Pipeflow: An Efficient Task-Parallel Pipeline Programming Framework using Modern C++

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Abstract

Pipeline is a fundamental parallel programming pattern. Mainstream pipeline programming frameworks count on data abstractions to perform pipeline scheduling. This design is convenient for data-centric pipeline applications but inefficient for algorithms that only exploit task parallelism in pipeline. As a result, we introduce a new task-parallel pipeline programming framework called *Pipeflow*. Pipeflow does not design yet another data abstraction but focuses on the pipeline scheduling itself, enabling more efficient implementation of task-parallel pipeline algorithms than existing frameworks. We have evaluated Pipeflow on both micro-benchmarks and real-world applications. As an example, Pipeflow outperforms oneTBB 24% and 10% faster in a VLSI placement and a timing analysis workloads that adopt pipeline parallelism to speed up runtimes, respectively.

1 Introduction

Motivation: Pipeline is a fundamental parallel pattern to model parallel executions through a linear chain of stages. Each stage processes a data token after the previous stage, applies an abstract function to that data token, and then resolves the dependency for the next stage. Multiple data tokens can be processed simultaneously across different stages whenever dependencies are met. For example, in circuit simulation, some operations on a gate (e.g., NAND, OR, AND) do not depend on other gates and thus can be done at multiple logic levels simultaneously, while operations at the same levels require processing prior levels first [14]. As modern computing applications continue to adopt pipeline parallelism in various forms, there is always a need for new pipeline programming frameworks to streamline the implementation complexity of pipeline algorithms.

Limitation of state-of-art approaches: Recent years have seen much research on pipeline programming frameworks to assist developers in implementing pipeline algorithms without worrying about scheduling details. Some famous frameworks are oneTBB [1], FastFlow [4], GrPPI [8], Cilk-P [19], SPar [10], and HPX-pipeline [17]. While each of these frameworks has its pros and cons, a common design philosophy

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is to achieve transparent pipeline scheduling using *data abstractions*. This design is convenient for data-centric pipeline applications, but it also brings three limitations: 1) Users are forced to design their pipeline algorithms in the center of data. As we shall give a concrete example, many applications exhibit pipeline parallelism among *tasks* rather than data. 2) Under this circumstance, users need to sort out a data mapping strategy between applications and frameworks to perform pipeline scheduling, although such mapping is totally redundant. 3) Existing frameworks have very limited composability with other types of parallelism, such as task graphs which have become essential to many irregular parallel algorithms.

Key insights and contributions: After years of research, we have arrived at the key conclusion that data abstraction and task scheduling should be decoupled from each other in programming pipeline parallelism. Consequently, we introduce in this paper Pipeflow, a new task-parallel pipeline programming framework to overcome the limitations of existing ones. We establish Pipeflow atop the open-source task graph programming system, Taskflow, developed by Huang et al. [15], to leverage its powerful tasking infrastructure. As Taskflow is being used by several important research projects [3, 22, 36], building Pipeflow on top will not only benefit existing users but also allow us to gain timely feedback from the Taskflow community. We summarize our contributions as follows:

- **Programming Model.** We have introduced a new C++ programming model for developers to create a *pipeline scheduling framework*. Unlike existing models, we do not provide yet another data abstraction but a flexible framework for users to fully control their application data atop a task-parallel pipeline scheduling framework.
- Task Composition. We have introduced a composable interface to enable seamless integration of Pipeflow into Taskflow. Users can combine pipeline tasks with all existing task types of Taskflow to express a large parallel workload in a single end-to-end task graph.
- **Scheduling Algorithm.** We have introduced a light-weight scheduling algorithm to schedule stage tasks across

parallel lines. Our algorithm formulates the pipeline scheduling into a task graph and thus can efficiently solve the scheduling problem with dynamic load balancing using Taskflow's work-stealing runtime.

Experimental methodology and artifact availability: We have evaluated Pipeflow on both micro-benchmarks and real-world applications. As an example, Pipeflow outperforms one TBB 24% and 10% faster in a VLSI placement and a timing analysis workloads that adopt pipeline parallelism to speed up runtimes, respectively. Pipeflow is open-source and available in Taskflow as an algorithm module [2].

Limitations of the proposed approach: Like all programming frameworks, Pipeflow is not perfect. Specifically, our design choice sacrifices the expressiveness for data-parallel pipeline applications, as users need to explicitly manage data storage using Pipeflow's runtime methods. Yet, our experience leads us to believe that this challenge can be mitigated by deriving an application-dependent data abstraction from our pipeline programming interface.

2 Background

We first review mainstream pipeline models and detail the motivation of Pipeflow. We then argue that a new task-parallel pipeline programming model is needed for many important industrial and research areas, e.g., circuit design.

2.1 Pipeline Basics

Pipeline parallelism is commonly used to parallelize various applications, such as stream processing, video processing, and dataflow systems. These applications exhibit parallelism in the form of a linear pipeline, where a linear sequence of abstraction functions, namely stages, $F = \langle f_1, f_2, \dots, f_j \rangle$, is applied to an input sequence of data tokens, $D = \langle d_1, d_2, \cdots, d_i \rangle$. A linear pipeline can be thought of a loop over the data tokens of D. Each iteration i processes an input token d_i by applying the stage functions F to d_i in order. Depending on the number of *parallel lines*, $L = \langle l_1, l_2, \dots, l_k \rangle$, to process data tokens, parallelism arises when iterations overlap in time. For instance, the execution of token d_i at stage f_i of line l_k , denoted as $f_j^k(d_i)$, can overlap with $f_{j-1}^{k+1}(d_{i+1})$. A stage can be a parallel type or a serial type to specify whether $f_i^k(d_i)$ can overlap with $f_i^{k+1}(d_{i+1})$ or not. Figure 1 shows the dependency diagram of a 3-stage (serial-parallel-serial) pipeline.

