A Modern C++ Parallel Task Programming Library

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ABSTRACT
In this paper we present Cpp-Taskflow, a C++ parallel programming library that enables users to quickly develop parallel applications using the task dependency graph model. Developers formulate their application as a task dependency graph and Cpp-Taskflow will manage the task execution and concurrency control. The task graph model is expressive and composable. It can express both regular and irregular parallel patterns, and developers can quickly compose large programs from small parallel modules. Cpp-Taskflow has an intuitive and unified API set. Users only need to learn the APIs to build and dispatch a task graph and no complex parallel programming concept is required. We have conducted experiments using both micro-benchmarks and real-world applications and Cpp-Taskflow outperforms state-of-the-art parallel programming libraries in both runtime and coding effort. Cpp-Taskflow is open-source and has been used in both industry and academic projects. From our users’ feedback, we believe Cpp-Taskflow can benefit the industry and research community greatly through its ease-of-programming and inspire new research directions in multimedia system/software design.

KEYWORDS
Parallel programming; task parallelism; task dependency graph

ACM Reference Format:

1 INTRODUCTION
Multicore processors are prevalent from desktops, laptops, tablets to mobile devices. How to effectively utilize those computing resources to maximize software performance? This is a critical question that software developers must consider, especially when building complex parallel applications such as artificial intelligence, numerical simulation, machine learning and multimedia big data analytics [1] [2] [3] [4] [5]. Writing parallel code is considered much more difficult than the sequential counterpart. Programmers have to pay extra attention to the concurrency control to avoid unexpected behavior during runtime, for example, using locks to protect shared data or atomic variables to avoid data race. The situation is getting more challenging when applications exhibit complex data or operation dependency, which is typical in real-world problems. As a result, it’s necessary to have an efficient approach to write parallel code.

In this paper, we present Cpp-Taskflow, a modern C++ task-based parallel programming library. Cpp-Taskflow was motivated from a real-world project of VLSI timing analysis [6]. Cpp-Taskflow lets users express their parallelism using the intuitive task graph model. The task graph model is simple yet very powerful as it can represent both regular and irregular parallel patterns. The task graph model abstracts away complex concurrency management and allows users to focus on exploiting parallelism within their applications. Cpp-Taskflow provides well-designed APIs to keep the code concise and readable. We have a unified task graph construction interface for both static and dynamic parallelism, so users can learn those APIs quickly and utilize them to implement various parallel patterns. Cpp-Taskflow supports visualization for program debugging and profiling. Users can dump the task graph to inspect the program execution flow and they can view the thread activities in a Chrome browser. We have conducted experiments on a set of micro-benchmarks and a real-world application [7] against Intel Threading Building Blocks [8] and OpenMP [9]. Cpp-Taskflow achieves comparable performance with fewer lines of code, faster runtime, and better scalability.

We understand each library has its own uniqueness and value, and it’s up to users to decide which best suits their needs. Cpp-Taskflow has been used in many industrial and academic projects [10]. We are committed to free sharing of our technical innovation to facilitate the research in parallel computing, machine learning, and multimedia. We are working actively with our users to improve Cpp-Taskflow. The project is open-source and more details can be found in [10].

2 CPP-TASKFLOW
In Cpp-Taskflow, the programming is centered around two classes: tf::Taskflow and tf::Executor. We will explain how to use them in this section.

2.1 Task Dependency Graph
In Cpp-Taskflow, a task is a C++ object of Callable type [7]. To create tasks, the first step is to create an object of the tf::Taskflow class. A taskflow object allows you to build a task dependency graph where nodes are tasks and directed edges indicate dependency. Listing 1 shows an example of adding three tasks via the...
emplace method. The emplace method can create multiple tasks at one time. After tasks are created, users can assign names to tasks and specify the dependency between tasks via the name and precede method, respectively. A task A precedes a task B if task B can only run after task A completes its execution.

```cpp
Listing 1: Create a task dependency graph.

// Create a task
auto taskA = taskflow::emplace([](std::cout << "Task A\n") {});

// Create two tasks at one time
auto [taskB, taskC] = taskflow::emplace([](std::cout << "Task B\n") {},
    [ ](std::cout << "Task C\n") {},
    [ ](std::cout << "Task D\n") {});

// Name the tasks
taskA.name("taskA");

// Specify the dependency
taskA.precede(taskB, taskC);
```

2.2 Dynamic Tasking

C++-Taskflow has another powerful feature: dynamic tasking that enables a task to create and dispatch a task dependency graph at runtime to obtain dynamic parallelism. Listing 2 shows an example of dynamic tasking. In this example task B spawns a task dependency graph that has three tasks. A task that requires dynamic parallelism has to take an additional argument of type tf::Subflow and uses the emplace method to create a new task dependency graph. The new task dependency graph will by default join its parent task. However, users can make it run independently by calling the detach method. A detached task dependency graph will join the end of its parent’s task dependency graph. Figure 1 shows the spawned task dependency graphs in joined and detached modes, respectively. Dynamic tasking empowers users to parallelize frequently used computing patterns such as recursive and nested flows.

```cpp
Listing 2: An example of dynamic tasking.

// Create four tasks
auto [fA1, fA2, fA3, fA4] = fA.emplace([](std::cout << "Task fA1\n") {},
    [ ](std::cout << "Task fA2\n") {},
    [ ](std::cout << "Task fA3\n") {},
    [ ](std::cout << "Task fA4\n") {});

// Create three tasks
auto [taskA, taskC, taskD] = flow::emplace([](std::cout << "Task A\n") {},
    [ ](std::cout << "Task C\n") {},
    [ ](std::cout << "Task D\n") {});

// Create a task with subflow
auto taskB = flow::emplace([auto &subflow](){
    std::cout << "Task B\n";
    // Spawn a new task dependency graph
    auto [B1, B2, B3] = subflow::emplace([](std::cout << "Task B1\n") {},
        [ ](std::cout << "Task B2\n") {},
        [ ](std::cout << "Task B3\n") {});
    }
}
);
```

