Taskflow: A General-purpose Parallel and Heterogeneous Task Programming System using Modern C++

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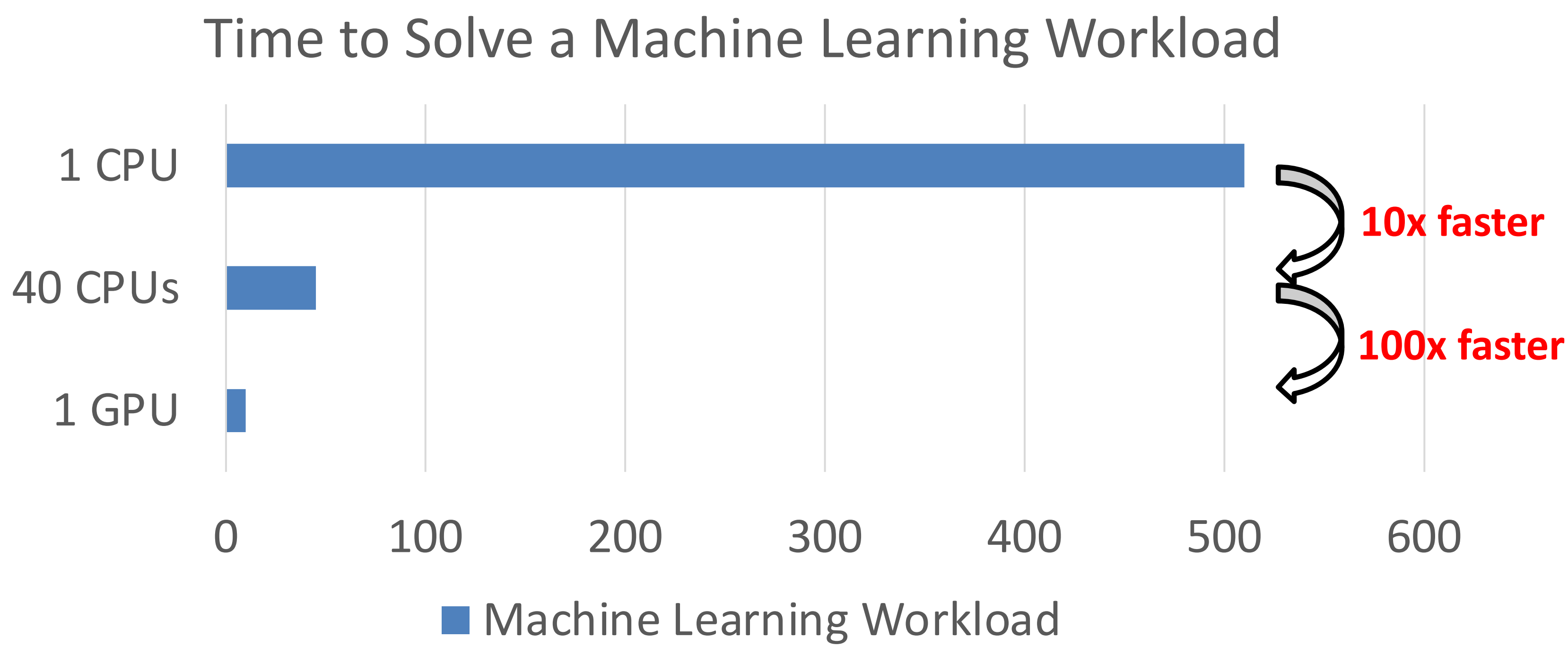
https://taskflow.github.io/

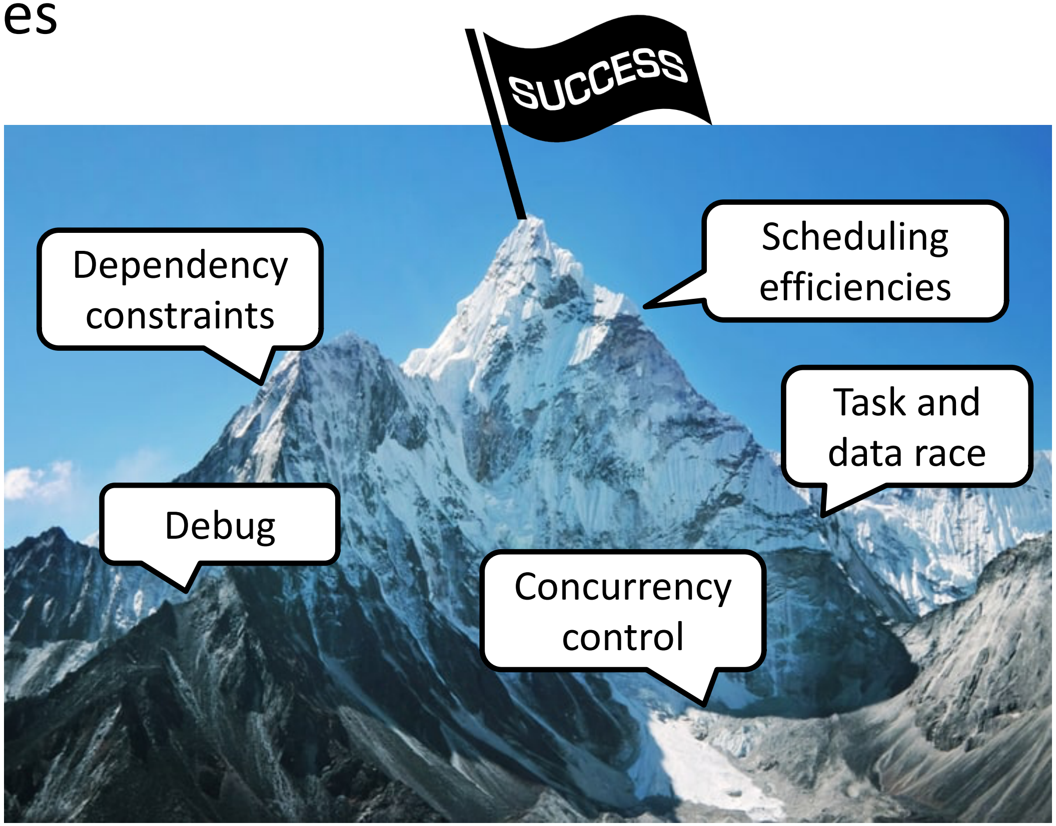
Why Parallel Computing?

- It's critical to advance your application performance



Parallel Programming is Not Easy, Yet

- **You need to deal with many difficult technical details**
  - Standard concurrency control
  - Task dependencies
  - Scheduling
  - Data race
  - … (more)



Many developers have hard time in getting them right!

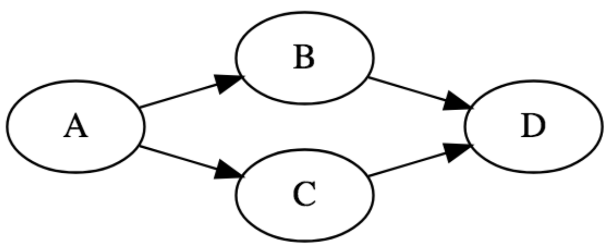
Taskflow offers a solution

How can we make it easier for C++ developers to quickly write parallel and heterogeneous programs with high performance scalability and simultaneous high productivity?

“Hello World” in Taskflow

```
#include <taskflow/taskflow.hpp>   // Taskflow is header-only
int main(){
  tf::Taskflow taskflow;
  tf::Executor executor;
  auto [A, B, C, D] = taskflow.emplace(
    [] () { std::cout << "TaskA\n"; }
    [] () { std::cout << "TaskB\n"; },
    [] () { std::cout << "TaskC\n"; },
    [] () { std::cout << "TaskD\n"; }
  );
  A.precede(B, C);  // A runs before B and C
  D.succeed(B, C);  // D runs after    B and C
  executor.run(taskflow).wait(); // submit the taskflow to the executor
  return 0;
}
```

*Only **15 lines** of code to get a parallel task execution!*



Agenda

- ❑ Express your parallelism in the right way
- ❑ Parallelize your applications using Taskflow
- ❑ Understand our scheduling algorithm
- ❑ Boost performance in real applications
- ❑ Make C++ amenable to heterogeneous parallelism

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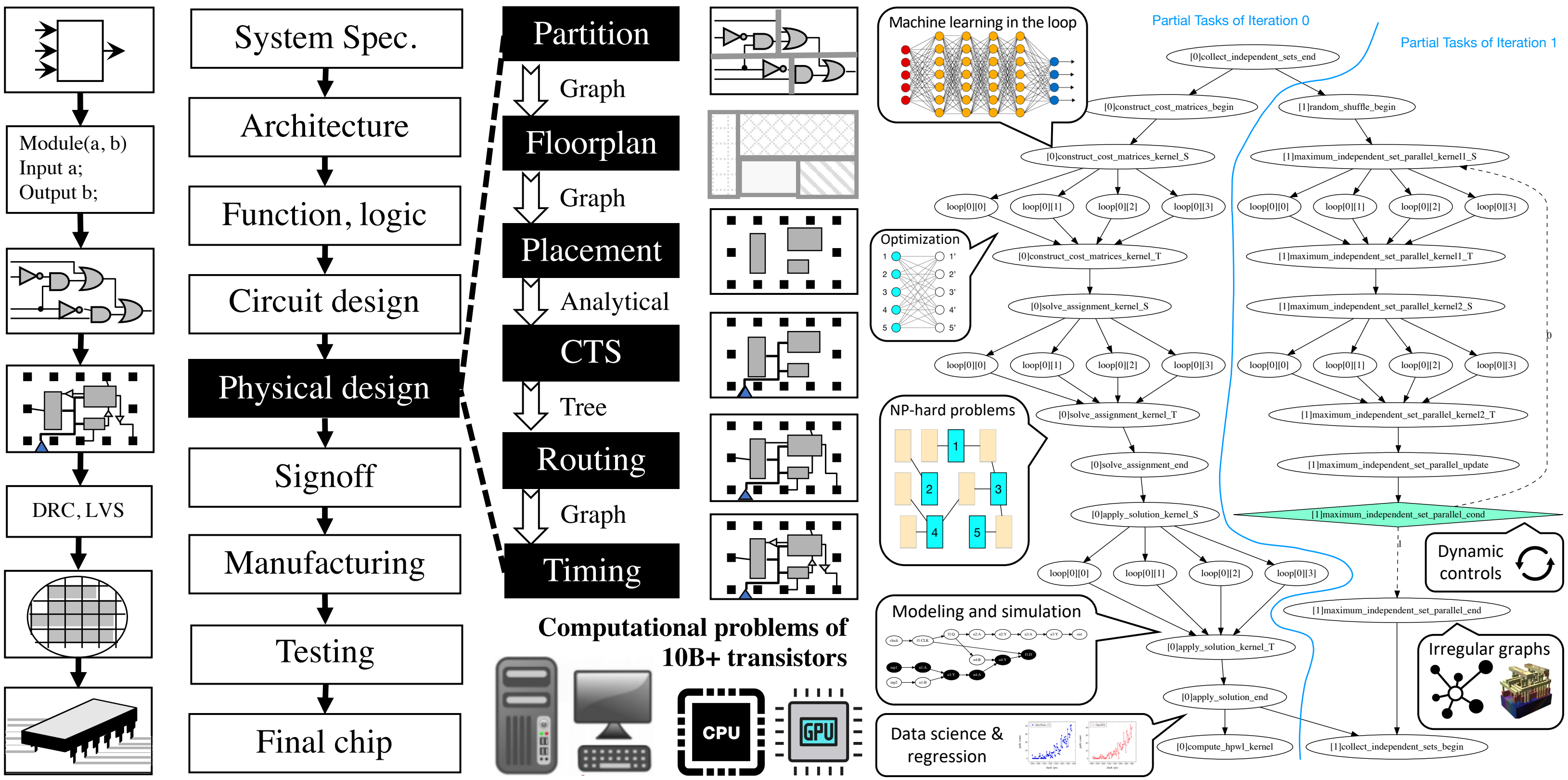
Motivation: Parallelizing VLSI CAD Tools

