, S \cup \{u\}, v)$ then
26: $h(j, S \cup \{u\}, v) = C$;
27: $precursor(j, S \cup \{u\}, v) = (i, u)$
28: end if
29: end if
30: end for
31: end for
32: end for
33: end for
34: // Find the optimal results
35: Initial $T_{opt} ← +\infty$;
36: while enumerate each subset $S \subseteq D$ do
37: $T_{opt} = \min(h(L, S, \emptyset), T_{opt})$
38: end while
39: // Find the optimal strategy
40: $(i, S, u) = index$;
41: Add $(i + 1 \rightarrow L, u)$ to $R$;
42: while $i > 0$ do
43: $(i, u) = precursor(index)$
44: Add $(i + 1 \rightarrow index[0], u)$ to $R$;
45: $index = (i, S \setminus \{u\}$
46: end while
47: Return: $T_{opt}$, $R$

5 Evaluation

This section describes the EdgePipe experimental evaluation. We first show the runtime performance on homogeneous clusters using two DCompTB device types. We then demonstrate the effectiveness of our partitioning method on heterogeneous clusters. We also explore the effects of communication bandwidth and the relationship between microbatch size and throughput. Finally, we evaluate EdgePipe with compressed models.

5.1 Runtime Performance Analysis

We first evaluate EdgePipe’s performance on the 2 GB MinnowBoard and the 8 GB RCC-VE Network Board devices in homogeneous clusters. Figure 3 presents throughput on these clusters for up to 16 stages (devices).

For MinnowBoard devices, we achieve 0.63 images per second throughput with 4 devices using the ViT-Base model.
which is $1.98 \times$ faster compared to the single-device performance. The ViT-Large and ViT-Huge models cannot fit in memory on a single MinnowBoard device. Hence, we use 2-stage and 4-stage throughput as the speedup baselines for the ViT-Large and ViT-Huge models, respectively. With 16 MinnowBoard devices, EdgePipe achieves 1.95 images per second throughput, which is a $7.48 \times$ speedup over the 2-stage baseline (where the optimal speedup is $16/2=8$). For the ViT-Huge model, EdgePipe achieves 0.77 images per second throughput with 16 MinnowBoard devices, which gives a $3.93 \times$ speedup over the 4-stage baseline (where the optimal speedup is $16/4=4$).

We achieve similar scalability on the RCC-VE Network Board devices. With the ViT-Base model, EdgePipe achieves 0.82 images per second throughput with $1.99 \times$ speedup with four devices. Compared with the single-device baseline, EdgePipe achieves 2.43 and 1.01 images per second throughput for the ViT-Large and ViT-Huge models with $10.59 \times$ and $11.88 \times$ speedup using 16 devices, respectively.

The sub-linear performance for the ViT-Base model is primarily due to uneven execution times of different stages. We observe the performance difference for the slowest and fastest stages is about 25% for the 2-stage pipeline. With 4 stages, this time difference increases to 80% and causes a more serious performance loss. Figure 4 illustrates the issue by quantifying each ViT-Base layer’s execution time on the MinnowBoard. The second dense layer in the 11-th transformer layer, which only includes the linear transformation with the matrix multiplication operation and thus cannot be further partitioned with pipeline parallelism, requires considerably more execution time than other layers. The variation in execution time is due to differences in the sparsity of weights. We observe the similar performance behavior on the RCC-VE Network Board devices. In contrast, each transformer layer in the ViT-Large and ViT-Huge models have similar inference times, so EdgePipe scales better on the ViT-Large and ViT-Huge models. In addition, we observe compressed models reduce stage imbalances and mitigate this challenge. We report on compressed models in subsection 5.5.

EdgePipe achieves nearly linear performance improvements with the ViT-Large and ViT-Huge models when pipelining with both edge device types. EdgePipe achieves $3.93 \times$ speedup (over a 4-node baseline) on 16 MinnowBoard devices and $11.88 \times$ speedup on 16 RCC-VE Network Board devices with the ViT-Huge model. These results demonstrate EdgePipe’s effectiveness for large-scale models, including ones that otherwise cannot fit on single devices.