2.3 Composition

An useful feature of task dependency graph is the composability. Users can use the composed_of method to compose several task dependency graphs to a large and complex task dependency graph. The composed_of method returns a module task. Users can use the precede method to add dependency between module tasks and other tasks. Listing 3 shows an example of task dependency graph composition.

```cpp
Listing 3: An example of task dependency graph composition.

// Create three tasks
auto [fB1, fB2, fB3] = fB.emplace([](std::cout << "Task fB1\n") {},
    [ ](std::cout << "Task fB2\n") {},
    [ ](std::cout << "Task fB3\n") {});

auto moduleA = fB.composed_of(fA);

fB1.precede(moduleA, fB2);
moduleA.precede(fB3);
```

Figure 1: Comparison of joined and detached subflows.
2.4 Execution

After creating task dependency graphs, the next step is to dispatch graphs to an executor object of type `tf::Executor`. An executor object manages thread construction and destruction and provides several methods to execute task dependency graphs through an efficient work-stealing algorithm. Table 1 summarizes the execution methods and Listing 4 demonstrates the usage of those execution methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>run</td>
<td>Execute a graph once</td>
</tr>
<tr>
<td>run_n</td>
<td>Execute a graph multiple times</td>
</tr>
<tr>
<td>run_until</td>
<td>Execute a graph until a condition is met</td>
</tr>
<tr>
<td>wait_for_all</td>
<td>Wait until all running graphs finish</td>
</tr>
</tbody>
</table>

Table 1: Summary of execution methods.

Listing 4: Demonstration of different execution methods.

```cpp
tf::Taskflow tf;
// Add tasks to tf ...
tf::Executor executor;
executor.run(tf); // Run the flow once
executor.run_n(tf, 6); // Run the flow six times
// Run the flow until the number becomes 0
executor.run_until(tf, [number=4] () mutable {
    return number-- == 0;
});
```

Listing 5: Visualization of a task dependency graph.

```cpp
tf::Taskflow taskflow;
tf::Executor executor;
auto observer = executor.make_observer<
tf::ExecutorObserver>();
```

2.5 Debugging and Profiling

Debugging a parallel program is very challenging due to the non-deterministic nature. Cpp-Taskflow supports the visualization of task dependency graphs to let users inspect the task execution flow. Users can use the `name` method to assign a taskflow object a name and the `dump` method to export the object’s task graph in DOT format [11]. Listing 5 shows an example of naming and dumping a task dependency graph. Figure 3 demonstrates the task dependency graphs of two taskflow objects.

Listing 5: Visualization of a task dependency graph.
// Add tasks and dispatch the flow to execution
...
// Dump the timestamps to a JSON file
std::ofstream ofs("timestamps.json");
observer->dump(ofs);

Listing 6: Use an observer to monitor the thread activities.

Figure 4: Thread activities displayed in chrome://tracing.

3 A MACHINE LEARNING APPLICATION

Machine learning has been successfully applied to several multimedia topics such as image classification, speech recognition and so on [4] [5]. We demonstrate applying Cpp-Taskflow to parallelize a machine learning application: MNIST [12] dataset, and compare its performance and coding effort with OpenMP [9]. The MNIST dataset contains images of handwritten digits and it is widely used to test the effectiveness of machine learning algorithms. In this demonstration, we build a 5-layer deep neural network (DNN) to classify those images. We adopt the task pipeline strategy proposed by [7] to parallelize the DNN training. Each batch starts with a task for forward propagation and then followed by a sequence of gradient calculation and weight update tasks for each layer. We pipeline the gradient calculation and weight update tasks between successive layers to enable parallelism within each batch. Next we create tasks for data shuffle per epoch. We allocate additional data storages to have a shuffle task start earlier preparing the data for later epochs. We compare the implementations of OpenMP [9] and Cpp-Taskflow. OpenMP is the most popular parallel programming library in high-performance computing and we use OpenMP’s task depend clause to implement this parallelization strategy. For Cpp-Taskflow, we implement this application using the taskflow object.

Taskflow with using taskflow object.

Table 2: Code complexity [13] of the three implementations.

<table>
<thead>
<tr>
<th>Library</th>
<th>Total NLOC</th>
<th>Avg Token</th>
<th>Avg CCN</th>
</tr>
</thead>
<tbody>
<tr>
<td>OpenMP</td>
<td>93</td>
<td>1058</td>
<td>11</td>
</tr>
<tr>
<td>Taskflow</td>
<td>60</td>
<td>600</td>
<td>11</td>
</tr>
</tbody>
</table>

NLOC: lines of code. CCN: cyclomatic complexity number.

4 AVAILABILITY

Cpp-Taskflow is open-source on Github [10] under MIT license. The API documentation, tutorials and cookbook are also available on Github. We have presented Cpp-Taskflow at CppCon which is the premier C++ developer conference and the video is on YouTube [14].

5 ACKNOWLEDGEMENT

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REFERENCES