- ❑ **Billions of tasks with diverse computational patterns**



How can we write efficient C++ parallel programs for this *monster computational task graph* with ***millions of CPU-GPU dependent tasks along with algorithmic control flow***”

We Invested a lot in Existing Tools …

pthreads

OpenMP®

C++

TBB

NVIDIA® CUDA®

SYCL™

PaRSEC

Open MPI

STE||AR GROUP

StarPU

ECP
EXASCALE COMPUTING PROJECT

OpenCL

RAJA

kokkos

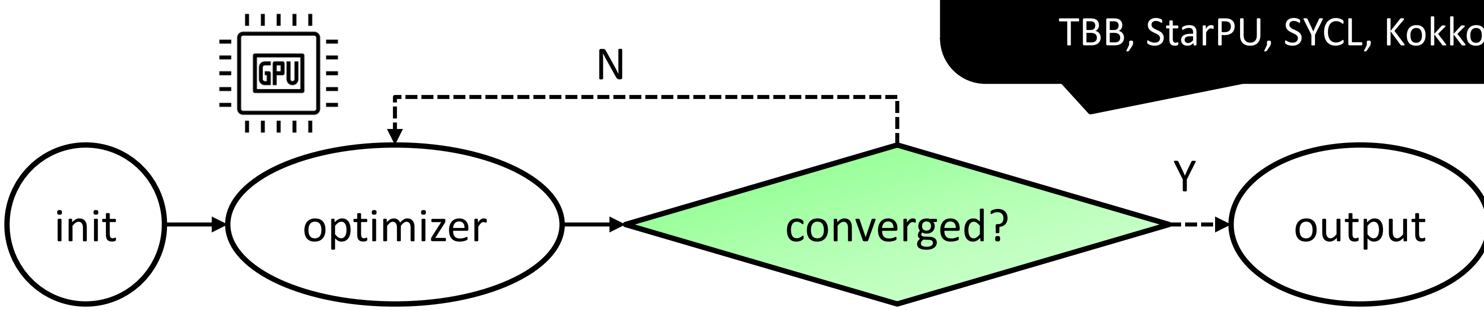
Two Big Problems of Existing Tools

- **Our problems define *complex task dependencies***
  - **Example**: analysis algorithms compute the circuit network of million of node and dependencies
  - **Problem**: existing tools are often good at loop parallelism but weak in expressing heterogeneous task graphs at this large scale
- **Our problems define *complex control flow***
  - **Example**: optimization algorithms make essential use of *dynamic control flow* to implement various patterns
    - Combinatorial optimization, analytical methods
  - **Problem**: existing tools are *directed acyclic graph* (DAG)-based and do not anticipate cycles or conditional dependencies, lacking *end-to-end* parallelism

Example: An Iterative Optimizer

- **4 computational tasks with dynamic control flow**
  - #1: starts with `init` task
  - #2: enters the `optimizer` task (e.g., GPU math solver)
  - #3: checks if the optimization converged
    - No: loops back to `optimizer`
    - Yes: proceeds to `stop`
  - #4: outputs the result

How can we easily describe this workload with *dynamic control flow* using existing tools (e.g., OpenMP, TBB, StarPU, SYCL, Kokkos) ?



Millions of such tasks?

End-to-end parallelism?

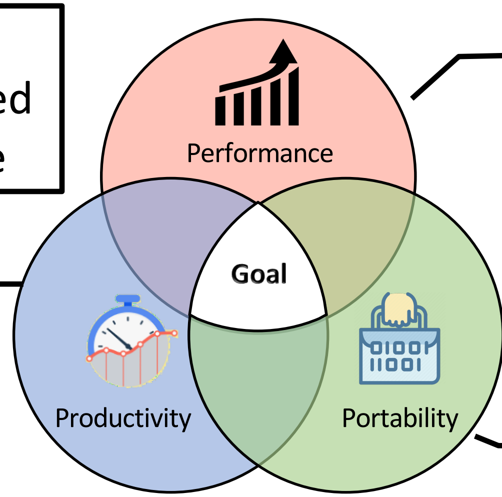
Need a New C++ Parallel Programming System

While designing parallel algorithms is non-trivial …

what makes parallel programming an enormous challenge is the infrastructure work of "***how to efficiently express dependent tasks along with an algorithmic control flow and schedule them across heterogeneous computing resources***"

Taskflow Project Mantra

We maximize productivity compared to handcrafted time



We maximize the performance compared to handcrafted solution

We maximize the portability using the power of modern C++

- ❑ **We are not to replace existing tools but**
  1. Address their limitations on task graph parallelism
  2. Develop compatible interface to reuse their facilities

Together, we can deliver complementary advantages to advance C++ parallelism

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- ❑ Make C++ amenable to heterogeneous parallelism

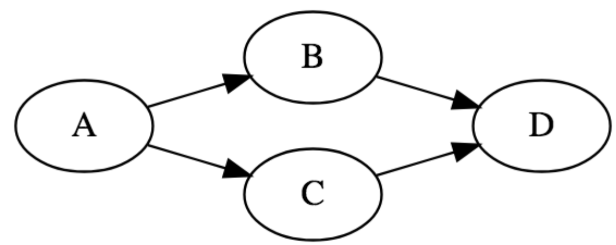
Many arguments are based on my personal opinions – no offense, no criticism, just plain C++ from an end user's perspective

"Hello World" in Taskflow (Revisited)

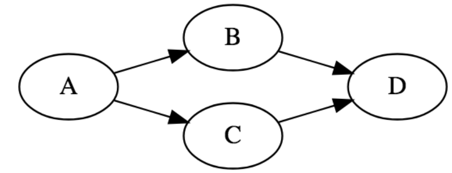
```
#include <taskflow/taskflow.hpp>   // Taskflow is header-only
int main(){
  tf::Taskflow taskflow;
  tf::Executor executor;
  auto [A, B, C, D] = taskflow.emplace(
    [] () { std::cout << "TaskA\n"; }
    [] () { std::cout << "TaskB\n"; },
    [] () { std::cout << "TaskC\n"; },
    [] () { std::cout << "TaskD\n"; }
  );
  A.precede(B, C);  // A runs before B and C
  D.succeed(B, C);  // D runs after    B and C
  executor.run(taskflow).wait(); // submit the taskflow to the executor
  return 0;
}
```

Taskflow defines five tasks:

1. static task
2. dynamic task
3. cudaFlow task
4. condition task
5. module task



“Hello World” in OpenMP




```
#include <omp.h>  // OpenMP is a lang ext to describe parallelism using compiler directives
int main(){
  #omp parallel num_threads(std::thread::hardware_concurrency())
  {
    int A_B, A_C, B_D, C_D;
    #pragma omp task depend(out: A_B, A_C)
    {
      std::cout << ”TaskA\n” ;
    }
    #pragma omp task depend(in: A_B; out: B_D)
    {
      std::cout << ” TaskB\n” ;
    }
    #pragma omp task depend(in: A_C; out: C_D)
    {
      std::cout << ” TaskC\n” ;
    }
    #pragma omp task depend(in: B_D, C_D)
    {
      std::cout << ”TaskD\n” ;
    }
  }
  return 0;
}
```

Task dependency clauses

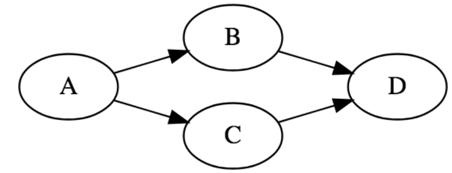
Task dependency clauses

Task dependency clauses

Task dependency clauses

OpenMP task clauses are static and explicit; Programmers are responsible for a proper order of writing tasks consistent with sequential execution

“Hello World” in TBB




```
#include <tbb.h>  // Intel’s TBB is a general-purpose parallel programming library in C++
int main(){
   using namespace tbb;
   using namespace tbb:flow;
   int n = task_scheduler init::default_num_threads () ;
   task scheduler_init init(n);
   graph g;
   continue_node<continue_msg> A(g, [] (const continue msg &) {
      s t d : : c o u t << “TaskA” ;
   }) ;
   continue_node<continue_msg> B(g, [] (const continue msg &) {
      s t d : : c o u t << “TaskB” ;
   }) ;
   continue_node<continue_msg> C(g, [] (const continue msg &) {
      s t d : : c o u t << “TaskC” ;
   }) ;
   continue_node<continue_msg> C(g, [] (const continue msg &) {
      s t d : : c o u t << “TaskD” ;
   }) ;
   make_edge(A, B);
   make_edge(A, C);
   make_edge(B, D);
   make_edge(C, D);
   A.try_put(continue_msg());
   g.wait_for_all();
}
```

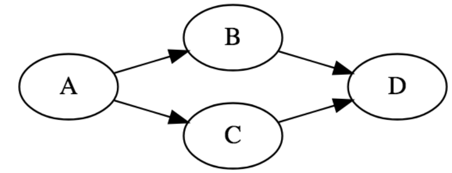
Use TBB’s FlowGraph for task parallelism

Declare a task as a continue_node

TBB has excellent performance in generic parallel computing. Its drawback is mostly in the ease-of-use standpoint (simplicity, expressivity, and programmability).

TBB FlowGraph: https://software.intel.com/content/www/us/en/develop/home.html

“Hello World” in Kokkos




```
struct A {
  template <class TeamMember> KOKKOS_INLINE_FUNCTION
  void operator()(TeamMember& member) {std::cout << "TaskA\n"; }
};
struct B {
  template <class TeamMember> KOKKOS_INLINE_FUNCTION
  void operator()(TeamMember& member) {std::cout << "TaskB\n"; }
};
struct C {
  template <class TeamMember> KOKKOS_INLINE_FUNCTION
  void operator()(TeamMember& member) {std::cout << "TaskC\n"; }
};
struct D {
  template <class TeamMember> KOKKOS_INLINE_FUNCTION
  void operator()(TeamMember& member) {std::cout << "TaskD\n"; }
};
auto scheduler = scheduler_type(/* ... */);
auto futA = Kokkos::host_spawn( Kokkos::TaskSingle(scheduler), A() );
auto futB = Kokkos::host_spawn( Kokkos::TaskSingle(scheduler, futA), B() );
auto futC = Kokkos::host_spawn( Kokkos::TaskSingle(scheduler, futA), C() );
auto futD = Kokkos::host_spawn(
  Kokkos::TaskSingle(scheduler, when_all(futB, futC)), D()
);
```

Fixed-layout task functor (no lambda interface …?)