Mainstream pipeline programming libraries employ data-centric models. Users declare input and output data types for each stage using library-specific data abstractions (e.g., template instantiation). Taking oneTBB [1] for example, Listing 1 implements Figure 1 using four parallel lines and a series of callable objects called *filter*, where each filter receives an input data, performs work on that data, and then produces a result for the next filter. To support arbitrary application data types, libraries typically leverage dynamic polymorphism to

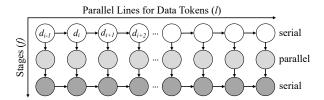


Figure 1. Dependency diagram of a 3-stage (serial-parallel-serial) pipeline. Each node represents a task that applies a stage function to a token. Each edge represents a dependency between two tasks.

allocate and convert data from a generic type (e.g., void*, std::any) to an application type. To further minimize the allocation cost, some libraries, such as oneTBB [1], have implemented specialized object allocators and buffer structures to handle temporary results between stages.

```
tbb::parallel_pipeline(4, // four parallel lines
  tbb::make_filter < void, float > (
    tbb::filter_mode::serial_in_order,
    [&](tbb::flow_control& fc)-> float {
      if ( data.ready() ) {
        return data.get();
        else {
        fc.stop();
        return 0.0f;
                       // dummy data
  ) &
  tbb::make_filter < float, std::string >(
    tbb::filter_mode::parallel,
    [&](float p) { return make_string(p); }
  tbb::make_filter<std::string, void >(
    tbb::filter_mode::serial_in_order,
    [&](std::string x) { std::cout << x; }
);
```

Listing 1. one TBB code of Figure 1, assuming a void-floatstring-void data transformation.

2.2 Pipeline Parallelism in CAD Algorithms

Pipeflow is motivated by our research projects on developing parallel timing analysis algorithms for very large scale integration (VLSI) computer-aided design (CAD). Timing analysis is a critical step in the overall CAD flow because it validates the timing performance of a digital circuit. As design complexity continues to grow exponentially, the need to efficiently analyze the timing of large designs has become the major bottleneck to the design closure flow. For instance, generating a comprehensive timing report (e.g., pessimism removal, hundreds of corners, etc.) for a multi-million-gate design can take several hours to finish [16]. To reduce the long analysis runtime, recent years have seen increasing adoptions of manycore parallelism by new timing analysis algorithms [3].

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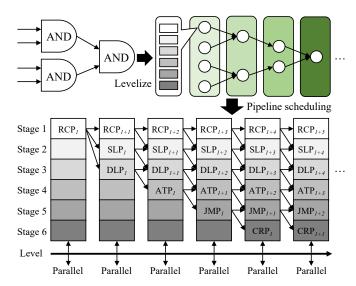


Figure 2. Parallel timing propagations using pipeline [14]. Linearly dependent timing data (e.g., slew, delay, arrival time) is updated across graph nodes in a pipeline fashion.

The most widely used strategy, including commercial timers, to parallelize timing analysis is *pipeline*. Figure 2 illustrates this strategy using forward timing propagation as an example [14]. The circuit graph is first *levelized* into a level list using topological sort. Nodes at the same level are independent of each other and can run in parallel. Each node runs a sequence of *linearly dependent* propagation tasks, including parasitics (RCP), slew (SLP), delay (DLP), arrival time (ATP), jump points (JMP), and common path pessimism reduction (CRP) to update its timing data from a custom circuit graph data structure. Different propagation tasks can overlap across different levels using pipeline parallelism.

In fact, this type of task-parallel pipeline strategy is ubiquitous in many parallel CAD algorithms, such as logic simulation and physical design, because computations frequently depend on circuit networks. We have observed three important properties that make mainstream pipeline programming frameworks fall short of our need: 1) Unlike the typical dataparallel pipeline, the pipeline parallelism in many CAD algorithms is driven by tasks rather than data. 2) Data is not directly involved in the pipeline but the graph data structure crafted by a custom algorithm. 3) From user's standpoint, the real need is a pipeline scheduling framework to help schedule and run tasks on input tokens across parallel lines, while leaving data management completely to applications; in our experience, users disfavor another library data abstraction to perform pipeline scheduling, as it often incurs development inconvenience and unnecessary data conversion overheads.

3 Pipeflow

Inspired by the need of parallel CAD algorithms, Pipeflow introduces a new task-parallel pipeline programming model

for users to create a pipeline scheduling framework without data abstraction. We establish Pipeflow atop the open-source parallel task graph programming system, Taskflow [15], because it has been successfully adopted by many important CAD projects under the DARPA IDEA program [3, 22, 36]. In this section, we will first give a brief introduction about Taskflow and then dive into the technical details of Pipeflow.

3.1 State of the Art: Taskflow

Taskflow is a general-purpose parallel and heterogeneous programming system using modern C++ [15]. Taskflow introduces a new *control taskflow graph* (CTFG) model that enables end-to-end implementation of task graph parallelism coupled with in-graph control flow. A CTFG consists of several task types, such as static task, dynamic task, condition task, module task, runtime task, and so on. Figure 3 shows a CTFG of iterative tasking, implemented in Listing 2. The loop continuation condition is implemented by a single condition task, cond, that precedes two static tasks, body and done. When cond returns 0, the execution loops back to body. When cond returns 1, the execution moves onto done and stops. This example uses four tasks to implement a tasking loop of 100 iterations.

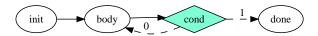


Figure 3. A Taskflow graph of iterative control flow using one condition task and three static tasks.

```
tf::Taskflow taskflow;
tf::Executor executor;
int i;
auto [init, body, cond, done] = taskflow.emplace(
    [&](){ i = 0; },
    [&](){ i ++; },
    [&](){ return i < 100 ? 0 : 1; },
    [&](){ std::cout << "done"; }
);
init.precede(body);
body.precede(cond);
cond.precede(body, done);
executor.run(taskflow).wait();</pre>
```

Listing 2. Taskflow program of Figure 3.

