Breaking the Computation and Communication Abstraction Barrier in Distributed Machine Learning Workloads

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Abstract

Recent trend towards increasing large machine learning models require both training and inference tasks to be distributed. Considering the huge cost of training these models, it is imperative to unlock optimizations in computation and communication to obtain best performance. However, current logical separation between computation and communication kernels in deep learning frameworks misses the optimization opportunities across such barrier. Breaking this abstraction with a holistic consideration can provide many optimizations to provide performance improvements in distributed workloads. Manually applying these optimizations needs modifications in underlying computation and communication libraries for each scenario, which is time consuming and error-prone.

Therefore, we present CoCoNet, with a DSL to express a program with both computation and communication. CoCoNet contains several machine learning aware transformations to optimize a program and a compiler to generate high performance kernels. Providing both computation and communication as first class constructs allows users to work on a high-level abstraction and apply powerful optimizations, such as fusion or overlapping of communication and computation. CoCoNet enables us to optimize data-, model- and pipeline-parallel workloads in large language models with only a few lines of code. Experiments show CoCoNet significantly outperforms state-of-the-art distributed machine learning implementations.

1 Introduction

As the trend towards larger machine-learning models continue, from BERT [10] with 340 million parameters, GPT-2 [39] with 8.3 billion parameters, to GPT-3 [5] with 175 billion parameters, training and inferencing computations have to be distributed. Moreover, as the computations become resource hungry, optimizing for even the last percentage can have huge benefits in terms of time, energy, and money savings [20, 41].

In machine learning systems today, computation and communication are treated as independent abstractions implemented in different libraries. For instance, computation libraries such as cuBLAS [29] provide optimized tensor algebra operations, while communication libraries such as NVIDIA Collective Communication Library [32] (NCCL) provide high-performance implementations of communication collectives like AllReduce. Deep learning frameworks like PyTorch [33] and Tensorflow [1] are responsible for calling computation and communication kernels from these libraries. Therefore, deep learning applications built atop of such frameworks, such as Megatron-LM [39] and GShard [21], have to invoke computation and communication operations separately.

While such a separation by allows independent optimization of compute and communication kernels, breaking this abstraction boundary unlocks new optimizations that are otherwise not feasible. These optimizations include the following. Interface optimizations eliminate a mismatch between the caller and the callee of an abstraction. For example, ML model parameters are stored in non-contiguous buffers, one per neural network layer and hence, need to be copied into a single buffer before calling a collective operation such as AllReduce. This copy can be avoided if the communication kernel takes a list of arrays as input instead of requiring a single buffer. Fusion optimizations decreases memory bandwidth usage by generating a single kernel to
performs multiple communication and computation operations. For instance, the output of an AllReduce might be used in activations like Dropout. Reorder optimizations can move parts of the computation before or after communication, thereby either distributing the computation or enabling new fusion possibilities. Finally, pipelining optimizations orchestrate multiple computation and communication in a fine-grained manner to overlap multiple kernels. We elaborate on this possibility below.

In model parallelism, each layer is distributed across multiple GPUs [39]. Hence, the computation at each layer consists of (distributed) matrix multiplications (GEMM) followed by AllReduce (AR). Figure 1 shows the improvement achieved by overlapping the two kernels. The idea is to slice the output into smaller chunks and start the AR communication on a chunk as soon as the GEMM kernel has produced it. The key here is to schedule the GEMM kernel so that the chunks are produced in the order AR kernel requires them. For instance, in the ring algorithm for AllReduce, the \( n \)th node sends the chunks to the next node in a order starting from the \( n \)th chunk. As such, the GEMM kernel on the \( n \)th nodes needs to generate the chunks in this order. To avoid kernel launch overheads, only one GEMM kernel and one AllReduce kernel are launched. Figure 1 shows that across various batch sizes during model parallel training of the GPT-2 model, this optimization provides up to 1.36x speedup and hides 80% of the execution time of GEMM.

Since manually writing these optimizations for each scenario is unproductive, we show that by carefully designing a language for expressing combinations of compute and communication the benefits of existing deep learning framework’s abstraction can be maintained while simultaneously allowing a compiler to apply powerful optimizations. To this effect, we propose CoCoNet\(^1\) for generating highly-optimized custom computation and communication kernels.

Figure 2 presents the overview of CoCoNet. CoCoNet includes a DSL to express programs containing both computation and communication primitives. Inspired by Halide [34], CoCoNet includes a scheduling language to specify an execution schedule of the program using a set of transformations. CoCoNet’s auto tuner automatically applies these transformations to optimize a program by breaking the communication and computation boundary and hence, allows users to quickly generate optimized implementations for specific hardware, topology, and data sizes. CoCoNet’s code generator automatically generates high-performance computation and communication kernels from a program and its schedule. We used CoCoNet to optimize data parallel training, model parallel inference, and pipeline parallel inference. CoCoNet generated kernels for the Adam [18] and LAMB [44] optimizers speeds up the training time of BERT models by upto 1.68x and can train BERT 3.9 Billion parameter models using only data parallelism which is not possible with state of the arts. CoCoNet’s kernels for model parallelism speeds up the inference in BERT 3.9 Billion and GPT-2 8.2 Billion parameter models by 1.51x. CoCoNet’s optimized pipeline parallelism kernels speeds up inference times in GPT-2 8.2 Billion and GPT-3 175 Billion parameter models by upto 2.45x.