Define team handle

Task dependency is represented by instances of `Kokkos::BasicFuture`

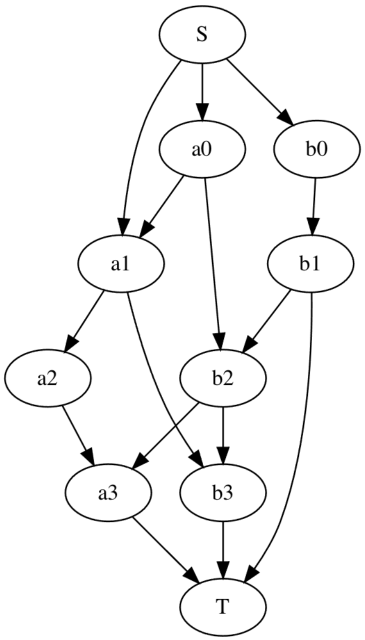
Aggregated dependencies

More scheduling code to follow …

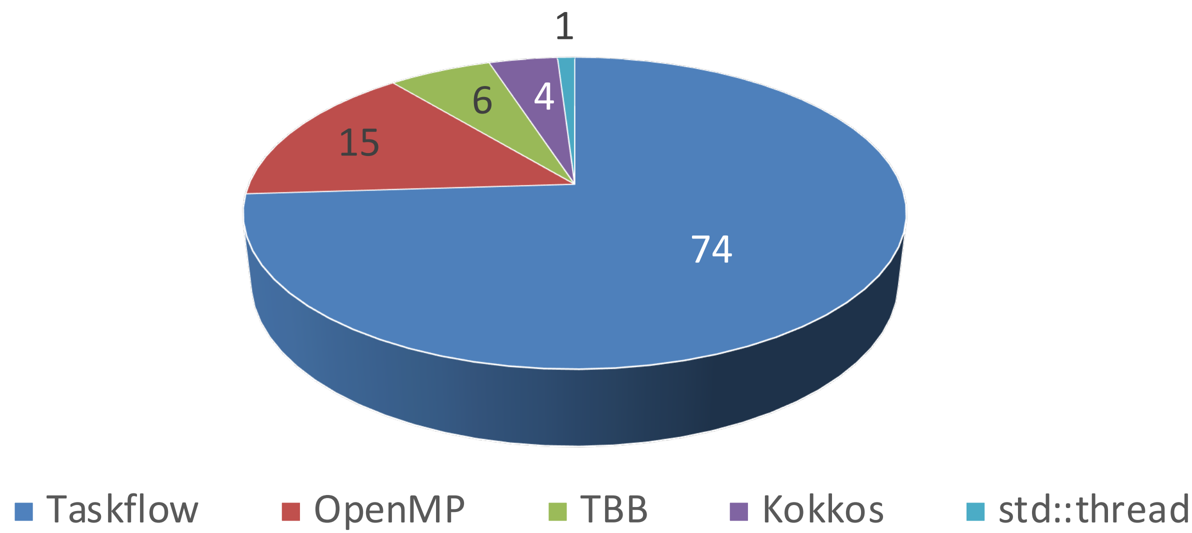
Kokkos is powerful in describing asynchronous tasks but not efficient in large task graph parallelism

Kokkos task parallelism: https://github.com/kokkos/kokkos/wiki/Task-Parallelism

“Hello World” Summary (Less Biased)



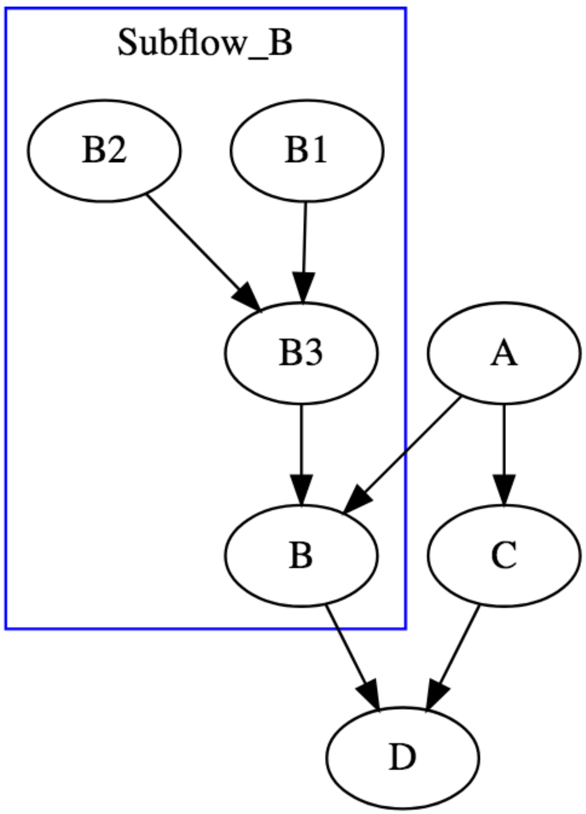
Vote for Simplicity
(100 C++ programmers of 2-5 years of C++11 experience)



#1 concern: *“My application is already very complex; it’s important the parallel programming library doesn’t become another burden.”*

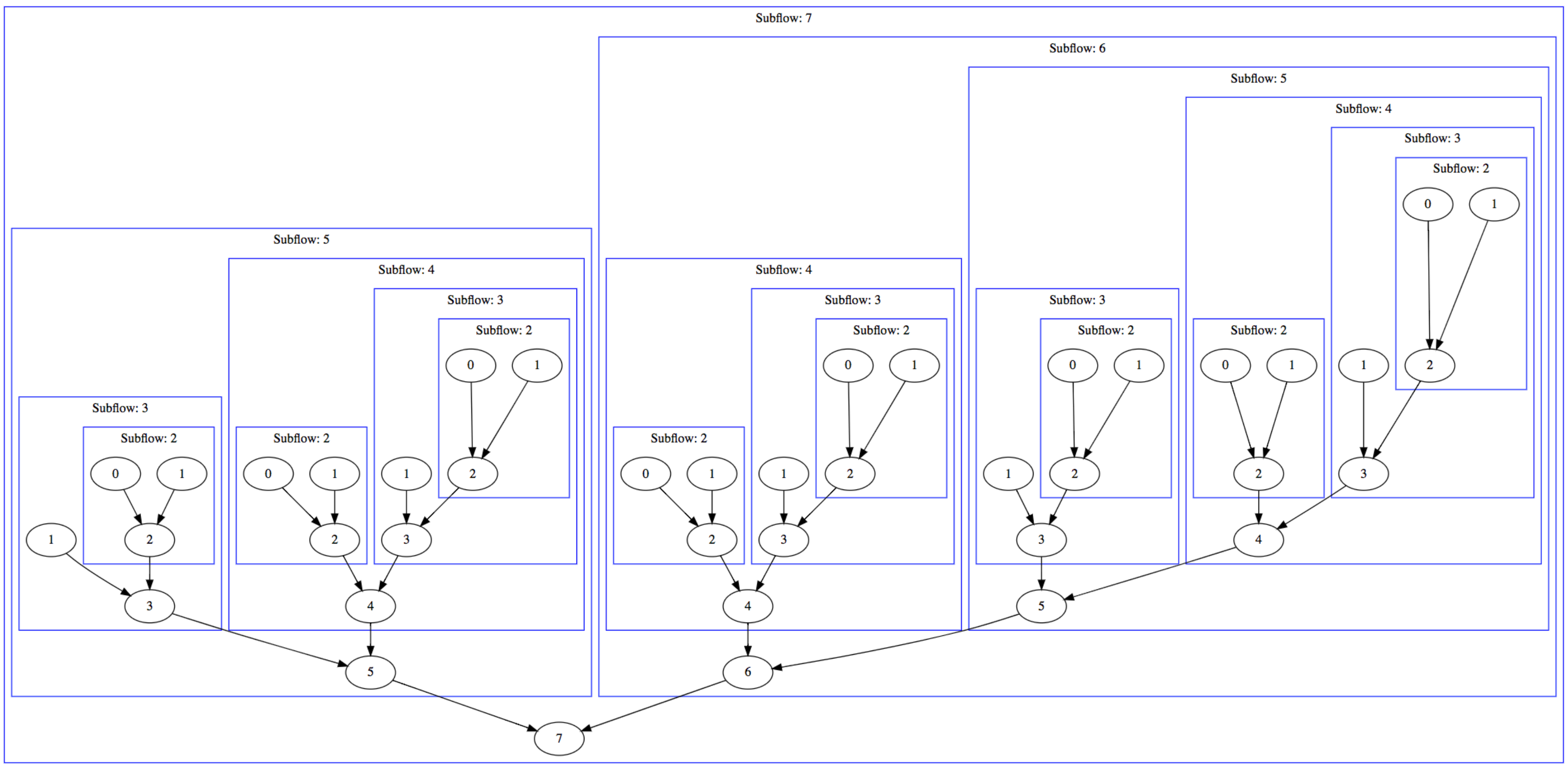
Dynamic Tasking (Subflow)

```
// create three regular tasks
tf::Task A = tf.emplace([](){}).name("A");
tf::Task C = tf.emplace([](){}).name("C");
tf::Task D = tf.emplace([](){}).name("D");

// create a subflow graph (dynamic tasking)
tf::Task B = tf.emplace([] (tf::Subflow& subflow) {
  tf::Task B1 = subflow.emplace([](){}).name("B1");
  tf::Task B2 = subflow.emplace([](){}).name("B2");
  tf::Task B3 = subflow.emplace([](){}).name("B3");
  B1.precede(B3);
  B2.precede(B3);
}).name("B");

A.precede(B); // B runs after A
A.precede(C); // C runs after A
B.precede(D); // D runs after B
C.precede(D); // D runs after C
```



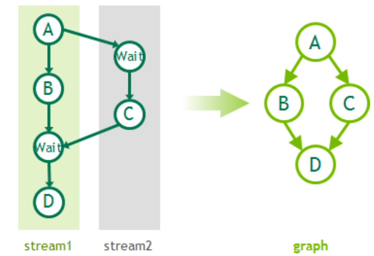
Subflow can be Nested

- Find the 7th Fibonacci number using subflow
  - Fib(n) = Fib(n-1) + Fib(n-2)



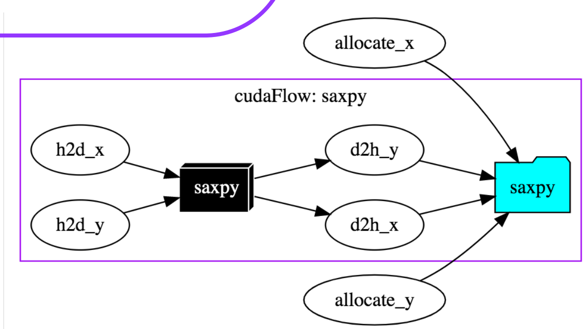
Heterogeneous Tasking (cudaFlow)

```
const unsigned N = 1<<20;
std::vector<float> hx(N, 1.0f), hy(N, 2.0f);
float *dx{nullptr}, *dy{nullptr};
auto allocate_x = taskflow.emplace([&](){ cudaMalloc(&dx, 4*N);});
auto allocate_y = taskflow.emplace([&](){ cudaMalloc(&dy, 4*N);});

auto cudaflow = taskflow.emplace([&](tf::cudaFlow& cf) {
   auto h2d_x = cf.copy(dx, hx.data(), N);  // CPU-GPU data transfer
   auto h2d_y = cf.copy(dy, hy.data(), N);
   auto d2h_x = cf.copy(hx.data(), dx, N);  // GPU-CPU data transfer
   auto d2h_y = cf.copy(hy.data(), dy, N);
   auto kernel = cf.kernel((N+255)/256, 256, 0, saxpy, N, 2.0f, dx, dy);
   kernel.succeed(h2d_x, h2d_y).precede(d2h_x, d2h_y);
});

cudaflow.succeed(allocate_x, allocate_y);
executor.run(taskflow).wait();
```



