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

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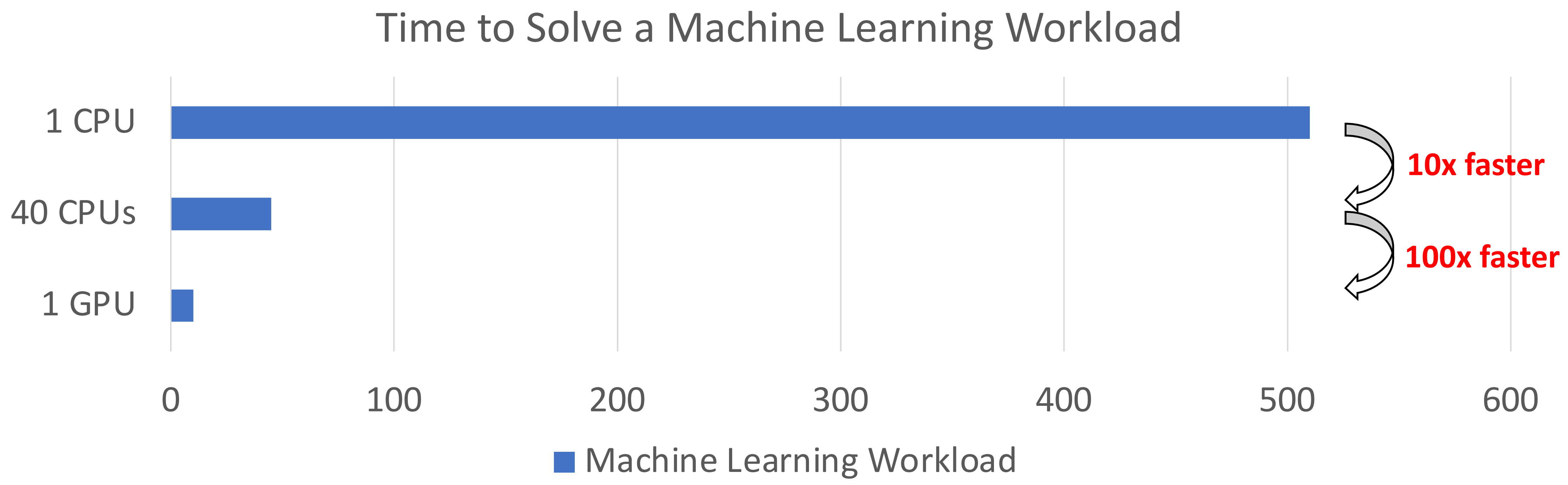
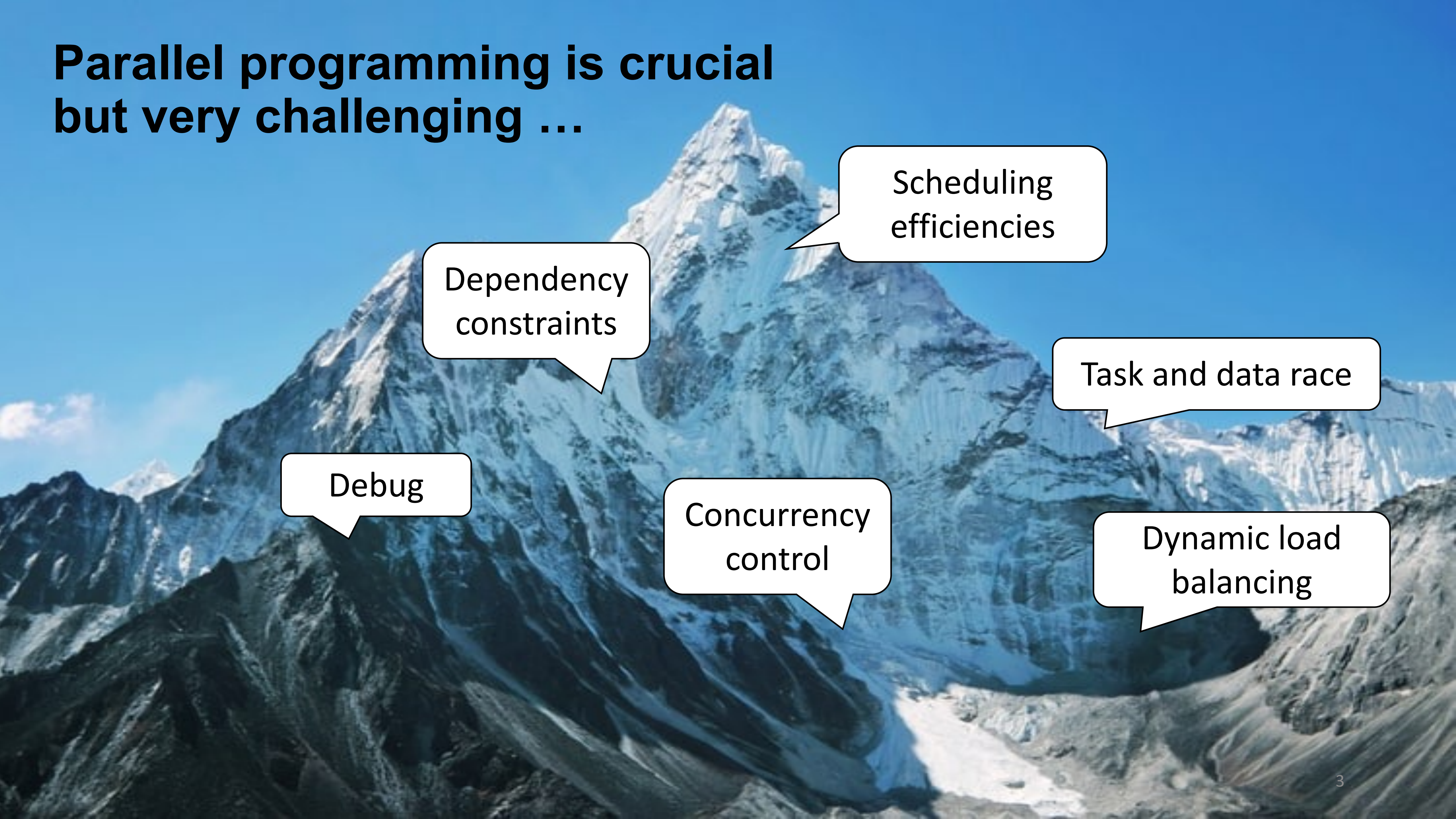
Why Parallel Computing?