2 \textbf{CoCoNet DSL}

CoCoNet extends data representation in existing deep learning and allows expressing both computation and communication in its domain specific language. Unifying the expression of computation and communication for distributed deep learning in the same DSL is the foundation to enable optimizations across computation and communication.

2.1 Tensor Layout

CoCoNet extends the concept of tensor in deep learning frameworks from single device data into distributed forms. Besides item datatype (INT32, FP16) and shape of a traditional tensor, a CoCoNet tensor also includes a description of how it is distributed across a set of ranks. We follow MPI [11] terminology: \texttt{RANK} is the process ID of a distributed process and \texttt{GROUP} is a set of concurrent distributed processes (\texttt{WORLD} is the \texttt{GROUP} that includes all processes). CoCoNet supports dividing consecutive ranks into one or more groups. Inside a group, CoCoNet follows a single program multiple data (SPMD) paradigm where each rank in the same group runs the same pattern but with different ID.

CoCoNet includes three distributed layouts: \textit{sliced}, \textit{replicated}, and \textit{local}. A \textit{sliced} tensor represents one that is equally distributed to all the nodes in a group along specified dimension with \texttt{RANK} identifying the slice. For example, in Figure 3, \( w \) is sliced among all ranks in \texttt{WORLD} in the first dimension and \( i \) is sliced in the third dimension. A tensor can also be \textit{replicated} across all ranks in a group where it has the same value on each rank and it does not have a rank identifier.

\(^1\)CoCoNet stands for \textquote{C}ommunication and \textquote{C}omputation optimization for neural \textquote{N}etworks. We will make our implementation publicly available.
Figure 2. Overview of CoCoNet’s workflow. First, a user expresses a deep learning algorithm in the DSL that contains both computation (MatMul) and communication (AllReduce). Then, the autotuner applies several transformations to optimize the program while keeping the algorithm unchanged, such as fusing AllReduce and Dropout into FusedAllReduce and overlapping this with MatMul. Finally, CoCoNet generates custom communication and computation code, which is available through PyTorch.

For example the bias b and the residual connection r are replicated as shown in Figure 3. A local tensor is one that has equal shape on all ranks but with different values on different ranks. Unlike replicated, local requires a RANK to identify the values. For example, in Figure 3, layer is a local tensor that represents the partial result of a matrix multiplication (MatMul) operation. A Scalar is a zero-dimensional Tensor that represents a variable available on all ranks. We discuss distributed property of intermediate tensors in the next section.

2.2 CoCoNet’s Operations

CoCoNet programs inherit the concept of data-flow graph (DFG) from existing deep learning frameworks, with operations as vertices and data dependencies as edges. Moreover, each tensor has the update function that reflects the new values of tensor in that position in DFG.

CoCoNet operations include local computations and cross rank communications on tensors. This includes collective communications such as AllReduce and AllGather, and P2P communications like Send and Recv. CoCoNet’s local computation operations can be mapped to existing neural networks operations, such as dropout and matrix multiplication. A Var represents the intermediate values obtained after performing an operation. For instance, Figure 3 describes the Megatron-LM [39] model parallel logic of Self-Attention layer in CoCoNet. In this example, the linear layer’s weight (w) and the input (in) are sliced across all ranks while the bias (b) and residual (r) are replicated on all ranks. A Var’s shape and distribution layout is implied by the operation. For example, Line 7 performs a MatMul operation on the input and the weights of the linear layer. Since MatMul is performed in the sliced dimension H of in and w, which H disappears in output and layer represent a partial result of Matmul and is Local to each rank. AllReduce compute the sum of layer of all ranks (line 9) and get a replicated tensor with the same full value (non-partial) on each rank. Lines 11–13 perform computations that involves adding the bias, using dropout as the activation and adding the residual of previous layer. Note that b and sum have shapes [H] and [B,S,H], respectively. sum+b in Line 11 follows PyTorch’s standard semantics by replicating b in missing dimension of sum. The shape and distribution property of these operations are the same as sum. Finally, Execute defines the name, inputs and outputs of the program.

2.3 Fused Communication Collectives

CoCoNet enables efficient computations on the output of communication by providing fused communication collectives, such as FusedAllReduce. Consider AllReduce in Figure 3 (line 9) followed by a dropout (line 11). Due to the abstraction of communication and computation in existing deep learning frameworks, AllReduce stored output needs to be reloaded by the dropout kernel. FusedAllReduce avoids such stores and loads by directly passing output through registers as consecutive input. Comparing with AllReduce, a FusedAllReduce also takes computation operations (such as dropout) as extra augments. Section 5.3 discusses the implementation of Fused communication collectives.
2.4 Overlapping Operations
CoCoNet supports overlapping multiple dependent operations using the overlap primitive, including overlapping consecutive communication operations, as well as overlapping consecutive computation and communication operations such as MatMul and AllReduce in Figure 3 (line 7 and line 9). Section 5.4 discusses the implementation of this construct.

3 Schedules in CoCoNet
CoCoNet optimizes a user specified program in CoCoNet’s DSL by applying a sequence of transformation. We call an order of transformation a schedule. These schedules are applied by the CoCoNet’s Autotuner as shown in Figure 2. There are 5 class of transformations that CoCoNet provides. Each transformation replaces one or many source operations with one or many target operations, while it keeps the program output unchanged. CoCoNet automatically check if the transformation is valid by ensuring that the dependencies in the DFG after applying transformation are preserved. Next, we present each transformation by applying them on the program from Figure 3 as a running example in the order presented in the autotuner of Figure 2.