To Nvidia ***cudaGraph***

Users define GPU work in a graph rather than aggregated operations → single kernel launch to reduce overheads



Three Key Motivations

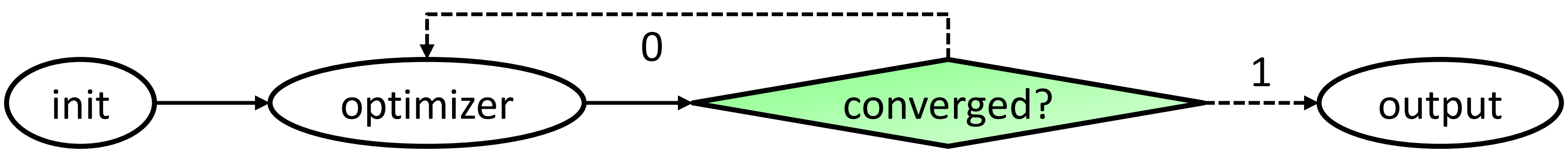
- Our closure enables stateful interface
  - Users capture data in reference to marshal data exchange between CPU and GPU tasks
- Our closure hides implementation details judiciously
  - We use cudaGraph (since cuda 10) due to its excellent performance, much faster than streams in large graphs
- Our closure extend to new accelerator types
  - syclFlow, openclFlow, coralFlow, tpuFlow, fpgaFlow, etc.

```
auto cudaflow = taskflow.emplace([&](tf::cudaFlow& cf) {
  auto h2d_x = cf.copy(dx, hx.data(), N);  // CPU-GPU data transfer
  auto h2d_y = cf.copy(dy, hy.data(), N);
  auto d2h_x = cf.copy(hx.data(), dx, N);  // GPU-CPU data transfer
  auto d2h_y = cf.copy(hy.data(), dy, N);
  auto kernel = cf.kernel((N+255)/256, 256, 0, saxpy, N, 2.0f, dx, dy);
  kernel.succeed(h2d_x, h2d_y).precede(d2h_x, d2h_y);
});
```

We do not simplify kernel programming but **focus on *CPU-GPU tasking* that affects the performance to a large extent!** (same for data abstraction)

Conditional Tasking

```
auto init          = taskflow.emplace([&](){ initialize_data_structure(); } )
                                .name(”init");
auto optimizer     = taskflow.emplace([&](){ matrix_solver(); } )
                                .name(”optimizer");
auto converged     = taskflow.emplace([&](){ return converged() ? 1 : 0 } )
                                .name(”converged");
auto output        = taskflow.emplace([&](){ std::cout << ”done!\n"; } );
                                .name(”output");
init.precede(optimizer);
optimizer.precede(converged);
converged.precede(optimizer, output);  // return 0 to the optimizer again
```

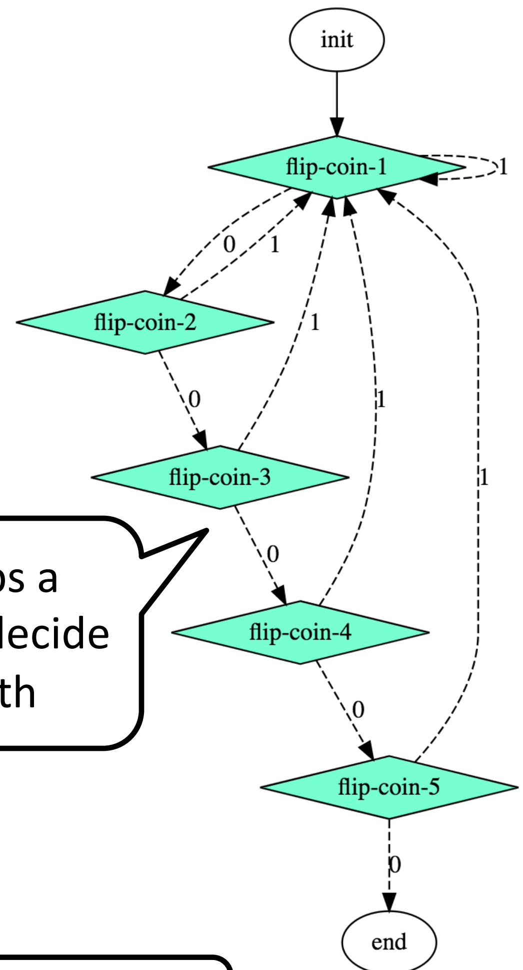


Condition task integrates control flow into a task graph to form end-to-end parallelism; in this example, there are ultimately four tasks ever created

Conditional Tasking (cont'd)

```
auto A = taskflow.emplace([&](){ } );
auto B = taskflow.emplace([&](){ return rand()%2; } );
auto C = taskflow.emplace([&](){ return rand()%2; } );
auto D = taskflow.emplace([&](){ return rand()%2; } );
auto E = taskflow.emplace([&](){ return rand()%2; } );
auto F = taskflow.emplace([&](){ return rand()%2; } );
auto G = taskflow.emplace([&](){});

A.precede(B).name("init");
B.precede(C, B).name("flip-coin-1");
C.precede(D, B).name("flip-coin-2");
D.precede(E, B).name("flip-coin-3");
E.precede(F, B).name("flip-coin-4");
F.precede(G, B).name("flip-coin-5");
G.name("end");
```

Each task flips a binary coin to decide the next path



Tip!

You can describe non-deterministic, nested control flow!

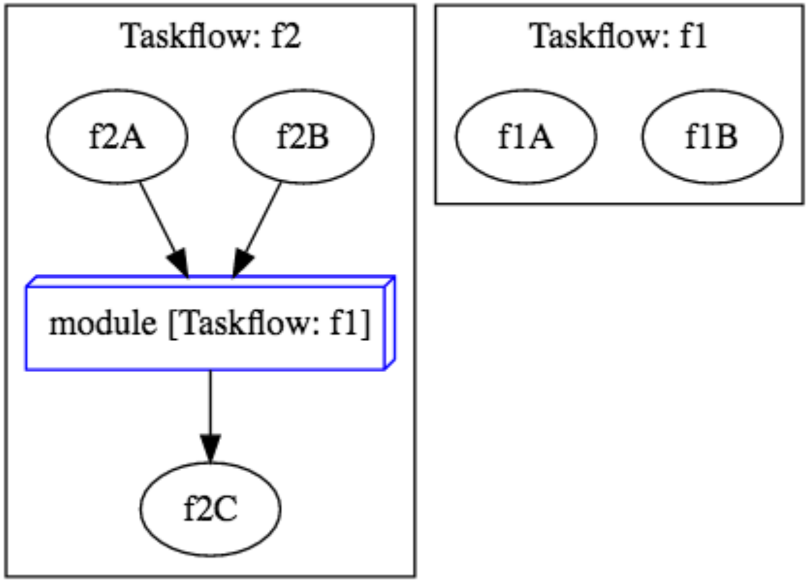
Existing Frameworks on Control Flow?

- **Expand a task graph across fixed-length iterations**
  - Graph size is linearly proportional to decision points
- **Unknown iterations? Non-deterministic conditions?**
  - Complex dynamic tasks executing "if" on the fly
- **Dynamic control flows and dynamic tasks?**
- **… (resort to client-side decision)**

Existing frameworks on expressing conditional tasking or dynamic control flow suffer from exponential growth of code complexity

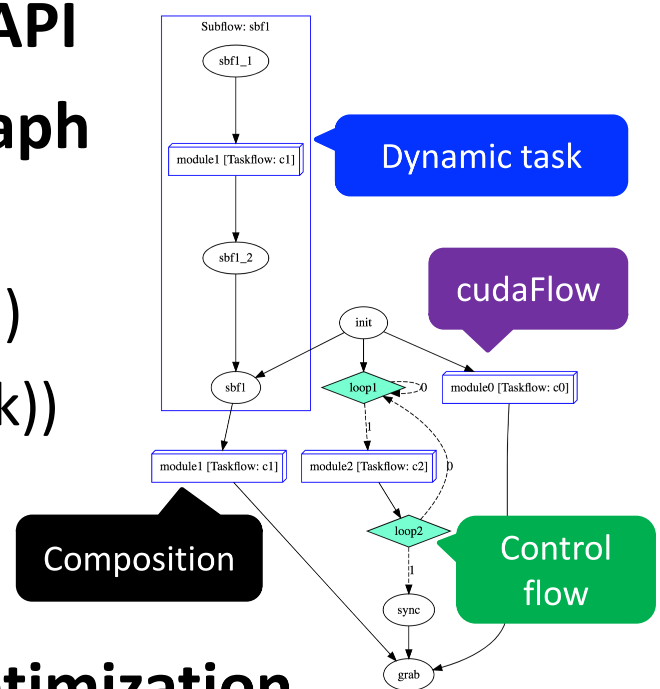
Composable Tasking

```
tf::Taskflow f1, f2;

auto [f1A, f1B] = f1.emplace(
  [](){ std::cout << "Task f1A\n"; },
  [](){ std::cout << "Task f1B\n"; }
);
auto [f2A, f2B, f2C] = f2.emplace(
  [](){ std::cout << "Task f2A\n"; },
  [](){ std::cout << "Task f2B\n"; },
  [](){ std::cout << "Task f2C\n"; }
);

auto f1_module_task = f2.composed_of(f1);

f1_module_task.succeed(f2A, f2B)
              .precede(f2C);
```