Another powerful feature of Taskflow is *composable tasking*. Composable tasking enables users to define task hierarchies and compose large task graphs from modular and reusable algorithm blocks that are easier to optimize. Figure 4 gives an example of a Taskflow graph using composition. The top-level taskflow defines one static task C that runs before a dynamic task D that spawns two dependent tasks D1 and D2. Task D precedes a module task E composed of a taskflow of two dependent tasks A and B. Listing 3 shows the Taskflow code of Figure 4. It declares two taskflows, taskflow1 and

taskflow2. The second taskflow defines a module task that is composed of the first taskflow, preceded by task D. A module task does not own the taskflow but maintains a soft mapping to the taskflow. Users can create multiple module tasks from the same taskflow, but they must not run concurrently.

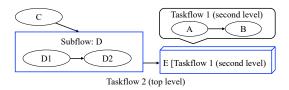


Figure 4. An example of taskflow composition.

```
tf::Taskflow taskflow1, taskflow2;
auto [A, B] = taskflow1.emplace(
    () { std::cout << "TaskA"; },
    () { std::cout << "TaskB"; }
  []
auto [C, D] = taskflow2.emplace(
  [] () { std::cout << "TaskC"; },
  [] (tf::Subflow& sf) {
    std :: cout << "TaskD";</pre>
    auto [D1, D2] = sf.emplace(
      [] () { std::cout << "D1"; },
      [] () { std::cout << "D2"; }
    D1. precede(D2);
);
auto E = taskflow2.composed_of(taskflow1);
A. precede(B);
C. precede(D);
D. precede(E);
```

Listing 3. Taskflow code of Figure 4.

Integration with Taskflow: Pipeflow leverages conditional tasking and composable tasking to implement the pipeline algorithm in a *module task*. Unlike existing pipeline programming frameworks that often operate in a standalone programming environment, Pipeflow is designed to work seamlessly with Taskflow. We make this architecture-level decision for three reasons: First, the tasking patterns of parallel CAD algorithms are massive and *irregular*. Pipeline is just one part and needs to work with other tasks, such as graph traversal and control flow, to compose the whole application algorithm. Second, integrating Pipeflow into Taskflow enables a unified scheduling runtime with dynamic load balancing and improved inter-operability with other Taskflow tasks. Third, from the ease of use standpoint, existing Taskflow users need not to learn a different set of application programming interface (API) but the scheduling concept of Pipeflow to implement pipeline algorithms. While Pipeflow is primarily designed as an algorithm module of Taskflow, we believe many of our ideas are applicable to other task-based parallel programming frameworks.

3.2 Programming Model

Pipeflow leverages modern C++ and template techniques to strike a balance between expressiveness and generality. Listing 4 shows the Pipeflow counterpart of the oneTBB code in Listing 1 that implements the pipeline in Figure 1. There are three steps to create a Pipeflow application, 1) define the pipeline structure using template instantiation, 2) define the data storage, if needed, and 3) define the pipeline task using taskflow composition. Users define the number of parallel lines and the abstract function of each stage in a tf::Pipeline object. For each stage, users define the stage type and a pipe callable using tf::Pipe. A stage can be either a serial type (tf::PipeType::SERIAL) or a parallel type (tf::PipeType::PARALLEL). The pipe callable takes an argument of tf::Pipeflow type which is created by the scheduler at runtime. A tf::Pipeflow object represents a scheduling token and contains several extensible methods for users to query the runtime statistics of that token, including the line, pipe, and token numbers. In Pipeflow, pipe and stage are interchangeable.

```
tf::Taskflow taskflow;
tf::Executor executor;
const size_t num_lines = 4;
std::variant < float, std::string > dtype;
std::array < dtype, num_lines > buf;
tf::Pipeline pl(num_lines,
  tf::Pipe{tf::PipeType::SERIAL,
    [&](tf::Pipeflow& pf) {
      if ( !data.ready() ) {
        pf.stop();
      } else {
        buf[pf.line()] = data.get();
    }
  },
  tf :: Pipe { tf :: PipeType :: PARALLEL,
    [&](tf::Pipeflow& pf) {
      buf[pf.line()] =
      make_string(std::get<0>(buf[pf.line()]));
  },
  tf::Pipe { tf::PipeType::SERIAL,
    [&](tf::Pipeflow& pf) {
      std::cout << std::get<1>(buf[pf.line()]);
auto pipeline = taskflow.composed_of(pl);
executor.run(taskflow).wait();
```

Listing 4. Pipeflow code of Figure 1.

Pipeflow does not have any data abstraction but gives applications full control over data management. In our example, since the first and the second pipes generate float and std::string outputs, respectively, we create a one-dimensional (1D) array, buf, to store data in a uniform storage using std::variant<float, std::string>. The dimension of the array is equal to the number of parallel lines,

as Pipeflow schedules only one token per line. Each entry buf[i] stores the data that is being processed at line *i*, which can be retrieved by tf::Pipeflow::line. This organization is very space-efficient because we use only 1D array to represent data processing in a two-dimensional (2D) scheduling map. Additionally, by delegating data management to applications, we can avoid dynamic data conversion between the library and the application, which typically counts on virtual function calls to convert a generic type (e.g., void*, std::any) to an arbitrary user type [1, 4].