- It's critical to advance your application performance



Parallel programming is crucial but very challenging …

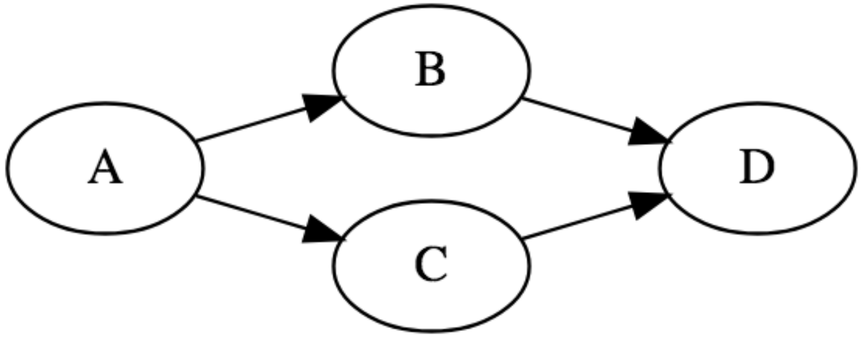


Taskflow offers a solution

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;
}
```



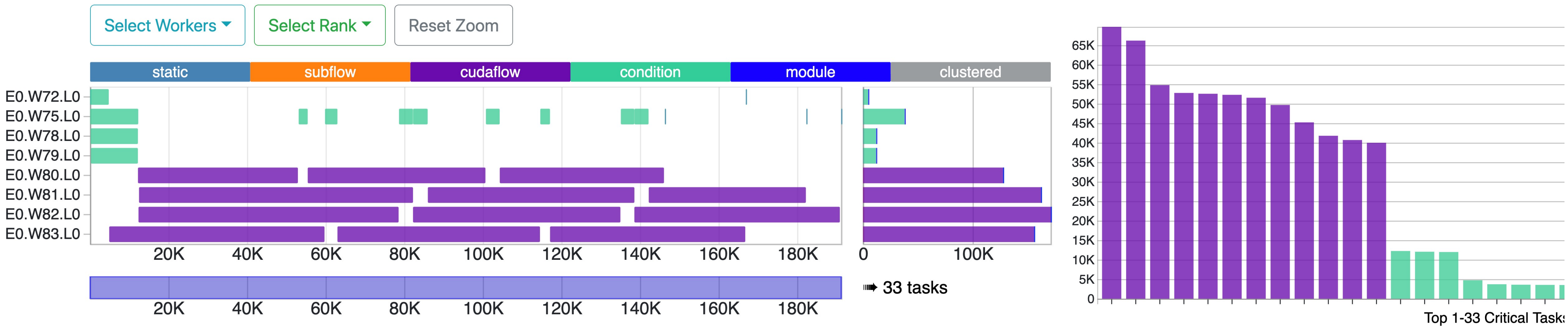
Drop-in Integration

- Taskflow is header-only – *no wrangle with installation*

```
~$ git clone https://github.com/taskflow/taskflow.git  # clone it only once
~$ g++ -std=c++17 simple.cpp -I taskflow/taskflow -O2 -pthread -o simple
~$ ./simple
TaskA
TaskC
TaskB
TaskD
```

Built-in Profiler/Visualizer