5.2 Heterogeneous Clusters

Compared with the data center, edge devices are more heterogeneous in computation and communication capabilities. To better simulate heterogeneous resource-constrained devices, we throttle the CPU usage of the RCC-VE Network Boards to emulate diminished inference performance. We also vary the maximum bandwidth for both MinnowBoard and RCC-
VE Network Board devices to emulate different network link capacities. We compare EdgePipe with GPipe and PipeDream on six clusters with increasing heterogeneity. Because GPipe and PipeDream do not specify the device mapping order, we test them with 10 random device orders and measure average performance and variance. Device configuration details are presented in Table 4, and experimental results are shown in Figure 5.

By comparing Cases 1 and 2, we show the effect of introducing heterogeneous computing capabilities on system performance. For the ViT-Base model, EdgePipe achieves the best performance of 0.82 images per second in both cases. GPipe and PipeDream show a significant variance with different device orders for the ViT-Base model. In Case 1, GPipe’s throughput ranges from 0.57 to 0.76 images per second, and PipeDream’s throughput ranges from 0.64 to 0.82 images per second. In Case 2, which introduces more heterogeneity, GPipe and PipeDream show a larger variance of 0.47 to 0.75 and 0.50 to 0.82 for the ViT-Base model. For the ViT-Large and ViT-Huge models, both GPipe and PipeDream adopt the same partitioning strategy and obtain the same performance. EdgePipe achieves 2.23 and 1.69 images per second for the ViT-Large model and 0.88 and 0.67 images per second for the ViT-Huge model in Cases 1 and 2, respectively. For the same two cases, GPipe and PipeDream only achieve 1.99 and 0.76 images per second for the ViT-Large model and 0.81 and 0.31 images per second for the ViT-Huge model. EdgePipe demonstrates both better performance and robustness when compute capabilities are more heterogeneous.

Case 3 has the same compute resources as Case 1, but with less communication bandwidth. We further vary the bandwidth in Case 4 with the same compute resources. For the ViT-Base model, EdgePipe achieves the best throughput of 0.78 and 0.63 images per second in both Cases 3 and 4. GPipe and PipeDream show a significant performance degradation due to the limited bandwidth. In Case 3 for the ViT-Base model, GPipe’s throughput ranges from 0.29 to 0.32 images per second, and PipeDream’s throughput ranges from 0.32 to 0.38 images per second. In Case 4 for the same model, GPipe’s throughput ranges from 0.16 to 0.20 images per second, and PipeDream’s throughput ranges from 0.18 to 0.32 images per second. For the ViT-Large and ViT-Huge models, EdgePipe achieves the best performance with fewer devices than GPipe and PipeDream for Cases 3 and 4. For the ViT-Large and ViT-Huge models on Case 3, EdgePipe selects 8 devices with 40 Mbps bandwidth and one device with 10 Mbps bandwidth as the last stage and achieves throughput of 1.37 and 0.53 images per second, respectively. GPipe and PipeDream use 16 devices and performance degrades with 1.02 and 0.44 images per second for the ViT-Large and ViT-Huge models in Case 3. In Case 4, EdgePipe selects 7 devices for the ViT-Large model and 9 devices for the ViT-Huge model to achieve throughput of 1.05 and 0.51 images per second, respectively. GPipe and PipeDream achieve 0.55 and 0.31 for the ViT-Large and ViT-Huge models. In Case 4, EdgePipe shows 1.90× and 1.54× speedup compared to PipeDream for the ViT-Large and ViT-Huge models, respectively. These two cases demonstrate the effectiveness of EdgePipe’s partitioning strategy for heterogeneous network.