Based on the above pipeline structure and data layout, we instantiate a tf::Pipeline object, pl. This template-based design enables the compiler to optimize each pipe type, such as using fixed-layout functor to store the callable and its captured data. Finally, we create a pipeline module task pipeline with pl using the taskflow composition method composed_of and submit this taskflow to an executor to run the pipeline.

```
using P =
   tf::Pipe<std::function <void(tf::Pipeflow&)>>;
std::vector<P> p(6, create_pipe()); // pipes
tf::ScalablePipeline pl(4, p.begin(), p.end());
taskflow.composed_of(pl);
executor.run(taskflow).wait();
p.resize(3);
pl.reset(p.begin(), p.end());
executor.run(taskflow).wait();
```

Listing 5. Scalable pipeline model in Pipeflow to accept variable assignments of pipes.

tf::Pipeline requires instantiation of all pipes at the construction time. While this design gives compilers freedom to optimize the layout of each pipe type, it prevents applications from varying the pipeline structure at runtime; for instance, the number of pipes might depend on the problem size, which can be runtime variables. To overcome this limitation, Pipeflow provides a scalable alternative, tf::ScalablePipeline, to allow variable assignments of pipes using range iterators. In Listing 5, we create a scalable pipeline, pl, from a vector of six pipes. After the first run, we reset pl to another range of three pipes for the next run. A scalable pipeline is thus more flexible for applications to create pipeline scheduling framework with dynamic structures

3.3 Pipeline Task Composition

A key advantage of Pipeflow is its composability with Taskflow. By encapsulating a pipeline in a module task, we enable seamless integration with all existing task types in Taskflow. This result largely facilitates the implementation of complex pipeline applications that require intensive interaction with different types of task parallelism. Figure 5 shows a Taskflow graph that emulates a data streaming application using a pipeline module task and a condition task. The condition task is used to decide if the pipeline needs to be run again depending on the application control flow. Listing 6 shows the Taskflow code of Figure 5, using the pipeline task in Listing 4. When the condition task cond returns 0, it informs the scheduler to rerun the pipeline task pl, or proceeds to done to stop the program otherwise.



Figure 5. A Taskflow graph of an iterative streaming application using one pipeline module task, one condition task, and one static task.

```
auto cond = taskflow.emplace([&](){
   if ( data.ready() ) {
      std::cout << "rerun the pipeline";
      return 0;
   } else {
      return 1;
   }
});
auto done = taskflow.emplace([&](){
   std::cout << "stop";
});
pipeline.precede(cond);
cond.precede(pipeline, done);</pre>
```

Listing 6. Taskflow code of Figure 5 using the pipeline of Listing 4.

Figure 6 demonstrates another common application that embeds task graph parallelism inside a pipeline. The pipeline consists of three serial stages and four parallel lines. Each scheduled token runs a taskflow that implements a stage algorithm in the pipeline. The three taskflows are self-explanatory. Different taskflows can overlap across different lines, but only one taskflow runs on the same stage due to the serial type. Listing 7 implements Figure 6. We create a 1D array, buf, to store the three taskflows (defined elsewhere). In each stage, we obtain its taskflow at buf[pf.pipe()], submit it to the executor, and wait until the execution finishes. As we need only four tokens, the first pipe stops the scheduler at the fifth.

```
tf::Taskflow taskflow;
tf::Executor executor;
const size_t num_lines = 4;
const size_t num_pipes = 3;
std::array < tf::Taskflow, num_pipes > buf;
tf::Pipeline pl(num_lines,
    tf::Pipe{tf::PipeType::SERIAL,
        [&](tf::Pipeflow& pf) {
        if (pf.token() == 4) {
            pf.stop();
            return;
        }
        executor.run(buf[pf.pipe()]).wait();
      }
},
```

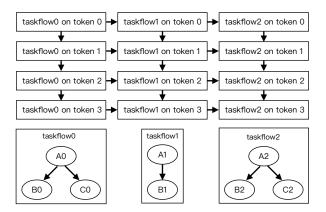


Figure 6. A pipeline of embedded taskflows. Each taskflow implements a parallel algorithm at a stage in the pipeline.

```
tf :: Pipe { tf :: PipeType :: SERIAL,
    [&](tf::Pipeflow& pf) {
      executor.run(buf[pf.pipe()]).wait();
  tf :: Pipe { tf :: PipeType :: SERIAL,
    [&](tf::Pipeflow& pf) {
      executor.run(buf[pf.pipe()]).wait();
);
auto init = taskflow.emplace([](){
  std::cout << "init";
});
auto pipeline = taskflow.composed of(pl);
auto done = taskflow.emplace([](){
  std::cout << "stop";
});
init.precede(pipeline);
pipeline.precede(done);
executor.run(taskflow).wait();
```

Listing 7. Pipeflow and Taskflow code of Figure 6.

Scheduling Algorithm

Pipeflow leverages Taskflow's work-stealing runtime to design an efficient scheduling algorithm with dynamic load balancing. As Pipeflow does not touch data abstraction, we can simplify the pipeline scheduling problem to deciding which task to run at which pipe and line. Similar to one TBB, the key idea of our scheduling algorithm is to enable only one scheduling token per line and process all tokens in a circular fashion across all parallel lines. Based on the idea, we formulate the pipeline scheduling into a lightweight Taskflow graph where 1) one task deals with a scheduling token per line and 2) each task decides which task to run on its next line and pipe using simple atomic operations.

Pipeflow creates a taskflow for each pipeline module task using one condition task and multiple runtime tasks one per line. A runtime task is a task type in Taskflow for users to interact with the executor [15], such as scheduling a task in the

graph. The condition task decides which runtime task to run when the pipeline starts. A runtime task deals with a scheduling token at a line and will create a pipeflow object (of type tf::Pipeflow) to pass to the pipe callable. Figure 7 shows the taskflow of the pipeline module task in Listing 7. As there are four parallel lines, the task graph consists of one condition task, cond, and four runtime tasks, rt-0, rt-1, rt-2, and rt-3. Ultimately, only five tasks are used to run the pipeline, even though the execution can involve many scheduling tokens.