```
# run the program with the environment variable TF_ENABLE_PROFILER enabled
~$ TF_ENABLE_PROFILER=simple.json ./simple
~$ cat simple.json
[
{"executor":"0","data":[{"worker":0,"level":0,"data":[{"span":[172,186],"name
]
# paste the profiling json data to https://taskflow.github.io/tfprof/
```



Agenda

- Express your parallelism in the right way
- Parallelize your applications using Taskflow
- Boost performance in real applications

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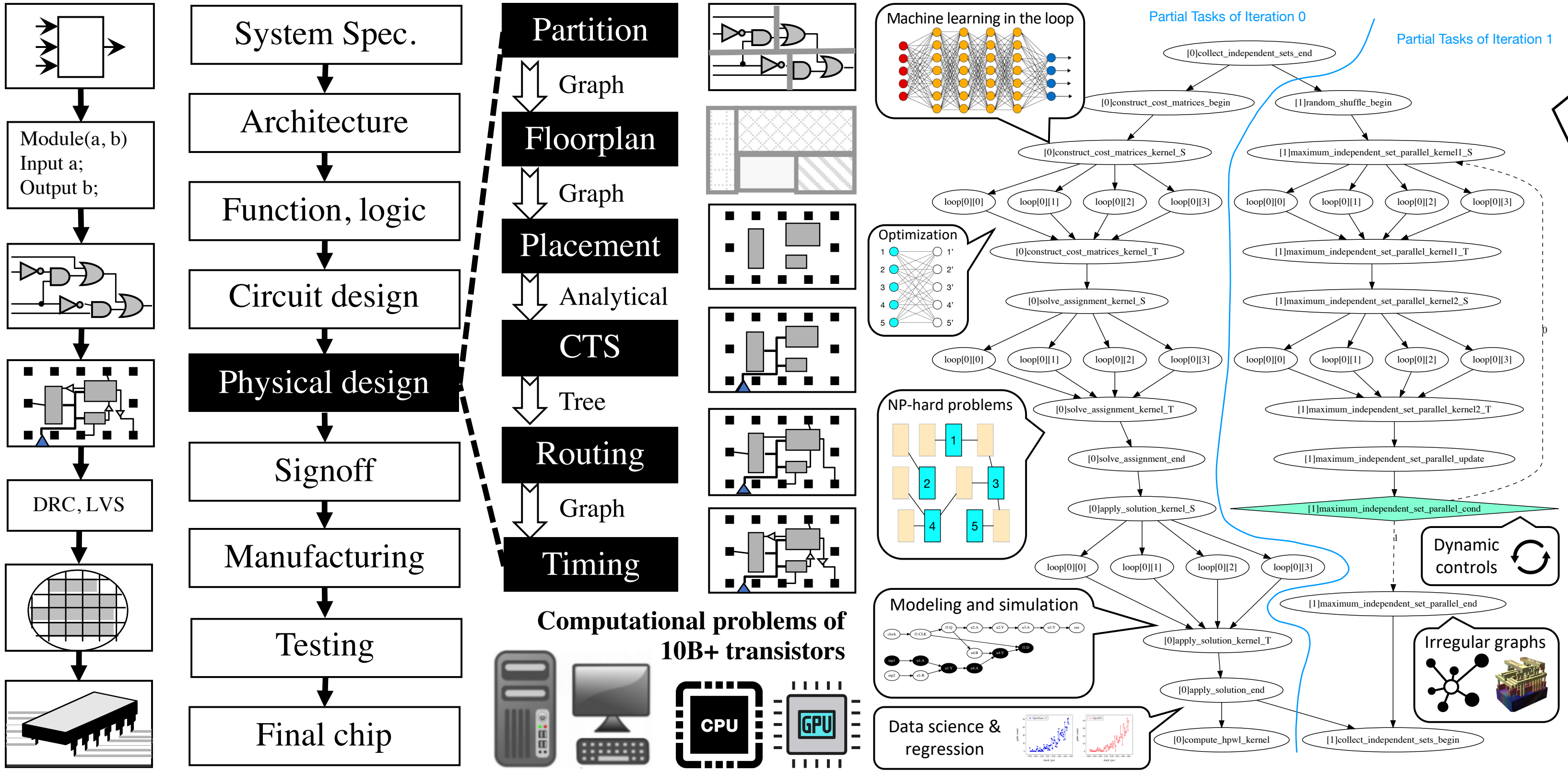
Motivation: Parallelizing VLSI CAD Tools

- 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