In Cases 5 and 6, we mix the heterogeneity of devices and networks. In Case 5, we added 8 extremely resource-constrained devices with CPUs at 10% capacity and 20 Mbps bandwidth. EdgePipe achieves the best throughput with 0.73, 0.99, and 0.39 images per second using 4, 7, and 7 devices for the ViT-Base, ViT-Large, and ViT-Huge models. For the ViT-Base model in Case 5, GPipe’s throughput ranges from 0.22 to 0.66 images per second, and PipeDream’s throughput ranges from 0.26 to 0.69 images per second. For the ViT-Large and ViT-Huge models in Case 5, GPipe and PipeDream achieve 0.26 and 0.10 images per second. In Case 5, EdgePipe shows 1.55×, 3.75×, 3.84× speedup relative to PipeDream’s average throughput for the ViT-Base, ViT-Large, and ViT-Huge models, respectively. Case 6 shows a scenario with 6 types of devices weighted toward devices with medium performance. In this case, EdgePipe uses 4, 12, and 14 devices to achieve 0.80, 1.33, and 0.57 images per second for these three ViT models. For the ViT-Base model in Case 6, GPipe’s throughput ranges from 0.18 to 0.48, and PipeDream’s throughput ranges from 0.22 to 0.54 images per second. GPipe and PipeDream achieve 0.33 and 0.14 images per second for the ViT-Large and ViT-Huge models, respectively. EdgePipe achieves speedup of 1.98×, 3.98×, and 4.16× for the ViT-Base, ViT-Large, and ViT-Huge models compared to PipeDream’s average throughput. Cases 5 and 6 demonstrate EdgePipe’s ability to schedule around low-performance devices and map the task reasonably to achieve the best throughput.

EdgePipe performs significantly better than the GPipe and PipeDream partition methods on all six heterogeneous clusters. Unlike GPipe and PipeDream, EdgePipe successfully avoids the lowest-performing devices by considering multiple factors in exploiting pipelining to improve performance.

### 5.3 Impact of Bandwidth

Edge computing often has more limited bandwidth between devices compared to the data center. To evaluate the relationship between system performance and bandwidth, we vary the bandwidth between all devices from 120 Mbps to 5 Mbps. We test with 4 pipeline stages using the ViT-Base model and

| Case | Devices | CPU | Memory | Bandwidth |
|------|---------|-----|--------|-----------|
| 1    | 8×RCC-VE 100% 8 GB 1 Gbps |
| 2    | 8×MimnowBoard 100% 2 GB 1 Gbps |
| 3    | 8×RCC-VE 100% 8 GB 1 Gbps |
| 4    | 8×MimnowBoard 100% 2 GB 1 Gbps |
| 5    | 8×RCC-VE 100% 8 GB 1 Gbps |
| 6    | 8×MimnowBoard 100% 2 GB 1 Gbps |
Throughput (images/sec)
0.30
0.35
0.40
0.45
0.50
0.55
0.0
0.2
0.4
0.6
0.8
Throughput (images/second)

As in other pipeline frameworks, performance is affected by microbatch size and the system throughput for EdgePipe. However, it achieves a significant performance improvement with a maximum throughput of 0.48 images per second with a microbatch size of 12. The fine-grained partitioning method in EdgePipe achieves more efficient CPU utilization than even partitioning. Other pipeline stages show similar behavior. To give a fair comparison of throughput, we choose the optimal microbatch size of 12 and its related performance for all methods in the evaluations.

### 5.4 Impact of Microbatch Size

As in other pipeline frameworks, performance is affected by microbatch size. We demonstrate the relationship between throughput and microbatch size in Figure 7. For a 2-stage pipeline, the maximum throughput of the even partitioning method in GPipe is around 0.34 images per second with a microbatch size of 12. The throughput shows a significant increase before microbatch size 14, which is mainly due to the continuous increase in CPU utilization as the microbatch size increases. Beyond this size, the throughput begins to slowly decline because larger microbatch sizes reduce the efficiency of the pipeline parallelism. There is a similar pattern for microbatch size and the system throughput for EdgePipe. However, it achieves a significant performance improvement with a maximum throughput of 0.48 images per second with a microbatch size of 12. The fine-grained partitioning method in EdgePipe achieves more efficient CPU utilization than even partitioning. Other pipeline stages show similar behavior. To give a fair comparison of throughput, we choose the optimal microbatch size of 12 and its related performance for all methods in the evaluations.

### 5.5 EdgePipe with Model Compression

Model compression techniques shrink the model size to reduce compute cost and potentially accelerate inference [Han et al., 2015; Hinton et al., 2015] and training [Kundu et al., 2020]. These approaches can be considered as important complementary strategies to EdgePipe to improve the performance on resource-constrained platforms. For example, compared to the ViT-Base model, DeiT-Tiny and DeiT-Small use distillation to achieve similar ImageNet top-1 accuracy with compressed models of up to $17.2\times$ and $3.9\times$, respectively [Touvron et al., 2021]. To demonstrate the efficacy of using compressed models, we compare EdgePipe with and without model compression. Figure 8 shows the impact of model compression on the performance of EdgePipe. The results demonstrate that model compression can significantly improve the efficiency of EdgePipe while maintaining or even improving the accuracy of the model.
models with EdgePipe, we evaluate DeiT-Base, Small, and Tiny on up to 4 RCC-VE Network Board devices. We also provide the throughput of the ViT-Base model on same devices for comparison. Figure 8 presents the throughput results.