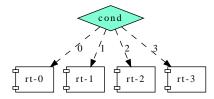


Figure 7. The Taskflow graph of the pipeline module task in Listing 7.

Algorithm 1 implements the construction of the Taskflow graph for a pipeline. First, we define the condition task to return on the index of the next task (line 1). Since the pipeline is running in a circular fashion, the index is equal to the remainder of the total number of scheduled tokens divided by the number of parallel lines. Next, we define the runtime task using build_runtime_task for each line (line 3) and specify the dependency between each runtime task and the condition task (line 4).

```
global: num_tokens: the number of tokens
  global: num_lines: the number of lines
  global: tasks: a vector of tasks
1 \ tasks[0] \leftarrow create\_condition\_task(
   [](){return num_tokens%num_lines});
2 foreach line l \in num lines do
```

build_runtime_task(l); tasks[0].precede(tasks[l+1]);

Algorithm 1: build task graph()

5 end

Algorithm 2 implements build_runtime_task. When a runtime task is scheduled, we need to know which stage at which line for the scheduling token to work. We keep the line and stage information in a Pipeflow object. Each runtime task owns a Pipeflow object pf of a specific line (line 1). Once a scheduling token is done, there are two cases for its runtime task to proceed: 1) for a parallel type, the runtime task moves to the next stage at the same line; 2) for a serial type, the runtime task additionally checks if it can move to the next line. To carry out such a dependency constraint, each stage keeps a join counter of an atomic integer to represent its dependency

Algorithm 2: build_runtime_task(*l*) **global:** pipe flows: a vector of Pipeflow objects **global:** *jcs*: a 2D array of join counters **global:** *num tokens*: the number of tokens **global:** *num_lines*: the number of lines **global:** *num_pipes*: the number of pipes **global:** tasks: a vector of tasks in Algorithm 1 **Input:** *l*: an integer 1 $pf \leftarrow pipeflows[l];$ 2 AtomStore(lines[pf.line][pf.pipe].jc, jc_of_pf.type); 3 if pf.pipe == 0 then $pf.token \leftarrow num_tokens;$ 4 invoke_pipe_callable(pf.pipe, pf); 5 **if** pf.stop == True **then** return; 7 end 8 Increment(num_tokens); end 10 11 **if** *pf.pipe* != 0 **then** invoke_pipe_callable(*pf.pipe*, *pf*); 12 13 end 14 $curr_pipe \leftarrow pf.pipe$; 15 $next_pipe \leftarrow (pf.pipe + 1)\%num_pipes;$ 16 $next_line \leftarrow (pf.line + 1)\%num_lines;$ 17 $pf.pipe \leftarrow next_pipe$; $next_tasks = \{\};$ 19 **if** curr_pipe is SERIAL **and** $AtomDec(lines[next_line][curr_pipe].jc) == 0$ next_tasks.insert(1); 20 21 end 22 if AtomDec(lines[pf.line][next_pipe]) == 0 then next_tasks.insert(0); 24 end 25 **if** next_task.size == 2 **then** call_scheduler(tasks[next_line + 1]); 26 goto Line 2; 27 end 28 **if** next_task.size == 1 **then** 29 if $next \ task[0] == 1$ then 30 $pf \leftarrow pipeflows[next_line];$ 31 end 32 goto Line 2; 33 34 end

value. The values of a serial stage and a parallel stage can be up to 2 and 1, respectively. We create a 2D array jcs to store the join counter of each stage at each line. Line 2 initializes

these join counters to either 2 or 1 based on the corresponding stage types that are enumerated on integer constants, 2 (serial) and 1 (parallel). At the first stage (line 3), the Pipeflow object updates its token number (line 4) and checks if the pipe callable requests to stop the pipeline (lines 5:8). If continued, we increment the number of scheduled tokens by one (line 9). For other stages, we simply invoke the pipe callables (lines 11:13).

After the pipe callable returns, we update the join counters based on the stage type and determine the next possible tasks to run (lines 14:24). When the join counter of a stage becomes 0, we bookmark this stage as a task to run next (line 20 and line 23). If two tasks exist (line 25), the current runtime task informs the scheduler to call a worker thread from the executor to run the task at the next line (line 26) and reiterates itself on the next pipe (line 27). The idea here is to facilitate data locality as applications tend to deal with the next stage as soon as possible. If there is only one task available, the current runtime task directly runs the next task with the updated pf object (lines 29:34).

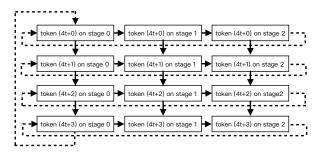


Figure 8. The scheduling diagram of the pipeline in Listing 7. Each line runs one scheduling token. Multiple lines overlap tokens in a circular fashion.

Figure 8 illustrates our scheduling algorithm using the pipeline in Listing 7. Since the pipeline runs in a circular fashion, there are four dependencies (dashed edges) from the last stages to the first stages, and one dashed edge from the first stage of the last line to the first stage of the first line. Each line runs only one scheduling token. Multiple lines overlap tokens in a circular fashion. Compared to existing algorithms, such as oneTBB [1], that count on non-trivial synchronization between tasks and internal data buffers, our algorithm focuses on the task parallelism itself and thus largely reduces the scheduling complexity of pipeline using simple atomic operations. We draw the following lemmas and sketch their proofs to justify the correctness of our scheduling algorithm:

Lemma 1. Only one runtime task runs a pipe callable (line 5 and line 12 in Algorithm 2) on a scheduling token.

Proof. Assuming there are two runtime tasks running the same pipe callable, this means one runtime task reiterates its execution from the previous stage and the other runtime task

comes from the previous line. In a parallel stage, this is not possible as there is no dependency from the previous line; only one runtime task decrements the join counter to 0 (line 22 in Algorithm 2). In a serial stage, this is also not possible because the dependency is resolved using atomic operations; only one runtime task will acquire the zero value of the join counter (line 19 in Algorithm 2).