3.1 Fusing Computation Operations
fuse transformation fuses multiple compute operations into a single operation. This is a well-known technique in many frameworks.

Running Example All pointwise computations in Figure 3 are fused into a single computation.

\[
\text{fuseOut} = \text{fuse}(d, out, \text{ComputeFuse});
\]

Figure 4 shows the equivalent CoCoNet implementation of this schedule in 1. The fuseOut operation performs both dropout and the residual addition in a single kernel and thus avoids redundant memory accesses and saves a kernel launch.

3.2 Splitting Operations
split transformation breaks a communication collective into two collectives based on two split policies:

AllReduce Split RS-AG splits an AllReduce into ReduceScatter to produce sliced tensors and AllGather on the sliced tensors to obtain a replicated tensor.

AllReduce Split B-R splits an AllReduce into Reduce to produce a tensor on rank 0 and then broadcast this tensor to all ranks in WORLD.

Running Example The AllReduce in Figure 3 is split into rsSum and agSum, where the former does a ReduceScatter on layer and the later does an AllGather on rsSum.

\[
(rsSum, agSum) = \text{split}(layer, \text{AllReduceSplitRSAG});
\]

Figure 4 in 2 is the CoCoNet implementation of this schedule, where the input to fuseOut is replaced by agSum.

3.3 Reordering Computation and Communication
CoCoNet provides reorder transformation that reorders an operation with AllGather or Broadcast based on two policies:

AllGather Reorder reorders AllGather with a pointwise communication operation. This transformation applied change to distribution properties which will explain in our running example.

Broadcast Reorder is similar to AllGather reorder except that it requires a root.

Running Example In Figure 3, reorder transformation changes the program 2 to 3 by reordering AllGather (agSum) with computation (fusedOut). This transformation performs two changes. (i) After reordering, all input tensors in the pointwise compute operation are changed to sliced tensors along their first dimension. For example, after the reordering transformation, r in fuseOut of 2 becomes Slicee(r) in scOut in 3 with Sliced(d) distribution property which is the same property for Dropout and scOut. (ii) The input and output of the compute and AllGather operations are exchanged. For example, in 2, Dropout is performed on the output of AllGather (agSum) but in 3 Dropout is performed on input of AllGather (rsSum). Also, in 3 AllGather is performed on output of the computation (scOut). reorder transformation takes agSum, AllGather’s output, and fusedOut, dropout’s output as inputs and generates: (i) scOut, which performs sliced computations, and (ii) agOut, which gathers the result of computation.

\[
(sOut, agOut) = \text{reorder}(agSum, fuseComp, AllGatherReorder);
\]

Figure 5 shows the workflow of this schedule and Figure 4 3 shows the equivalent CoCoNet program of this schedule.

3.4 Fusing Computation and Communication
CoCoNet provides fusedComm transformation to fuse communication and computation into a single operation. We explain this transformation for FusedAllReduce policy but this transformation can be generalized to other fused computation collects.

AllReduce Fuse RS-AG This transformation is only valid when source operations performs ReduceScatter, sliced computations, and AllGather on the output of the computation. The target operation FusedAllReduce performs all three operations into one.

Running Example From the previous schedule, we fuse operations in FusedAllReduce that generates a single kernel for communication and computations.

\[
fuseAR = \text{fuseComm}(rsSum, scOut, agOut, FusedAllReduce);
\]
Figure 4. Different schedules produced by performing transformations on parallel program from Figure 3. Each schedule can be represented as a standalone CoCoNet program. Lines in red highlights the changes on this step.

```
layer = MM(in, w);
sun = AllReduce(layer);
d = Dropout(sum+b);
out = d + r;
layer = MM(in, w);
 fuseAR = FusedAllReduce(layer);
scoOut = Dropout(fuseAR+b)+Slice(r);
 fuseOut = fuseAR.comp(scoOut);
out = Overlap(layer, fuseOut);
```

Figure 5. Equivalent programs (from Figure 3) using AllReduce (on left) or using ReduceScatter + AllGather (on right).

3.5 Overlapping Computation and Communication

CoCoNet provides overlap transformation to overlap a series of producer-consumer operations. This transformation is used to overlap several communication operations or a computation with communication. It takes two or more operations as input and returns a single operation.

Running Example We overlap the matrix multiplication with FusedAllReduce.

```
layerWithAR = overlap(layer, fuseAR);
```

Figure 4 shows the equivalent implementation of this schedule in (4), where FusedAllReduce is used instead of AllReduce. The comp method of fuseAR specifies the computation to be fused with FusedAllReduce and returned out is the output.

3.6 Automatic Exploration of Schedules

CoCoNet’s Autotuner automatically explores the space of all schedules by combining different transformations and validating each schedule. The output of the autotuner is a single schedule consist of a series of transformations with the best performance.

4 Optimizing Workloads with CoCoNet
fuses the P2P send with computations. Line 2 split the AllReduce and reorder the returned AllGather with fused send at Line 4. Hence, P2P send and computations are performed on only a slice of data on the next group where the AllGather is also performed. Finally, all three new operations get overlapped in Line 5. This overlapping can only be achieved by generating custom communication and computation kernels.

5 CoCoNet Implementation

CoCoNet generates both device code and host code for a program. The host code is generated by traversing the program’s DFG to add kernel calls for each operation. For pointwise computations that are not part of a communication primitive, CoCoNet generates a stand-alone CUDA kernel. All other codegen falls into one of the categories below: i) a call to a communication collective; ii) a custom kernel that extends a communication collective with a fused-collective (Section 5.3); and iii) a custom kernel that extends a communication collective with overlapping of communication and computation kernels (Section 5.4). CoCoNet wraps generated programs as custom operators and integrates them into deep learning frameworks, so that, applications like Megatron-LM can invoke them directly.