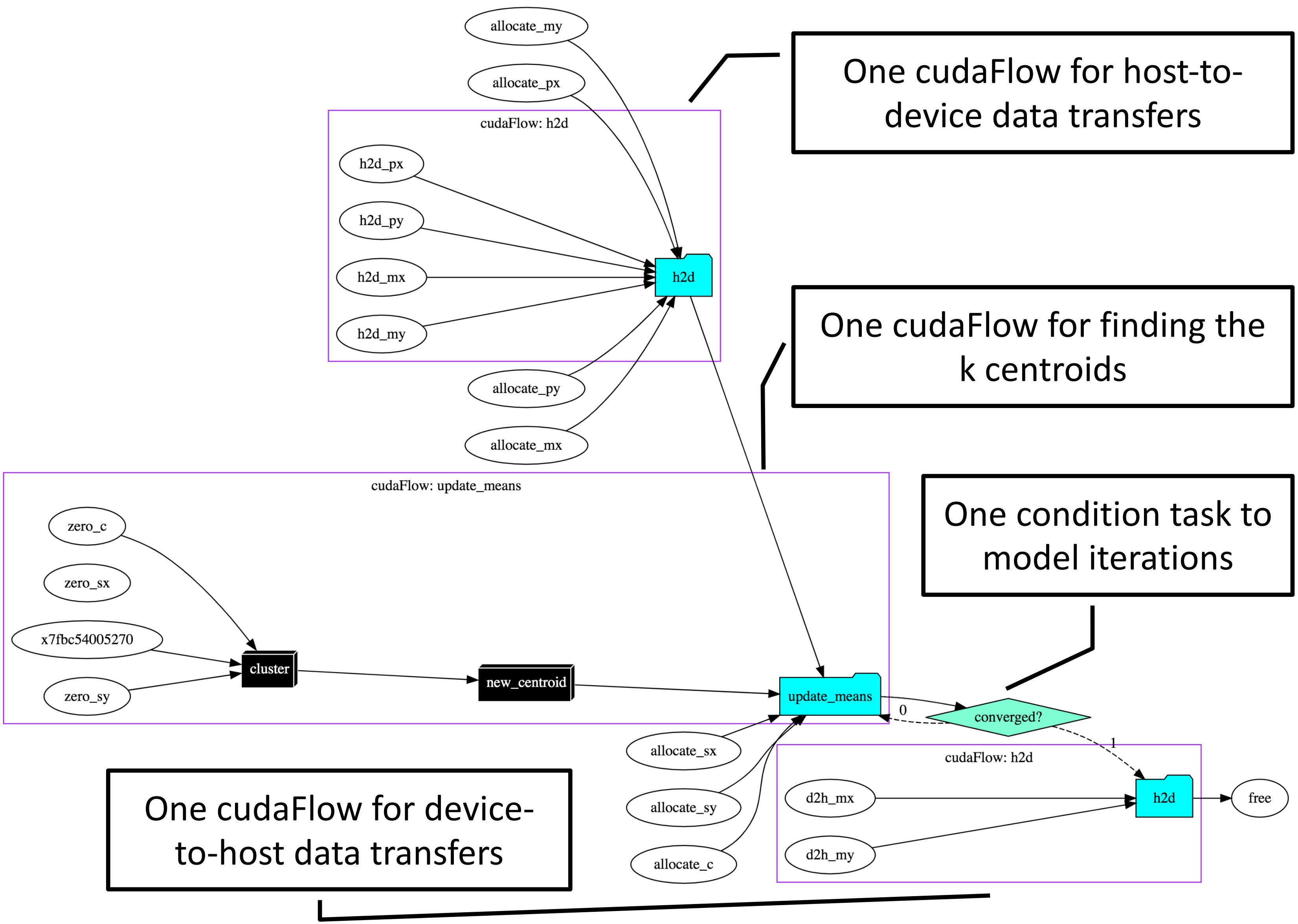


Everything is Unified in Taskflow

- Use “`emplace`” to create a task
- Use “`precede`” to add a task dependency
- No need to learn different sets of API
- You can create a really complex graph
  - Subflow(ConditionTask(cudaFlow))
  - ConditionTask(StaticTask(cudaFlow))
  - Composition(Subflow(ConditionTask))
  - Subflow(ConditionTask(cudaFlow))
  - …
- Scheduler performs end-to-end optimization
  - Runtime, energy efficiency, and throughput



Example: k-means Clustering



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- ❑ Make C++ amenable to heterogeneous parallelism

Submit Taskflow to Executor

- **Executor manages a set of threads to run taskflows**
  - All execution methods are *non-blocking*
  - All execution methods are *thread-safe*

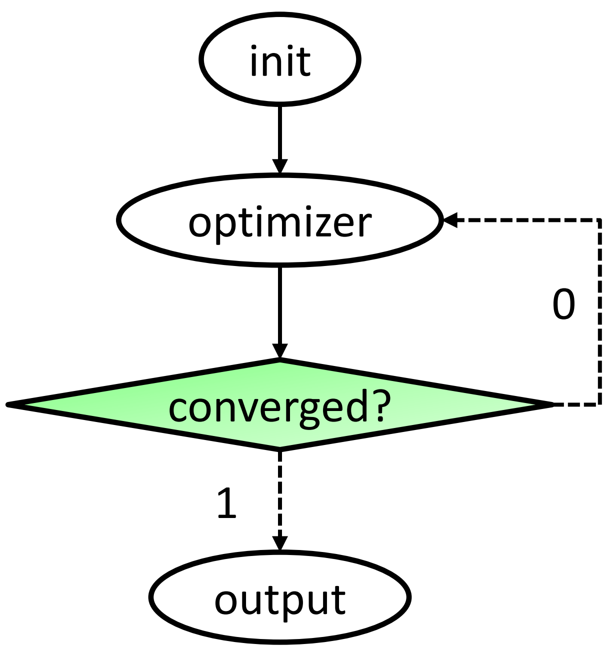
```
{
  tf::Taskflow taskflow1, taskflow2, taskflow3;
  tf::Executor executor;
  // create tasks and dependencies
  // …
  auto  future1 = executor.run(taskflow1);
  auto  future2 = executor.run_n(taskflow2, 1000);
  auto  future3 = executor.run_until(taskflow3, [i=0](){ return i++>5 });
  executor.async([](){ std::cout << "async task\n"; });
  executor.wait_for_all(); // wait for all the above tasks to finish
}
```

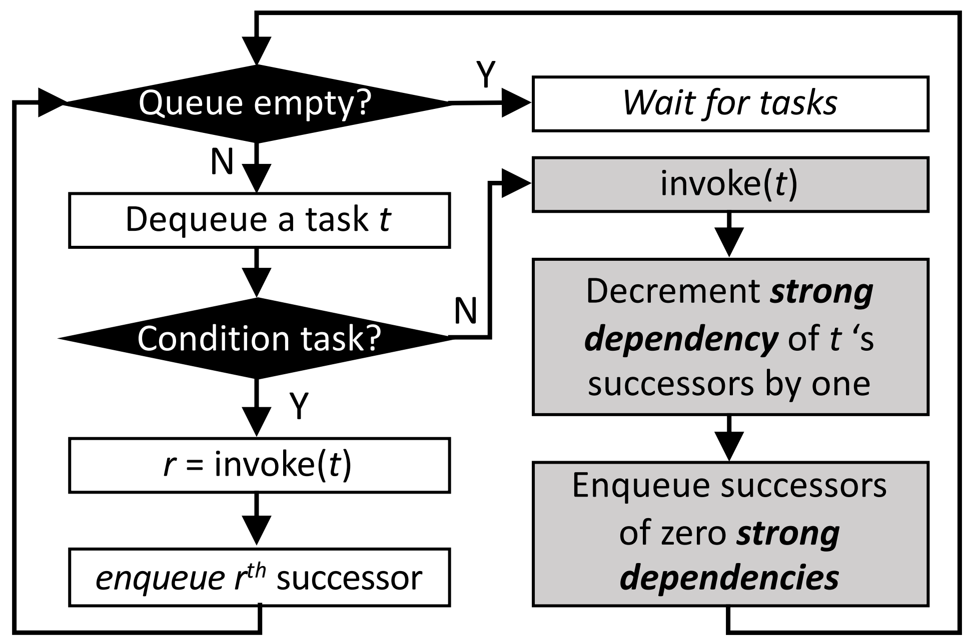
Executor Scheduling Algorithm

- **Task-level scheduling**
  - Decides how tasks are enqueued under control flow
    - Goal #1: ensures a feasible path to carry out control flow
    - Goal #2: avoids task race under cyclic and conditional execution
    - Goal #3: maximizes the capability of conditional tasking
- **Worker-level scheduling**
  - Decides how tasks are executed by which workers
    - Goal #1: adopts work stealing to dynamically balance load
    - Goal #2: adapts workers to available task parallelism
    - Goal #3: maximizes performance, energy, and throughput

Task-level Scheduling

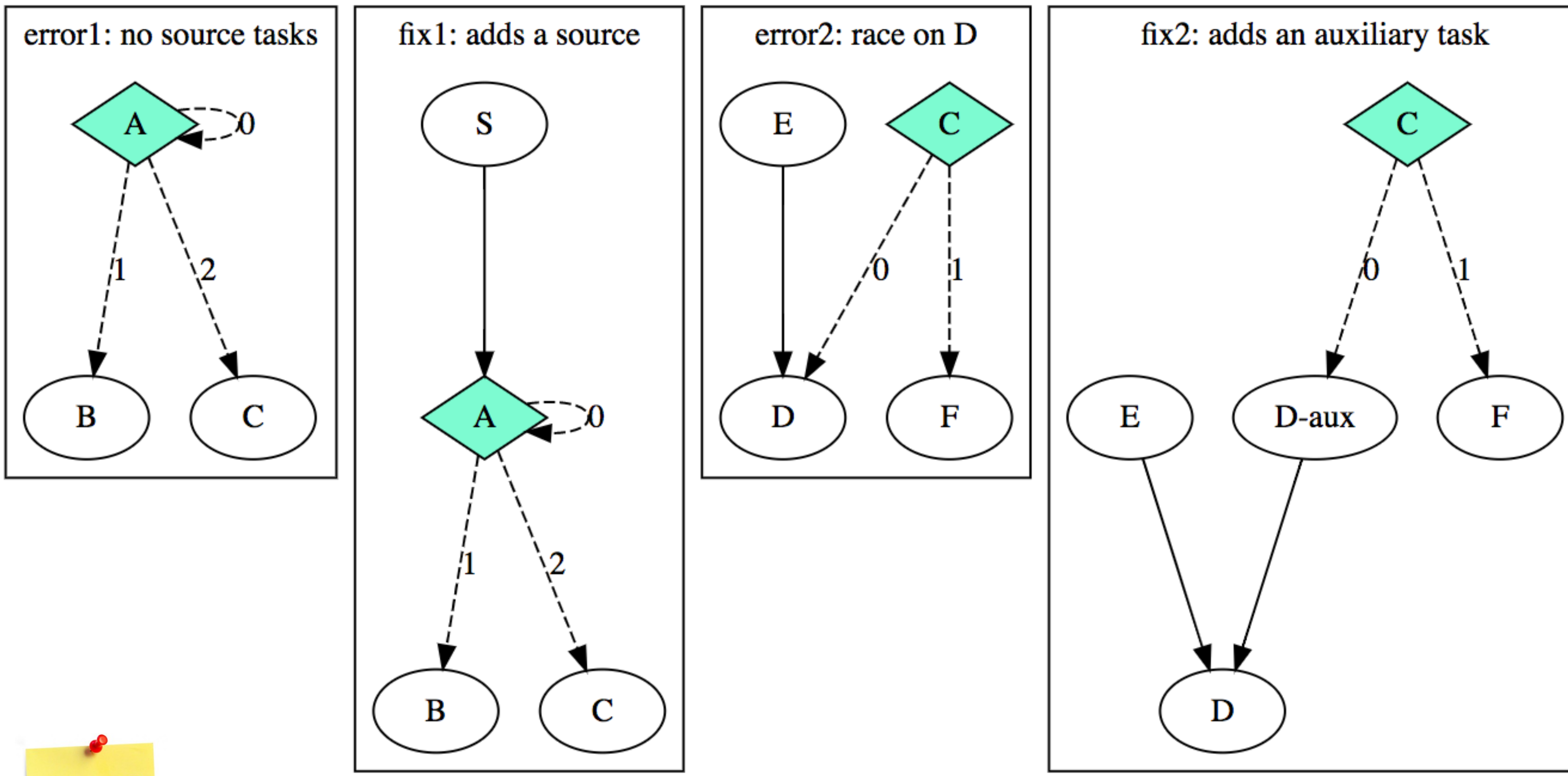
- ***"Strong dependency"* versus *"Weak dependency"***
  - Weak dependency: dependencies out of condition tasks
  - Strong dependency: others else