Lemma 2. The scheduler does not miss any stage.

Proof. We consider the situation where one runtime task moves to the next line (line 31 in Algorithm 2) instead of the next stage at the same line. Under this circumstance, we need to make sure one runtime task will run that next stage. Take Figure 8 for example, suppose a runtime task finishes token 4t+1 at stage 1 and precedes to token 4t+2 on stage 1, meaning that the join counter of token 4t+1 at stage 2 is not 0 yet. Another runtime task that works on token 4t+0 at stage 2 will eventually decrement the join counter to run it (line 27 in Algorithm 2) or invoke another worker thread to run it (line 26 in Algorithm 2). □

4 Experimental Results

We evaluate the performance of Pipeflow on two fronts: micro-benchmarks and two real-world industrial CAD applications. We study the performance across runtime, memory (RSS), and throughput. We do not use conventional pipeline benchmarks as their sizes are relatively small compared to CAD (e.g., 6 pipes in ferret[6]). The runtime difference between Pipeflow and the baseline is not obvious on small pipelines. We compiled all programs using clang++ v10 with C++17 standard -std=c++17 and optimization flag -03 enabled. We run all the experiments on a Ubuntu Linux 5.3.0-64-generic x86 machine with 40 Intel Xeon CPU cores at 2.00 GHz and 256 GB RAM. Each application thread corresponds to one CPU core. All data is an average of five runs.

4.1 Baseline

Given a large number of pipeline programming frameworks, it is infeasible to compare Pipeflow with all of them. Each of them has its pros and cons and dominates certain applications. Since Pipeflow is inspired by our CAD applications, we select oneTBB Parallel Pipeline (v2021.5.0) [1] as our baseline, which has been widely used in the CAD community. We believe this selection is sufficient and fair to highlight the advantage of Pipeflow, considering the similar tasking infrastructure between oneTBB and Pipeflow. For oneTBB pipelines, we pass a nominal integer between successive stages (i.e., tbb::filter), because oneTBB does not allow void type but implements a specialized memory allocator to hold intermediate results returned by stages.

4.2 Micro-benchmarks

The purpose of micro-benchmarks is to measure the pure scheduling performance of Pipeflow without much computation bias from the application. We compare the runtime and memory between Pipeflow and oneTBB for completing pipelines of different numbers of serial stages, scheduling tokens, and threads. We do not use parallel stages as the callable of a parallel pipe can be absorbed into the previous serial pipe. Each stage performs a nominal work of constant space and time complexity and forwards the scheduling token to the next stage.

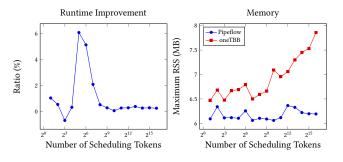


Figure 9. Runtime (improvement of Pipeflow over oneTBB) and memory performance at different numbers of scheduling tokens using 16 threads, 80 parallel lines, and 80 serial stages.

Figure 9 draws the runtime improvement of Pipeflow over oneTBB and memory data under different numbers of scheduling tokens. Here, we use 16 threads, which produce the best performance for both, to run a pipeline of 80 serial stages and 80 parallel lines. With more token numbers (>256), Pipeflow is consistently better than oneTBB, despite the slight improvement (<1%). When the number of scheduling tokens is small, the variation is large (e.g., up to 6% improvement at 32 tokens). This is because when oneTBB starts the pipeline, it requires expensive set-up time on the data buffers, whereas Pipeflow can immediately start the task scheduling. Yet, as we increase the number of tokens, such cost can be amortized. In terms of memory, oneTBB is always higher than Pipeflow (e.g., 21% at 65K tokens) since we do not manage any data buffers but focus on the task scheduling itself.

Figure 10 draws the runtime and memory performance using 16 threads to schedule 65K tokens through different numbers of stages, where the number of parallel lines is equal to the stage count. We observe that Pipeflow is consistently faster than oneTBB when the number of stages is larger than 16, despite the difference being slight (<1%). At 8 stages, the available task parallelism is smaller than the given thread parallelism, and oneTBB is faster in this scenario. This is due to Taskflow's scheduling algorithm. Taskflow always keeps one thread busy in stealing while there is an active worker. When the available task parallelism is scarce, the scheduling cost becomes expensive. Yet, this problem can be mitigated by users selecting the right line number in their pipeline applications.

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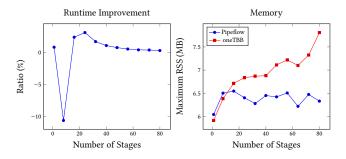


Figure 10. Runtime (improvement of Pipeflow over oneTBB) and memory performance at different numbers of serial stages using 16 threads and 65K scheduling tokens. The number of parallel lines equals the number of the stages.

For instance, beyond 8 stages, Pipeflow starts to outperform oneTBB. In terms of memory, we can clearly see the difference between Pipeflow and oneTBB (e.g., 19% at 80 stages). As we increase the number of stages, oneTBB needs more space for internal data buffers, whereas Pipeflow delegates the data management completely to applications.

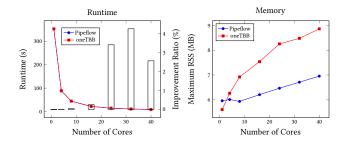


Figure 11. Runtime and memory performance at differents number of threads running 65K tokens on a pipeline of 80 stages and 80 parallel lines. The bars illustrate the runtime improvement of Pipeline over oneTBB.