The following sections discuss how CoCoNet adapts NCCL, a widely-used hand-optimized high performance communication library, into a runtime that can execute ii) and iii) above. NCCL is designed for single buffer tensor communications and is not built to execute arbitrary computations.

5.1 NCCL Architecture

NCCL’s architecture defines four key properties: (i) topology, (ii) protocols, (iii) channels, and (iv) threads in a thread block of the CUDA kernel. NCCL automatically sets key configuration values for these properties based on the size of input buffer, network architecture, and size of WORLD. To get good performance, CoCoNet’s codegen must carefully reconfigure these properties when extending NCCL to custom computation. We now provide a high level overview of these properties.

Topology NCCL create logical topologies, such as ring and tree, over the underlying interconnect network.

Channels NCCL maps copies of a logical topology on the underlying interconnect network. Each copy is called a channel and is assigned to one CUDA thread block. To increase parallelism, more channels are used as the buffer size grows.

Protocols NCCL sends data using one of three protocols: LL, LL128, and Simple. These protocols make different tradeoffs between latency and bandwidth based on the type of inter-node synchronization used, with LL having the lowest latency and Simple having the highest bandwidth.

Number of Threads NCCL sets a fixed number of threads for each channel (and thread block). NCCL’s kernels have
high register usage, which in practice limits the number of thread blocks per SM to one.

**CoCoNet + NCCL** CoCoNet modifies NCCL so it can do custom computation and overlap other kernels with communication. After determining the topology, protocol, number of channels, and number of threads, NCCL calls the CUDA kernel for the collective. Each collective communication has three levels of tiling due to the fine-grained parallelism of GPUs. Data is first divided into buffer tiles equal to the size of the communication buffer. Each buffer tile is further divided among all ranks and channels to obtain chunks. Each channel communicates a chunk of data at a time. The threads in channels copy elements in and out of the communication buffers and apply reduction operations (sum, min, max) if needed. The following sections goes into more detail about CoCoNet’s codegen.

### 5.2 CodeGen for Scattered Tensor Communications

In data parallelism, communication and computation occur on different layers of widely different sizes. Since deep learning frameworks allocate parameters and gradients of layers in non-contiguous buffers, gradients should be copied to a large buffer to avoid launching too many AllReduce operations.

CoCoNet supports generating a single kernel for operations acting on several non-contiguous tensors. This code generation is non-trivial because NCCL’s code makes many assumptions of buffers being contiguous. For example, each thread of a NCCL channel copies only a few elements in each iteration, and hence indexing the correct tensor at the correct offset could have significant overhead. CoCoNet solve this problem by first dividing each tensor into buckets of size at most 1024 elements and then assigns buckets to warps in a round-robin manner. This mechanism allows each thread to quickly find the offset in a tensor since a warp can directly index in its assigned bucket. CoCoNet pre-calculates the number of buckets that belong to the same contiguous buffer and calculates the offset for all of them once.

The process of breaking each tensor to buckets has some compute and memory overhead. Since this bucketing is done only once on the CPU and training tasks run for thousands of iterations on the same tensors, the computation overhead is negligible. For each bucket, CoCoNet packs an 8-byte tensor address and a 4-byte bucket offset into the associated tensor. This requires \((8 + 4) \times \left \lceil \frac{N}{max} \right \rceil\) bytes of memory, where \(N\) is the number of elements in a tensor. This memory overhead is only about 0.3\% \sim 0.6\% of the size of the tensors.

We now compare the performance of CoCoNet scattered tensors against contiguous tensors to show that overhead introduced is insignificant in our implementation. The table below compares the performance of Adam/LAMB optimizers with mixed precision on 360 tensor in BERT model with elements from 1K to 31M against a single contiguous tensor with the size equal to the sum of all tensors which is 334M elements.

<table>
<thead>
<tr>
<th>Optimizer</th>
<th>Single Tensor</th>
<th>Scattered Tensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adam</td>
<td>33.21 ms</td>
<td>33.89 ms</td>
</tr>
<tr>
<td>LAMB</td>
<td>36.71 ms</td>
<td>37.04 ms</td>
</tr>
</tbody>
</table>

### 5.3 CodeGen for Fused Communication Collective

CoCoNet further extends the code generation described in the previous sections to support fused communication collectives. To achieve this, CoCoNet extends NCCL to allow for arbitrary pointwise computations and reductions (i.e., beyond \(\min, \max, \text{and sum}\)). We inspected more than 10K lines of code in NCCL to identify where computations can be added so that intermediate values from communication primitives can be directly passed to the computation through registers. CoCoNet supports fusion of both pointwise operations and reductions into NCCL collectives.

Each NCCL protocol utilizes a different mechanism for communication and CoCoNet generates code for all of them. The important features of a protocol are pack type (64-bit for LL, 128-bit for LL128 and Simple) and load/store access pattern (shared memory for LL128, global memory for LL and Simple). CoCoNet generates templates for all element types in NCCL, and dispatches accordingly at runtime. There are some subtleties in the code generation worth discussing:

**Mixed Precision** When the element types of computations and the input tensors are different, CoCoNet finds the largest element type and based on the pack type of the protocol calculates how many elements can be loaded at once. All code will then be generated to operate on this many elements.