Task-level Scheduling (cont'd)

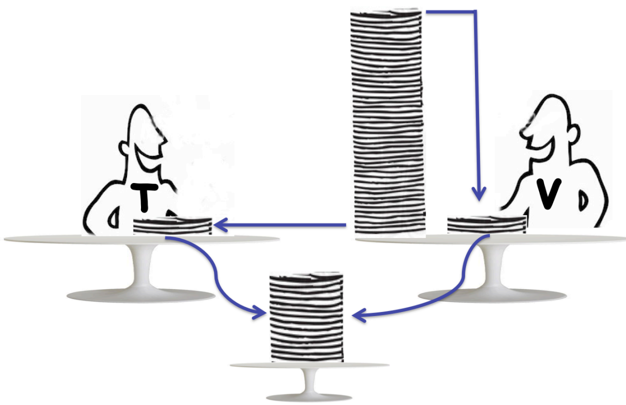
- Condition task is powerful but prone to mistakes …



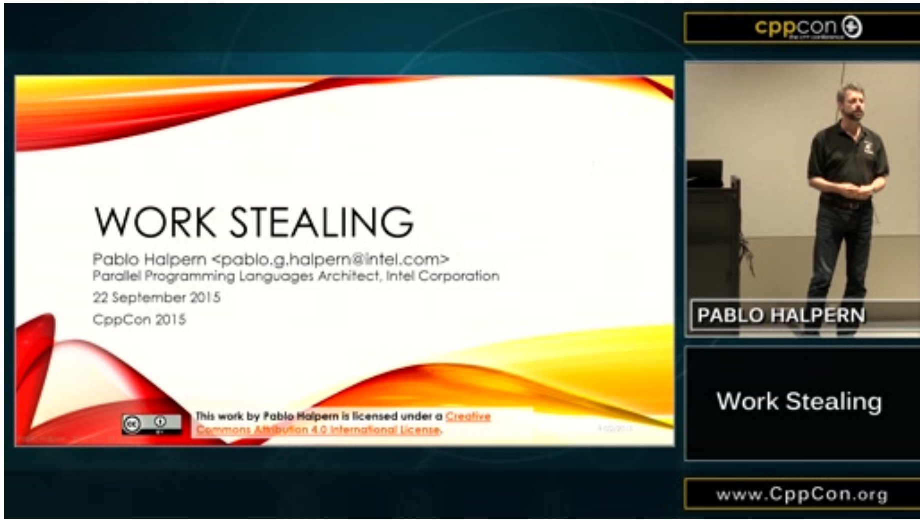
It is users' responsibility to ensure a taskflow is properly conditioned, i.e., no task race under our task-level scheduling policy

Worker-level Scheduling

- ❑ **Taskflow adopts *work stealing* to run tasks**
- ❑ **What is work stealing?**
  - ❑ I finish my jobs first, and then steal jobs from you
  - ❑ Improve performance through dynamic load balancing



Work stealing is commonly adopted by parallel task programming libraries (e.g., TBB, StarPU, TPL)



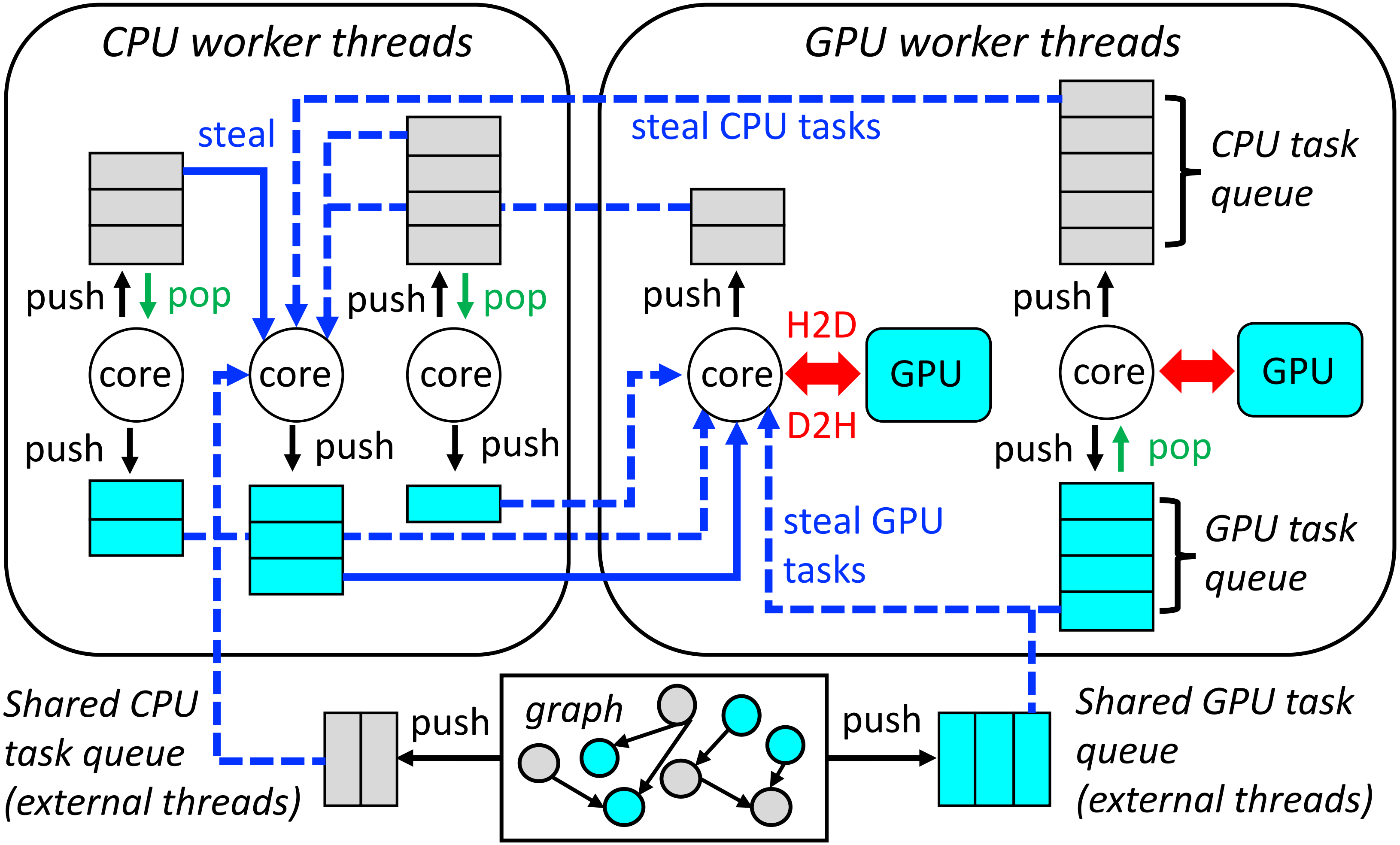
CppCon 2015: Pablo Halpern "Work Stealing," https://www.youtube.com/watch?v=iLHNF7SgVN4

Worker-level Scheduling (cont'd)

- **Challenge #1: distinct CPU-GPU performance traits**
- **Challenge #2: available task parallelism varies**
- **Challenge #3: wasteful steals eat out performance**

- **We solve the three challenges by the following:**
  1. Keep a different set of workers per heterogeneous domain (e.g., CPU workers, GPU workers)
  2. Keep an invariant that balances the active workers with available task parallelism
  3. Bring workers to sleep when tasks are scarce and wake up workers to run tasks following the invariant

Worker-level Scheduling (cont'd)



Generalizable to arbitrary heterogeneous domains

Agenda

- ❑ Express your parallelism in the right way
- ❑ Parallelize your applications using Taskflow
- ❑ Understand our scheduling algorithm
- ❑ Boost performance in real applications
- ❑ Make C++ amenable to heterogeneous parallelism

Micro-benchmarks

- **Randomly generate graphs with CPU-GPU tasks**
  - CPU task: aX + Y (saxpy) with 1K elements
  - GPU task: aX + Y (saxpy) with 1M elements
- **Comparison with TBB, StarPU, HPX, and OpenMP**
  - What is the turnaround time to program?
  - What is the overhead of task graph parallelism?

Table I: Programming cost

Method	LOC	#Tokens	CC	WCC	#People	Cost
Taskflow	69	650	6	8	0.14	$1630
oneTBB	182	1854	8	15	0.27	$4515
StarPU	253	2216	8	21	0.34	$6354
HPX	255	2264	10	24	0.34	$6433
OpenMP	182	1896	13	19	0.27	$4515

CC: maximum cyclomatic complexity in a single function
WCC: weighted cyclomatic complexity of the program
People: estimated number of developers required
Cost: estimated cost to develop

Table II: Task graph overhead (amortized)

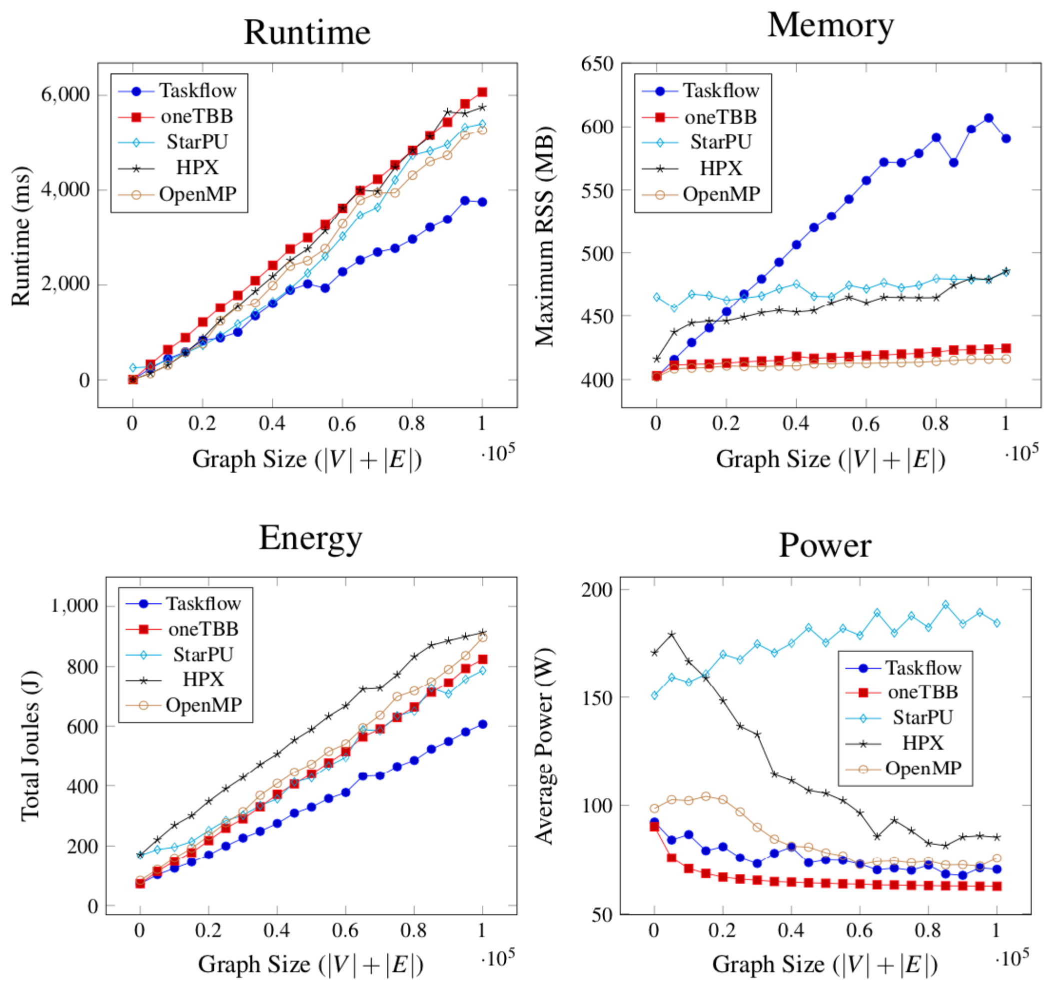
Method	S_{task}	T_{task}	T_{edge}	$\rho_{<10}$	$\rho_{<5}$	$\rho_{<1}$
Taskflow	272	61 ns	14 ns	550	2550	35050
oneTBB	136	99 ns	54 ns	1225	2750	40050
StarPU	1472	259 ns	384 ns	7550	-	-