Figure 11 shows the runtime and memory results at different numbers of threads to run 65K tokens on a pipeline of 80 stages and 80 parallel lines. Both Pipeflow and oneTBB scale equally well as the number of cores increases. At each point, we observe a small win of Pipeflow. For instance, at 32 cores, Pipeflow is 4.3% faster than oneTBB. In terms of memory, both Pipeflow and oneTBB use more memory with more threads. However, there remains a clear gap between Pipeflow and oneTBB (e.g., 22% less by Pipeflow at 40 cores).

Figure 12 compares the throughput by corunning the same program up to 10 times. We use the *weighted speedup* to measure the system throughput, which is the sum of the individual speedup of each process over a baseline execution time [9]. A throughput of one implies that the corun throughput is the same as if those processes run consecutively. On the left, the pipeline has 8 stages and 8 parallel lines. On the right, the pipeline has 80 stages and 80 parallel lines. Both of them

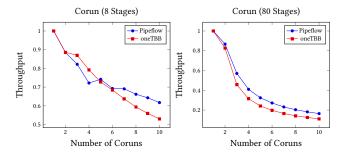


Figure 12. Throughput of corunning micro-benchmark programs with 8 and 80 stages.

run 65K scheduling tokens using 40 threads. The experiment emulates a server-like environment where different pipeline applications compete for the same resources. We can see that Pipeflow outperforms one TBB in most coruns. For example, at 10 coruns, Pipeflow is $1.1 \times$ and $1.5 \times$ better than one TBB with 8 and 80 stages, respectively.

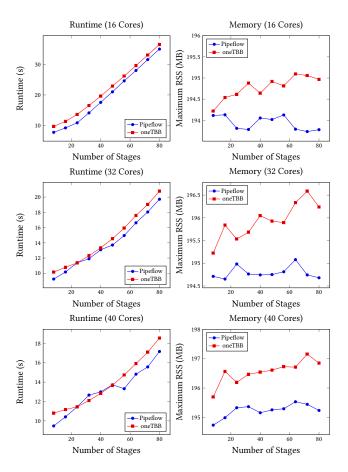


Figure 13. Runtime and memory comparisons between Pipeflow and one TBB to complete a design of 1.5M nodes and 3.5M edges with different numbers of serial stages.

4.3 VLSI Circuit Timing Analysis Algorithm

We applied Pipeflow to solve a VLSI static timing analysis (STA) problem. The goal is to analyze the timing landscape of a circuit design and report critical paths that do not meet the given constraints (e.g., setup and hold). As presented in Figure 2, modern STA engines leverage pipeline parallelism to speed up the timing propagations. However, nearly all of them count on OpenMP-based loop parallelism with layerby-layer synchronization [14]. With Pipeflow, we can directly formulate the problem as a task-parallel pipeline to improve task asynchrony. As the analysis complexity continues to increase, more analysis tasks (e.g., RC, delay calculators, pessimism reduction) are incorporated into each node in the STA graph. These tasks can be encapsulated in a sequence of stage functions to overlap in graph across parallel lines. We modify a large circuit design of 1.5M nodes and 3.5M edges from [14] and study the performance under different stage counts. Each node has a stage task to calculate delay values at a specific configuration using 2D matrix multiplication.

Figure 13 compares the runtime and memory between Pipeflow and oneTBB up to 80 stages. We use 80 parallel lines for all experiments; we do not observe much difference in other numbers of parallel lines as both Taskflow and one TBB have an adaptive work-stealing strategy to balance the number of running threads with dynamic task parallelism. In general, Pipeflow outperforms one TBB at large stage numbers. For example, using 40 cores and 72 stages, Pipeflow is 10% faster than one TBB. In terms of memory usage, Pipeflow is always better than oneTBB regardless of the number of stages and cores. Pipeflow consumes less memory than one TBB does because all stage tasks perform computations directly on a global graph data structure captured in the pipe callable. The data passing interface between successive stages in oneTBB thus becomes a significant yet unnecessary overhead.

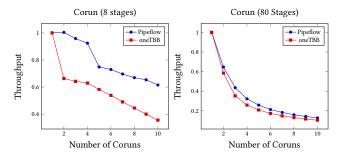


Figure 14. Throughput of corunning the STA program.

Next, we compare the throughput by corunning the same program up to 10 times. Corunning an STA program is very common for reporting the timing data of a design at different input library files [16]. The effect of pipeline scheduling propagates to all simultaneous processes. Hence, throughput

is a good measurement for the inter-operability of a pipeline-based STA algorithm. We corun the same analysis program up to 10 processes that compete for 40 cores. Again, we use the weighted speedup to measure the throughput. Figure 14 plots the throughput across 10 coruns at 8 and 80 stages. We can see that Pipeflow outperforms one TBB at all coruns. For instance, at 10 coruns, Pipeflow is $1.7 \times$ and $1.2 \times$ better than one TBB with 8 and 80 stages, respectively.

4.4 VLSI Detailed Placement Algorithm

We applied Pipeflow to solve a VLSI detailed placement problem. Detailed placement is a critical step in physical optimization. The goal is to optimize the interconnect among millions of logic gates or *instances* for improved timing and power. Connected instances are grouped to a *net* with interconnect modeled in Manhattan distance. We consider the detailed placement algorithm in DREAMPlace [22], namely *local reordering*. The algorithm decides an optimal order of four consecutive instances in a *window* of a placement row that produces minimum interconnect wirelength. We can parallelize the reordering algorithm using pipeline. Each row corresponds to a parallel stage that finds the best ordering of cells in a window from the top to the bottom. The scheduling tokens sweep through all windows from the left to the right. Figure 15 illustrates the algorithm.

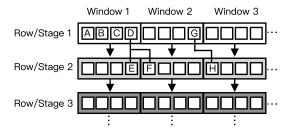


Figure 15. Parallel local reordering algorithm using pipeline. Reordering cells in window 1 of row 1 (R1W1) cannot run in parallel with R2W1 due to the vertical dependency D–E. However, R1W1 can overlap with R2W2 despite D–F, because the algorithm deals with Manhattan distance for wirelength. We can always assume that F is fixed on the right of window 1 within the view of R1W1. Thus, we update vertical windows in a linear pipeline, R1 \rightarrow R2 \rightarrow R3.