**Sliced Tensor** When a sliced tensor is used by a fused communication collective, accesses performed for each channel need to be mapped to elements of the sliced tensor. CoCoNet generates code that produces this mapping. For AllGather the inverse mapping is also produced.

**Tensor Reduction** To reduce a sliced tensor, each rank reduces locally and do an AllReduce. This AllReduce reuses already established connections among ranks in the surrounding communication kernel, to eliminate extra startup latency.

### 5.4 Overlapping of Communication and Computation

Overlapping consecutive dependent operations is achieved by dividing them into multiple sub-operations (data also divided into parts accordingly) while turning operation-level dependency into sub-operation-level. Then we can overlap the independent sub-operations. Existing implementations would call a kernel for each sub-operation by dispatching homogeneous kernels into the same CUDA stream, and use cross-stream events to guarantee inter sub-operation dependencies. With number of parts increasing, its performance
all the GEMM kernel wakes the AllReduce, which starts communicating chunk 0. While the GEMM kernels compute next chunks, the AllReduce finishes the computation of chunk 1 on rank 0 and chunk 2 on rank 1 and wakes up the AllReduce kernel to communicate these chunks. This process continues until all finishes.

This process allows the GEMM kernel and AllReduce to be overlapped in a fine-grained manner, which reduces the startup latency of AllReduce. Since AllReduce communicates on the same chunk sizes, it achieves maximum communication bandwidth. Furthermore, the GEMM kernel achieves maximum efficiency because the kernel is invoked on the full matrix size. Figure 1 shows that this pipelining provides up to 1.35x better performance and hides more than 80% of computation time.

6 Evaluation

We implemented CoCoNet compiler on top of NCCL [32] and integrated with PyTorch. This section evaluates the effectiveness of CoCoNet through standalone experiments as well as end-to-end distributed deep learning scenarios using data parallelism, model parallelism and pipeline parallelism.

Our experiments are performed on a cluster of NVIDIA DGX-2 nodes where each node contains dual 24-core Intel Xeon CPUs and 16 NVIDIA Tesla V100 (32GB) GPUs. Each GPU within a node is connected to six NVSwitches with six NVLinks (25 GBps per NVLink). Nodes are connected with 8 non-blocking EDR InfiniBand (100 Gbps) network. All nodes run Ubuntu 18.04, CUDA 10.2, cuDNN 7.5 and PyTorch 1.5.

6.1 Data Parallel Training
In data parallelism, communication involves an AllReduce of gradients among all ranks. The output is used by the optimizer to update the model parameters. We take two widely-used optimizers, Adam and LAMB, to demonstrate the performance of CoCoNet by fusing the communication with optimization update as well as performing AllReduce on scattered tensors.

6.1.1 Standalone Experiments. We first perform standalone experiments to explore different CoCoNet schedules over a range of input tensors from $2^{10}$ to $2^{30}$ elements. The autotuner generates and executes implementations with different configurations, including all NCCL protocols, all channels from 2 to 64. For each tensor, the autotuner reports the best average result of 1000 iterations.

Baselines The baselines perform parameter update by first doing AllReduce over gradients and then call FusedAdam or FusedLAMB from NVIDIA Apex Library [31]. FusedAdam and FusedLAMB fuse all the parameter update computations into a single kernel. CoCoNet additionally provides the ability to fuse such computation with the AllReduce kernel.

Figure 9. Workflow of CoCoNet's overlapping of producer GEMM with a consumer AllReduce for a Float 16 matrix size of [8192, 3072] on 8 ranks (R0 to R7) with 1 channel (C0) and 16 MB buffer size. Dimensions of each 2-D chunk (B0 to B15) is [1024, 1024]. CoCoNet's custom AllReduce and GEMM allows better overlapping without decreasing communication bandwidth and the efficiency of computation kernels.

would suffer from: (i) decreasing part size leads to low communication bandwidth utilization and computation kernel efficiency, and (ii) more kernel launches increasing cost to set-up communication.

We use GEMM and AllReduce example in Figure 9 to explain how CoCoNet addresses this issue. First, it schedules the GEMM kernel (based on CUTLASS [30]) to produce chunks in the same order as AllReduce consumes them. Figure 9 shows the working of a ring AllReduce among 8 ranks. Here, $n^{th}$ rank sends chunks in a order starting from $n^{th}$ chunk. Hence, GEMM kernel on $n^{th}$ rank produces chunks in the same order. Second, CoCoNet invokes both kernels only once on different streams and synchronize AllReduce with GEMM using an efficient fine-grained spin-lock on a memory buffer to ensure that AllReduce wakes up as soon as GEMM produces a chunk. Third, to provide better opportunities to tune tile sizes (2-dimensional) of GEMM, CoCoNet generates scattered AllReduce kernel that align communication chunks with tile size in GEMM, while NCCL AllReduce only supports continuous chunk (1-dimensional).

The example in Figure 9 works as follows. At T=1, all ranks invokes GEMM and AllReduce kernels. On rank 0, after computing chunk 0, the GEMM kernel wakes the AllReduce kernel at T=2, which starts communicating chunk 0. While on rank 1, at T=2 the GEMM kernel wakes the AllReduce kernel to communicate chunk 1. Concurrently, both GEMM kernels compute next chunks. At T=3, the GEMM kernels finishes the computation of chunk 1 on rank 0 and chunk 2 on rank 1 and wakes up the AllReduce kernel to communicate these chunks. This process continues until all finishes.
FusedAdam and FusedAdam are written in 6.2K lines of code, while CoCoNet schedules are roughly 10 lines of code.