S_{task}: static size per task in bytes
T_{task}/T_{edge}: amortized time to create a task/dependency
ρ_v: graph size where its creation overhead is below $v\%$

SLOCCount: https://dwheeler.com/sloccount/

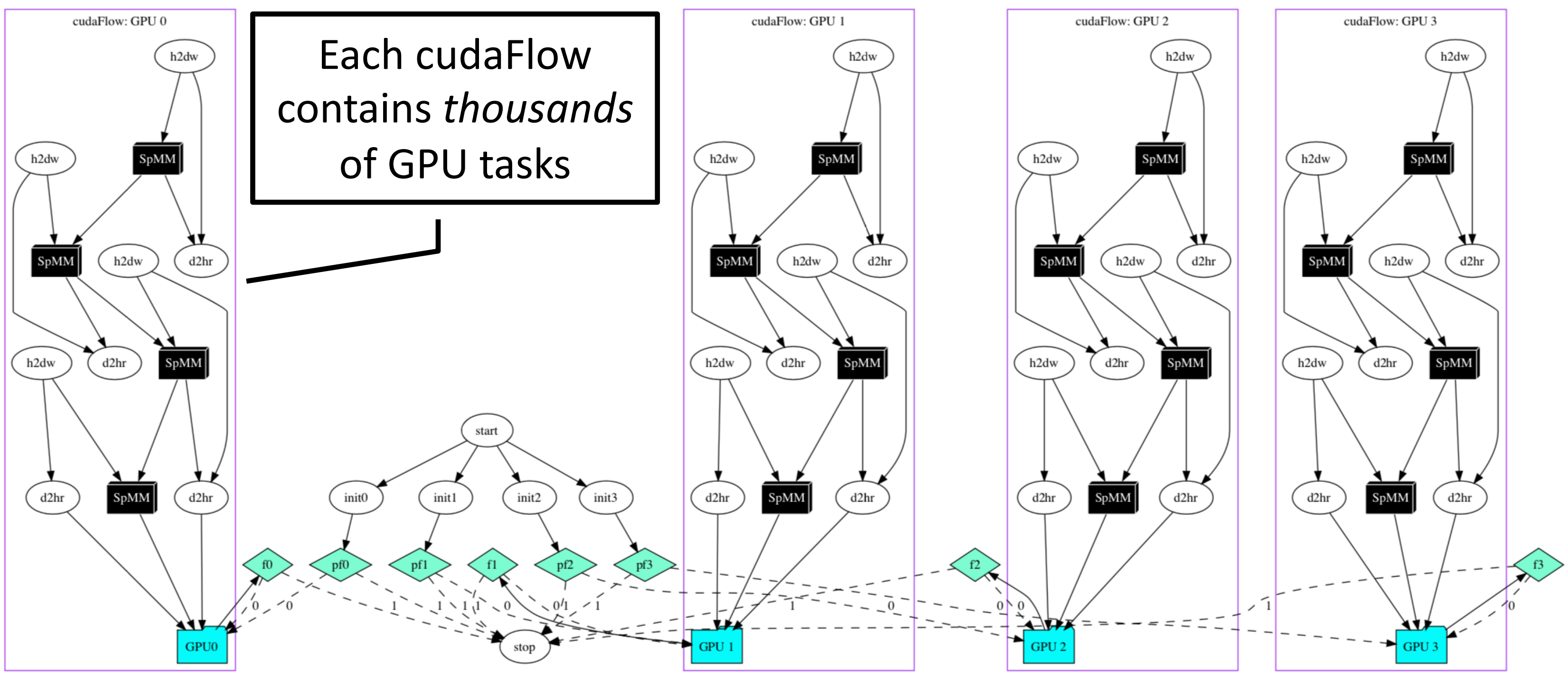
Micro-benchmarks (cont'd)

- Performance on 40 Intel CPUs and 4 Nvidia GPUs



Application 1: Machine Learning

- ❑ **Compute a 1920-layer DNN each of 65536 neurons**
  - ❑ IEEE HPEC 2020 Neural Network Challenge Compute

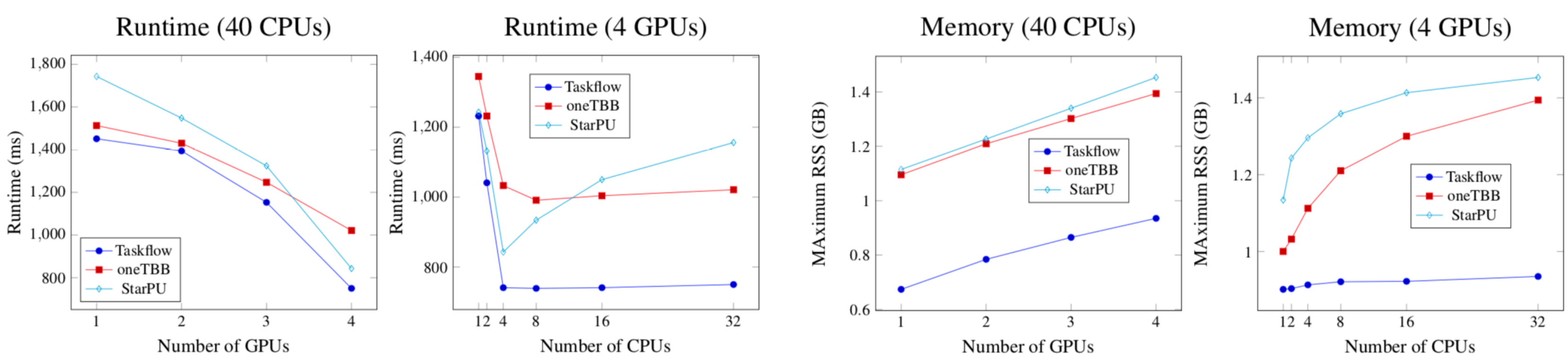


Each cudaFlow contains *thousands* of GPU tasks

A partial taskflow graph of 4 cudaFlows, 6 static tasks, and 8 conditioned cycles for this workload

Application 1: Machine Learning (cont'd)

- **Comparison with TBB and StarPU**
  - Unroll task graphs across iterations found in hindsight
  - Implement cudaGraph for all



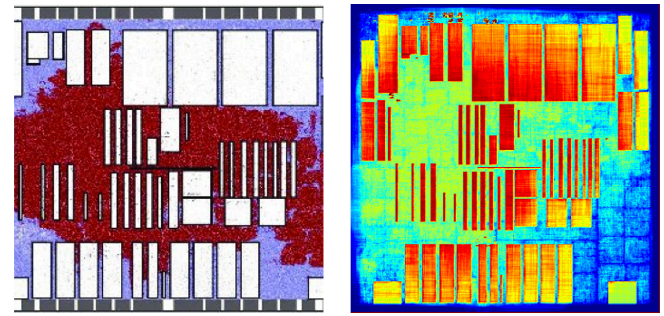
- **Taskflow's runtime is up to 2x faster**
- **Taskflow's memory is up to 1.6x less**

Due to the conditional tasking

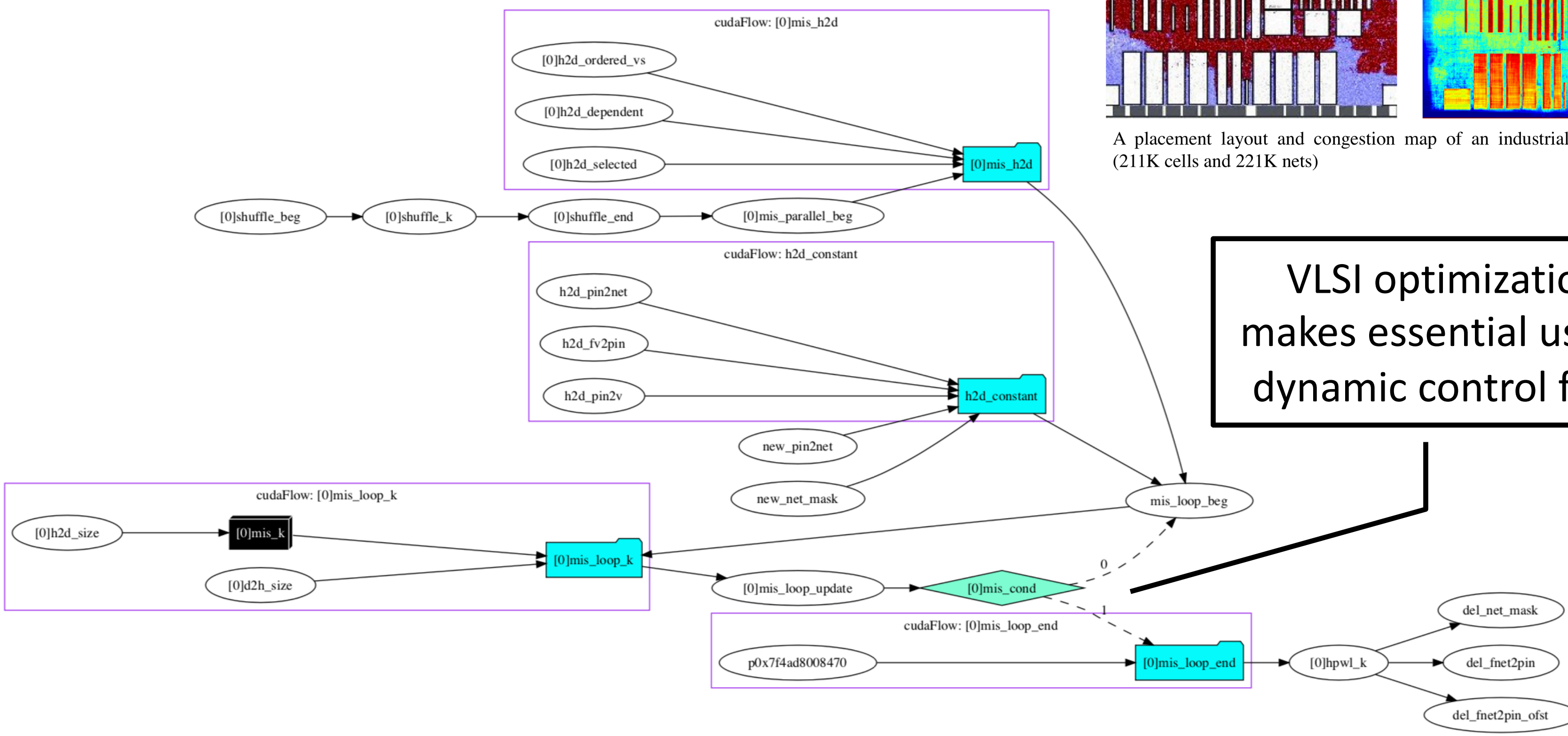
Champions of HPEC 2020 Graph Challenge: https://graphchallenge.mit.edu/champions