Figure 16 compares the runtime and memory data between Pipeflow and oneTBB for two industrial designs, adaptec1 and bigblue4. adaptec1 is a medium design with 211K instances and 221K nets (instance dependencies), defining 890 stages for 890 placement rows and 10692 windows. bigblue4 is a large design with 2.1M instances and 2.2M nets, defining 2694 stages for 2694 placement rows and 32190 columns. Both Pipeflow and oneTBB scale with increasing numbers of cores, whereas Pipeflow always outperforms oneTBB 3–24%. For instance, in bigblue4 (40 cores), Pipeflow finishes the placement

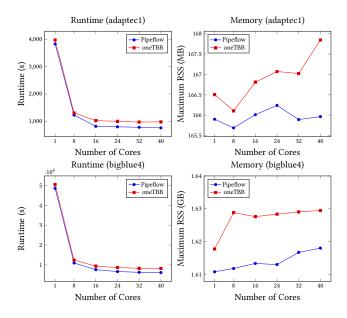


Figure 16. Runtime and memory data of the pipeline-based placement algorithm for two industrial designs, adaptec1 (890 stages) and bigblue4 (2694 stages).

algorithm in 6131 seconds, whereas oneTBB needs 8213 seconds. Such improvement is significant as practical design closure process can invoke millions of placement iterations to optimize the physical layout. Likewise, Pipeflow outperforms oneTBB in memory usage. The difference is slight (about 1%) because most memory is taken by the placement problem itself, including the data structure of rows and instances.

4.5 Insight from the CAD Algorithm Developers

As an experienced parallel CAD researcher, Pipeflow has assisted us to overcome many programming challenges. In the previous two experiments, the data is explicitly managed by the application algorithms and does not go through any data abstraction layers of one TBB. The real need is a task-parallel pipeline programming framework that 1) gives us full control over data and 2) allows us to probe each scheduled task. For instance, when implementing the placement algorithm, we capture the row data from a global database in each pipe callable and use the pipeflow variable to get the line numbers of a scheduled task to index its window locations. However, one TBB has abstracted these components out, and we have to implement another mapping strategy to get these data from each filter. Similar problems exist in other libraries too.

5 Related Work

Pipeline programming models have received intensive research interest. Most of them are data-centric using static template instantiation or dynamic runtime polymorphism to

model data processing in a pipeline. To name a few popular examples: oneTBB [1] and TPL [20] require explicit definitions of input and output types for each stage; GrPPI [8] provides a composable abstraction for data- and streamparallel patterns with a pluggable back-end to support task scheduling; FastFlow [4] models parallel dataflow using predefined sequential and parallel building blocks; TTG [7] focuses on dataflow programming using various template optimization techniques; SPar [10-12, 23] analyzes annotated attributes extracted from the data and stream parallelism domain, and automatically generates parallel patterns defined in FastFlow; Proteas [24] introduces a programming model for directive-based parallelization of linear pipeline; [34, 35] propose self-adaptive mechanism to decide the degree of parallelism and generate the pattern compositions in FastFlow. These programming models, however, constrain users to design pipeline algorithms using their data models, making it difficult to use especially for applications that only need pipeline scheduling atop custom data structures.

Existing pipeline scheduling algorithms typically codesign task scheduling and buffer structures to strive for the best performance. For instance, one TBB [1] defines a per-stage buffer counter to synchronize data tokens among stages and lines, coupled with a small object allocator to minimize the data allocation overhead; GRAMPS [32] designs a buffer manager with per-thread fix-sized memory pools to dynamically allocate new data and release used ones; FastFlow [4] design a lock-free queue with a mechanism to transfer data ownership between senders and receivers, but this method can incur imbalanced load and requires nontrivial back-pressure management; HPX [17] counts on a channel data structure and standard future objects to pass data around tasks, but the creation of share states becomes expensive when the pipeline is large; Cilk-P [19] employs per-stage queues coupled with two counter types to track static and dynamic dependencies of each node, but it targets on-the-fly pipeline parallelism which is orthogonal to our focus; FDP [33] proposes a learning-based mechanism to adapt scheduling to an environment, but it requires expensive runtime profiling that may not work well for highly irregular applications like CAD. In terms of load balancing, most pipeline schedulers leverage work stealing, which has been reported with better performance than static policies [5, 13, 19, 21, 28, 32]. However, for some special cases, such as fine-grained load-imbalanced pipelines, static policies perform comparably. For example, Pipelight [27] implements a load balancing technique based on two static scheduling algorithms, DSWP [29-31] and LBPP [18]; Pipelite [26] and URTS [25] introduce dynamic schedulers using ticket-based synchronization and directive-based model language for linearpipelines, respectively. While co-designing task scheduling and buffer structures has certain advantages for datacentric pipeline (e.g., data locality), the cost of managing data

can be significant yet unnecessary, especially for applications that only exploit task parallelism in pipeline.

6 Conclusion

We have introduced Pipeflow, an efficient C++ pipeline programming framework atop the Taskflow system. We have designed a new task-parallel programming model that separates data abstraction and task scheduling. By focusing on the pipeline tasking, we have introduced a simple yet efficient scheduling algorithm based on Taskflow's work-stealing runtime with dynamic load balancing. We have evaluated the performance of Pipeflow on micro-benchmarks and real applications. For example, Pipeflow outperforms oneTBB 24% and 10% faster in a VLSI placement and a timing analysis workloads that adopt pipeline parallelism to speed up runtimes, respectively. Our future work plans to apply Pipeflow to more CAD applications and bring interdisciplinary ideas to the HPC domain.

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