CoCoNet Schedules The autotuner generates the following three schedules of Adam and LAMB by applying different CoCoNet transformations for each input size and for each input size reports the best schedule to the user:

1. **AR-Opt** (Opt = Adam/LAMB) refer to the traditional parameter update technique, i.e., an AllReduce over gradients and then each GPU individually performs the optimizer computation. These schedules fuse all pointwise computations into a single kernel, thereby simulating the baseline implementations of FusedAdam and FusedLamb respectively when Opt = Adam and Opt = LAMB.

2. **GShard-Eq** or **RS-Opt-AG** (Opt = Adam/LAMB) are generated from **AR-Opt** by first splitting the AllReduce into ReduceScatter and AllGather, and then reordering AllGather with the fused optimizer computations. Hence, these schedules distributes parameter update across all ranks, similar to GShard [21] and ZeRO [35]. Since GShard does not support execution on GPUs, we represent this schedule as GShard-Eq in our results.

3. **fuse(RS-Opt-AG)** (Opt = Adam/LAMB) are generated by fusing all stages of **RS-Opt-AG** into FusedAllReduce.

### 6.1.2 Results

Figure 10 shows the speedup of CoCoNet schedules over the baseline for several tensor sizes. The results shown are for float 16 mixed-precision, and the results for float 32 are qualitatively similar. In these figures, UB represents the cost of AllReduce alone without doing any computation, and thus is the upper bound of possible speedups.

Even though the AR-Opt schedules emulate the baseline implementations, they are faster on smaller tensors. This is because the baseline implementations perform additional preprocessing to optimize the amount of thread-parallelism and instruction-level parallelism per invocation. While this preprocessing cost hurts smaller tensors, its benefit shows up for larger tensors where AR-Opt performs worse.

Since GShard-Eq and fuse(RS-Opt-AG) schedules distribute the optimizer computation, they perform better than the baseline for large tensors. The performance of fuse(RS-Opt-AG) shows the advantage of fusing computation and communication kernels as these schedules achieve near optimal speedups for large tensors. These schedules are respectively 13% and 14% faster than GShard-Eq for Adam and LAMB.

For smaller tensor sizes, the multiple kernel calls required for GShard-Eq schedules significantly hurt performance. Interestingly, fuse(RS-Opt-AG) schedules are slower than AR-Opt schedules for smaller tensor sizes though they require one less kernel call because the fused kernels have a higher register usage, thereby restricting the thread-level parallelism. This demonstrates that fusion of kernels is not always a good idea.

In summary, CoCoNet provides performance improvements over baselines including GShard with less lines of code. The AR-Opt and the fuse(RS-Opt-AG) reach close to optimal performance for smaller and larger tensors respectively. This amounts to a speedup of 1.2× to 1.7× for Adam and of 1.35× to 2.0× for LAMB. There is no schedule that performs best for all sizes, which demonstrates the need for the autotuner.

### 6.1.3 Integration with BERT

We use CoCoNet generated optimizers to train three large BERT model from NVIDIA [27]. We use mixed precision training with both Adam with 8192 global batch size and LAMB with 65536 global batch size.

#### Baselines

We consider three baselines for this experiments:

- **NV BERT** [27] is the NVIDIA BERT Script. It copies gradients from each layer into a single buffer and then calls AllReduce on the buffer. The result is copied back into original tensors and calls either FusedAdam or FusedLAMB.
• **PyTorch DDP** [22] stores all gradients in buckets of 25MB and overlaps the AllReduce on each gradient bucket with the computation during training. After reducing all gradients it calls FusedAdam or Fused-LAMB.

• **ZeRO** [35] copies gradients into a contiguous buffer and then distributes the optimizer computation similar to RS-Opt-AG schedules above. ZeRO is written in 3k LoC, while in CoCoNet the same schedule can be represented in 10 LoC. This baseline also represents the technique used by GShard. The ZeRO implementation of LAMB does not support distribution of optimizer state among GPUs because LAMB involves a reduction over gradients and parameters. Performing this reduction over distributed gradients and parameters requires significant engineering effort [7]. CoCoNet’s DSL approach generates scattered tensors implementation for both Adam and LAMB automatically, which perform these operations.

CoCoNet Integration We integrated scattered tensor implementation of fused schedules of both Adam and LAMB, i.e., fuse(RS-Opt-AG) in PyTorch. These implementations provide three benefits over the baselines: (i) the scattered tensor implementation avoids copying all gradients to a single buffer and allocating this buffer, (ii) the fused schedule performs best for the tensor sizes used in BERT, and (iii) the fused schedule distributes memory of optimizer state among all GPUs.

**Results** Table 1 shows the speedup provided by CoCoNet in training three BERT models over baselines. For Adam optimizer CoCoNet provides speedup over all baselines in training BERT 336M because CoCoNet’s fused schedules performs better than other implementations. For larger BERT models CoCoNet provide even higher speedup because the fused schedules decreases memory usage by distributing Adam’s state over all GPUs, which improves efficiency of GEMM calls by enabling higher batch size per iteration. For example, for BERT 1.2B CoCoNet provides 1.53x speedup over NV BERT and PyTorchDDP both because of optimized fused schedule and CoCoNet allows a batch size of 32 while both baselines supports a batch size of only 8. On 3.9B parameter model, both baselines goes Out of Memory. Since ZeRO uses RS-Adam-AG schedule, it also supports higher batch size. CoCoNet still gives speedup over ZeRO for BERT 1.2B and 3.9B because of the advantages of scattered tensor implementation of fused schedule.