Application 2: VLSI Placement

- Optimize cell locations on a chip



A placement layout and congestion map of an industrial circuit, adaptec1 (211K cells and 221K nets)

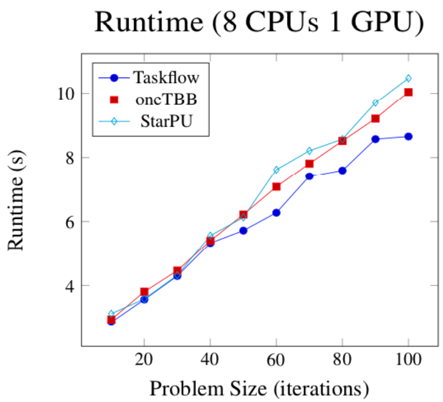


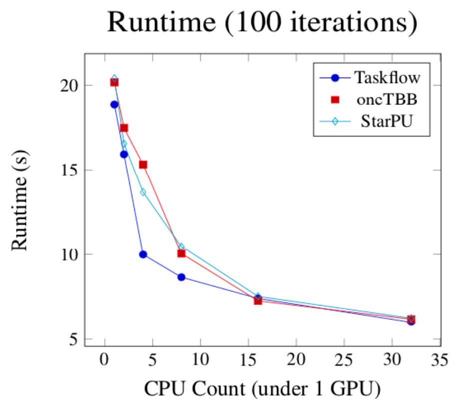
VLSI optimization makes essential use of dynamic control flow

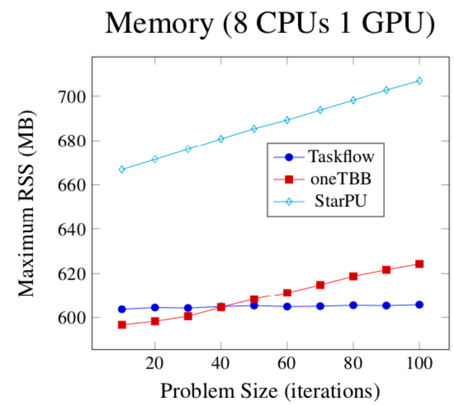
A partial TDG of 4 cudaFlows, 1 conditioned cycle, and 12 static tasks

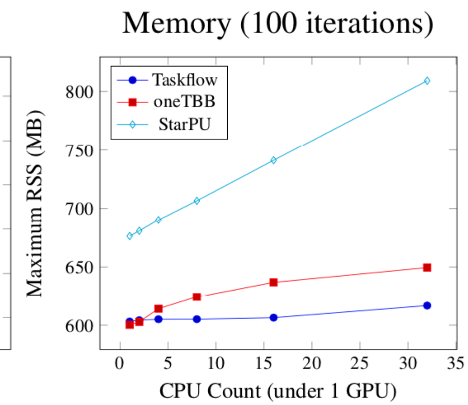
Application 2: VLSI Placement (cont'd)

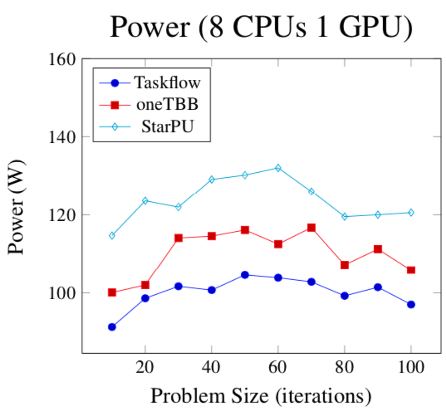
- ❑ **Runtime, memory, power, and throughput**

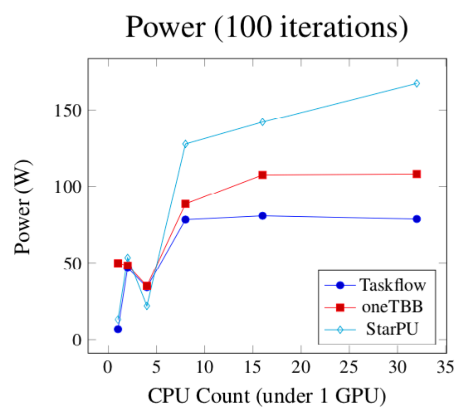












Performance improvement comes from *end-to-end* expression of CPU-GPU dependent tasks using condition tasks

Parallel programming infrastructure matters

Different models give different implementations. The parallel code/algorithm may run fast, yet the parallel computing infrastructure to support that algorithm may dominate the entire performance.

Taskflow enables *end-to-end* expression of CPU-GPU dependent tasks along with algorithmic control flow

Agenda

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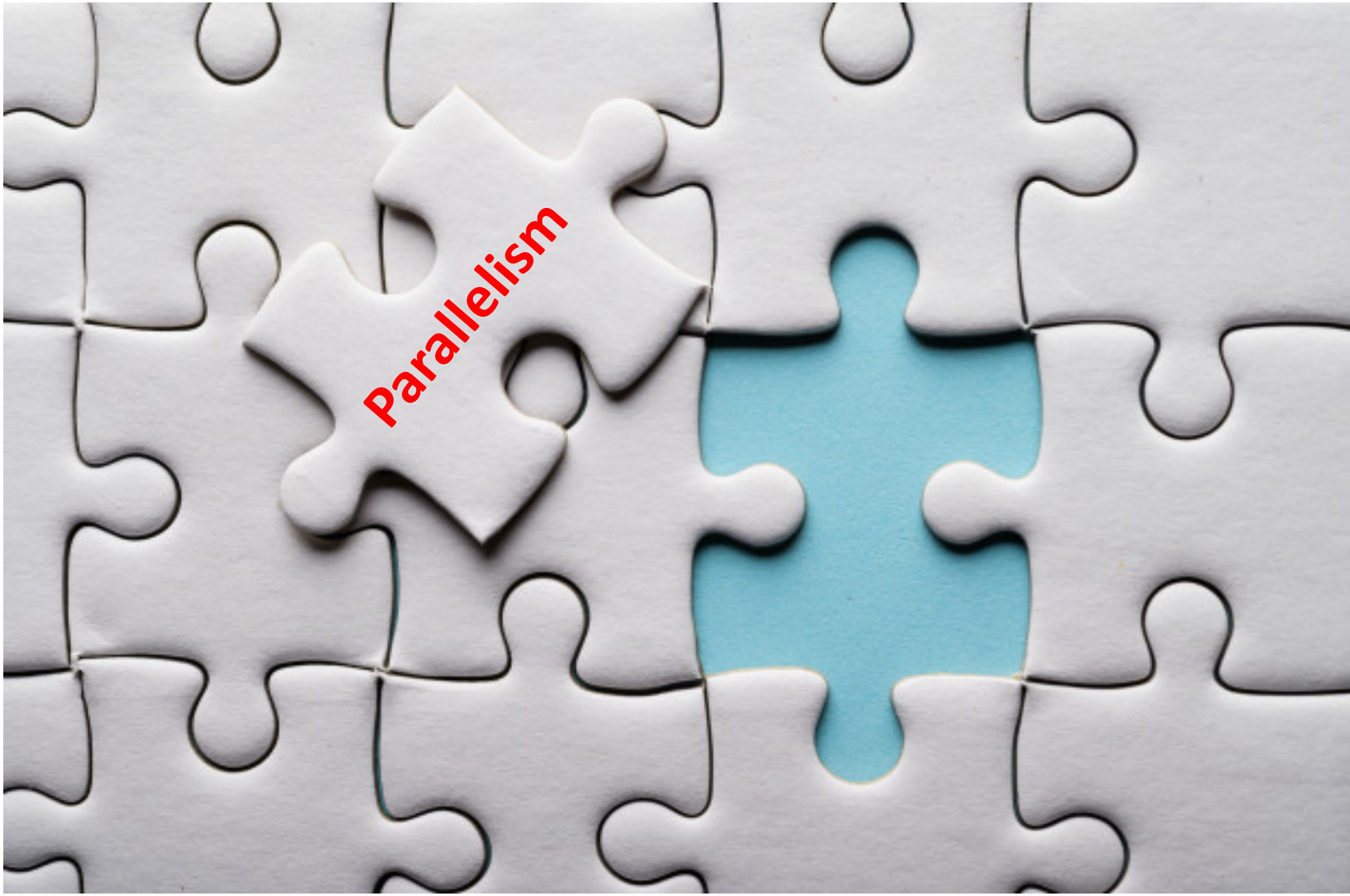
Parallel Computing is Never Standalone



No One Can Express All Parallelisms …

- **Languages** ∪ **Compilers** ∪ **Libraries** ∪ **Programmers**

IMHO, C++ Parallelism Needs Enhancement

- **C++ parallelism is primitive (but in a good shape)**
  - `std::thread` is powerful but very low-level
  - `std::async` leaves off handling task dependencies
  - No easy ways to describe control flow in parallelism
    - C++17 parallel STL count on bulk synchronous parallelism
  - No standard ways to offload tasks to accelerators (GPU)
- **Existing 3rd-party tools have enabled vast success but**
  - Lack an easy and expressive interface for parallelism
  - Lack a mechanism for modeling control flow
  - Lack an efficient executor for heterogeneous tasking
    - Good at either CPU- or GPU-focused workload, but rarely both simultaneously

Conclusion

- **Taskflow is a general-purpose parallel tasking tool**
  - Simple, efficient, and transparent tasking models
  - Efficient heterogeneous work-stealing executor
  - Promising performance in large-scale ML and VLSI CAD
- **Taskflow is not to replace anyone but to**
  - Complement the current state-of-the-art
  - Leverage modern C++ to express task graph parallelism
- **Taskflow is very open to collaboration**
  - We want to integrate OpenCL, SYCL, Intel DPC++, etc.
  - We want to provide higher-level algorithms
  - We want to broaden real use cases

Thank You All Using Taskflow!

Thank You

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Taskflow: https://taskflow.github.io