DeiT-Base, which has identical model structure as ViT-Base, achieves 0.62 images per second throughput on a single RCC-VE Network Board. With 4 devices, the DeiT-Base model achieves 0.96 images per second and outperforms ViT-Base’s 0.82 images per second. DeiT-Small and DeiT-Tiny demonstrate more significant improvements. In particular, DeiT-Small and DeiT-Tiny can provide throughput of up to 5.55 and 17.23 images per second, respectively. Interestingly, we observe DeiT-Small and DeiT-Tiny models ease the uneven execution times seen with ViT-Base and demonstrate better scalability with EdgePipe. The model compression technique, as an orthogonal method, can potentially further improve the performance of EdgePipe, making this combined approach a promising solution for large scale model inference at the edge.

6 Related Work

Current techniques to enable the execution of large models on edge devices mainly fall into two categories: single device optimization and distributed inference on multiple devices or servers. Aggressive model compression is an example of single device optimization methods. EdgeBERT [Tambe et al., 2020] combines network pruning, entropy-based early exit, and adaptive attention span to reduce the model size and the inference latency of Bidirectional Encoder Representations from Transformers (BERT) for NLP tasks. Lite Transformer [Wu et al., 2019] adopts adaptive inference to reduce inference computation cost. Another promising solution includes neural architecture search (NAS), that trains a flexible supernet model to yield various subnets suitable for different targeted hardware platforms [Wang et al., 2020]. However, most of the above methods are either not suitable for distributed platform or need redesigning and retraining of a pre-trained models and can potentially incur non-negligible drop in accuracy.

Through the assistance of cloud servers or distributed edge devices, the latency and computations for each device can be reduced without sacrificing accuracy. In several works [Chen et al., 2021; Kang et al., 2017; Eshratifar et al., 2021], the distributed inference of DNN models on edge devices is partitioned and offloaded to cloud servers to reduce the latency and computations. Considering the limited bandwidth and uncertain delay between the edge and the cloud, MoDNN [Mao et al., 2017] employs a MapReduce-like distributed inference paradigm and only utilizes idle mobile devices to execute CNN models. DeepThings [Zhao et al., 2018] proposes a fine-grain partition method for CNN models on edge clusters. In [Zhou et al., 2019], the proposed adaptive parallel inference method for CNN models is extend to heterogeneous edge devices.

With the emergence of transformer-based models, the model size continues to increase making distributed execution more important. Megatron-LM [Shoeybi et al., 2019] implements operation partitioning for transformer-based models. Pipeline parallelism is proposed to address the problem of communication overheads. GPipe [Huang et al., 2019] presents effective pipeline parallelism for training large models on multiple TPU accelerators. PipeDream [Narayanan et al., 2019] and its subsequent work [Narayanan et al., 2021a] target heterogeneous platforms and adopt pipeline parallelism to accelerate training. PipeMare [Yang et al., 2021] proposes a memory-efficient pipeline parallelism without sacrificing utilization. These work target data centers, and are difficult to directly apply to edge computing.

7 Conclusion

In this paper, we presented EdgePipe, a distributed inference acceleration system using pipeline parallelism. Unlike current pipeline parallelism frameworks for model training on cloud servers, EdgePipe focuses on heterogeneous resource-constrained devices. To address the workload balance problem for heterogeneous clusters, we design a dynamic programming-based partition method. We achieve 10.6× and 11.9× throughput speedup with 16 devices for the ViT-Large and ViT-Huge models, and demonstrate the ability to accelerate large-scale models on devices without sufficient memory. EdgePipe demonstrates effectiveness and robustness for multiple heterogeneous cases, e.g., we show up to 4.16× throughput speedup compared to GPipe and PipeDream when using a heterogeneous set of devices. Finally, we demonstrate the efficacy of our proposed scheme on compressed models to show that the throughput benefits of our pipelining approach are complementary to the improvement from compression and that we still achieve speedup by leveraging multiple devices.
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