Results for LAMB are similar. CoCoNet provide significant speedup over NV BERT, PyTorchDDP, and ZeRO. For LAMB, the speedup over ZeRO is higher than Adam because ZeRO does not support distribution of its implementation of LAMB optimizer state and it supports smaller batch sizes as compared to CoCoNet. For example, CoCoNet provides up to 1.68x speedup over all baselines because it supports batch size of 64 while baselines can have a batch size of 8.

In summary, CoCoNet significantly improves data parallel training time of BERT model. CoCoNet’s schedules can be automatically generated and CoCoNet’s scattered tensors implementation can support wide range of optimizers. Not only does fusion of computation and communication leads to performance improvement over the baselines of PyTorch DDP and ZeRO (ZeRO uses same technique as GShard), it also decreases the memory usage, which helps in increasing the batch size to train models faster.

6.2 Model Parallelism

Megatron-LM [39] uses a model parallel approach for inference and training of transformer models, such as BERT [10] and GPT-2 [5]. A transformer layer contains a self-attention block, and a multi-layer perceptron (MLP) block. Last few operations of a self-attention block are the same computations as shown in Figure 3. An MLP block’s last operations are similar to Figure 3 with the input tensor and weight sizes as $[B, S, 4 \times H]$ and $[4 \times H, H]$. $B$, $S$ and $H$ are batch size, sequence length and hidden size, respectively. We implemented both computations in CoCoNet and compare following schedules:

1. **MM+AR+C** is the baseline schedule described in Figure 3 and fuses all pointwise computations into a single kernel.

2. **GShard-Eq** or **MM+RS+C+AG** uses same techniques as GShard. It is generated from **MM+AR+C** by splitting AllReduce into ReduceScatter and AllGather, and reordering AllGather with computations. This schedule represents GShard in our results as GShard is not available for GPUs.

3. **OL(MM,fuse(RS+C+AG))** is generated from previous schedule by fusing the ReduceScatter, computation, and AllGather into a FusedAllReduce and then overlapping it with matrix multiplication. AUTOTUNER returned this as best schedule and hence represents CoCoNet in our results. Since overlapping and fusion is not supported by GShard, GShard cannot represent this schedule.

**Results** We evaluate these schedules with sizes of GPT-2 8.3 Billion parameter model (i.e., $S = 1024, H = 3072$) with 16 GPUs for 8 and 16 batch sizes. Figure 11 shows the times of all schedules normalized to time of **MM+AR+C**. The schedule similar to GShard (**MM+RS+C+AG**) provides 1.09x to 1.23x speedup by distributing computations on all ranks. CoCoNet’s best schedule (**OL(MM,fuse(RS+C+AG))**) provides 1.33x to 1.62x speedup over baseline and 1.21x to 1.34x over GShard schedule because it uses FusedAllReduce and overlaps it with the matrix multiplication.

6.2.1 Integration with Megatron-LM. After integrating CoCoNet’s overlap schedule in Megatron-LM, we found that CoCoNet improved inference times of BERT 3.9 Billion parameter model by 1.51x and GPT-2 8.3 Billion parameter
Table 1. Maximum Micro Batch Size supported by all implementations and speedup of CoCoNet over the baselines when training BERT model with three different parameter configurations using Adam and LAMB optimizer. OOM means Out of Memory.

<table>
<thead>
<tr>
<th>Optimizer</th>
<th># of Parameters</th>
<th>Maximum Micro Batch Size</th>
<th>Speedup of CoCoNet over</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>NV BERT</td>
<td>PyTorch DDP</td>
</tr>
<tr>
<td>Adam</td>
<td>336M</td>
<td>32</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>1.2B</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>3.9B</td>
<td>OOM</td>
<td>OOM</td>
</tr>
<tr>
<td>LAMB</td>
<td>336M</td>
<td>64</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>1.2B</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>3.9B</td>
<td>OOM</td>
<td>OOM</td>
</tr>
</tbody>
</table>

Figure 11. Times of three schedules of model parallel self-attention and multi-layer perceptron of GPT-2 in CoCoNet normalized to baseline schedule (MM+AR+C) for two matrix multiplication sizes for 16 Tesla V100 GPUs. Time spent in different kernels and speedup is shown for each schedule.

Figure 12. Times of four schedules for GPT-3 175B model in CoCoNet normalized to the baseline schedule (AR+P2P+C) for pipeline and model parallelism.

6.3 Pipeline Parallelism

CoCoNet can optimize inference in pipeline parallelism by fusing computation and communication and overlapping multiple communication operations (Section 4). We evaluate CoCoNet on computations of model and pipeline parallelism in Megatron-LM over GPT-3 175B model. A transformer layer contains several operations but the operations of interest for this experiment are presented in Figure 8a. We evaluate following best performing schedules obtained by the autotuner:

1. AR+P2P+C is the baseline schedule described in Figure 8a and fuses all pointwise computations.
2. AR+P2P+C+AG is generated from AR+P2P+C by slicing the output of AllReduce, performing P2P sends and compute on the sliced output, and AllGather to obtain final output. This optimizes the Narayanan et al. [26] by slicing the computation instead of replicating it.
3. GShard-eq or RS+P2P+C+AG is generated by splitting AllReduce into ReduceScatter and AllGather, then reordering AllGather with P2P send and computation. Since this schedule is similar to the schedule that will be generated by GShard [21], it represents GShard-Eq in our results.
4. OL(RS+C,P2P,AG) is generated from RS+P2P+C+AG by first fusing communication with ReduceScatter, and then overlapping all three communication operations (Figure 7b). This schedule is returned by autotuner as best performing and hence, represents CoCoNet in our results.

Results Figure 12 shows the breakdown of the computation/communication with one transformer layer assigned to each node. The sequence length ($S = 2048$) and the hidden size ($H = 12288$) are of GPT-3 175B model. CoCoNet’s best schedule $OL(RS+C,P2P,AG)$ is 11.75×−12.21× faster than $AR+P2P+C$, 2.84× faster than $AR+P2P+C+AG$, and 1.66×−1.72× faster than GShard ($RS+P2P+C+AG$). The speedups come from: (i) sliced P2Ps reduces cross node communication volume, (ii) fusing all communication and computation kernels improves memory bandwidth utilization, and (iii) overlapping communication in different connections (NVLink within node and InfiniBand across nodes) improves network
bandwidth utilization, while other schedules utilizes one stack at a time.

### 6.3.1 Integration with Megatron-LM.

We evaluated inference throughput of GPT-2 8.3 Billion and GPT-3 175 Billion parameter models by integrating CoCoNet’s OL(RS+C,F2P),AG schedule in Megatron-LM. Below table shows the results on 16 nodes with 16 GPUs per node.

<table>
<thead>
<tr>
<th>Model</th>
<th>Layers per node</th>
<th>Micro Batch Size</th>
<th>Speedup</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPT-2 8.3B</td>
<td>5</td>
<td>16</td>
<td>1.77x</td>
</tr>
<tr>
<td>GPT-3 175B</td>
<td>1</td>
<td>8</td>
<td>2.45x</td>
</tr>
<tr>
<td>GPT-3 175B</td>
<td>6</td>
<td>2</td>
<td>1.33x</td>
</tr>
</tbody>
</table>

We changed GPT-2 layers from 72 to 80 to make it divisible by 16 nodes. For GPT-3 we tried the 1 layer per node setting, which provides us with upper bound of speedup. In summary, CoCoNet significantly outperforms Megatron-LM due to its fusion and fine-grained overlapping of multiple communication operations. All these optimizations were possible only by breaking the computation and communication abstraction.

### 7 Related Work

#### Optimizing Stencil Computations

Prior work has proposed DSLs to optimize data-parallel stencil computations on CPUs, GPUs, and other accelerators. Halide [34] and Fireiron [13] separate the algorithm and schedule, which describes the optimizations like fusion, and loop tiling. TVM [6] extends Halide for generating optimized compute kernels. Lift [14, 40] includes a functional language and optimizes stencil computations by applying rewrite rules. None of these works support distributed systems. Distributed-Halide [9] extends Halide with scheduling primitives that allow distributing parallelizable dimensions of loops. CoCoNet extends this work to explicitly reason about and compose communication collectives with computation, which is crucial for distributed machine learning scenarios.

#### Overlapping Computation and Communication

Existing works [2, 19, 23, 24, 42] uses either pipelined execution to overlap communication and computation or non-blocking operations. Pencil [43] improves upon these works by performing pipelining within a process and supports computations in multiple connected iteration spaces. Several techniques distribute tiles and automatically generate communication [4, 9, 37]. Basu et al. [3] uses overlapped tiling in each process to remove communication between processes. Denis and Trahay [8] studied the efficiency of overlap. dCUDA [12] provides hardware supported overlap. These works for MPI+OpenMP are valid for stencil computations that require sends and receives to share the halo regions. However, CoCoNet supports collectives and several transformations that these works do not support. ACE [36] is a novel DL collective communication accelerator to enable overlap of communication and computation. CoCoNet supports overlap of computation and communication or communication operations on GPUs and without an accelerator.

#### Distributed Neural Network Training

Several works have improved data parallel and model parallel techniques. Mesh-Tensorflow [38] and GShard [21] create shards of weights and model state that can be split among ranks. ZeRO [35] splits weights and model state among ranks and uses ReduceScatter and AllGather to distribute computation. FlexFlow [16] performs operator splitting as a way to represent both data-parallelism and model-parallelism, but do not optimize computation with communication. CoCoNet improves on these works by providing a general abstraction that (i) supports computation and communication collectives, (ii) ensure correctness, and (iii) allows the developer to explore several optimizations. CoCoNet also provides several optimizations that are possible only due to the abstraction: (i) scattered tensors that removes extra storage and memory copy operations, (ii) fusion communication collectives, and (iii) novel communication and computation overlapping techniques. PyTorch’s DDP [22] overlaps AllReduce of gradients with the forward and backward pass. However, unlike CoCoNet, PyTorch’s DDP requires extra memory for overlapping, which can increase training time for very large models [28] and do not support slicing of optimizer parameter update that significantly decreases memory usage. GPipe [15], Pipedream [25] and Narayanan et al. [26] proposed pipeline training to improve model parallelism, by dividing the forward and backward pass into several mini-batches, which are then pipelined across devices. vPipe [45] improves these works by providing higher GPU utilization. CoCoNet improves on these works by overlapping inter and intra-node communication operations. BytePS [17] utilizes CPU in heterogenous clusters to improve training, which is complementary to CoCoNet.

### 8 Conclusion

This paper introduced CoCoNet a language to describe distributed machine learning workloads and optimize them across computation and communication boundary. We show that CoCoNet generated code is significantly improves several training and inference times of large language models. In future we plan to automate the optimizations through smart search.

### References