OpenCL
RAJA
StarPU
ECP EXASCALE COMPUTING PROJECT
kokkos

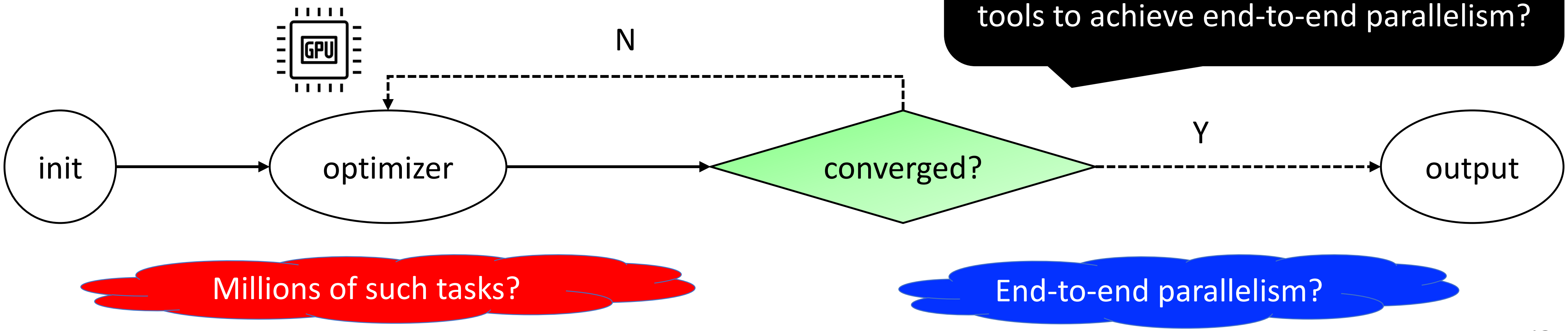
Two Big Problems of Existing Tools

- 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 of *dynamic control flow* using existing tools to achieve 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***"

Agenda

- Express your parallelism in the right way
- Parallelize your applications using Taskflow
- Boost performance in real applications

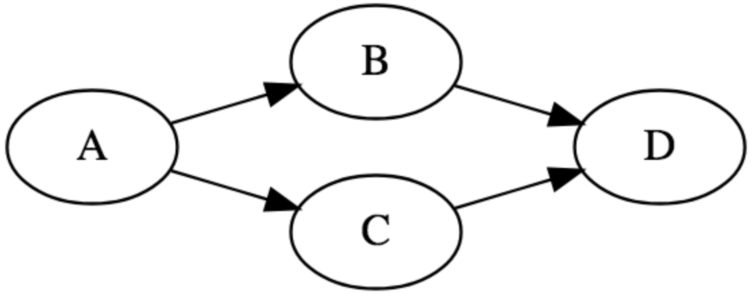

WARNING
Code Ahead

“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();
  return 0;
}
```

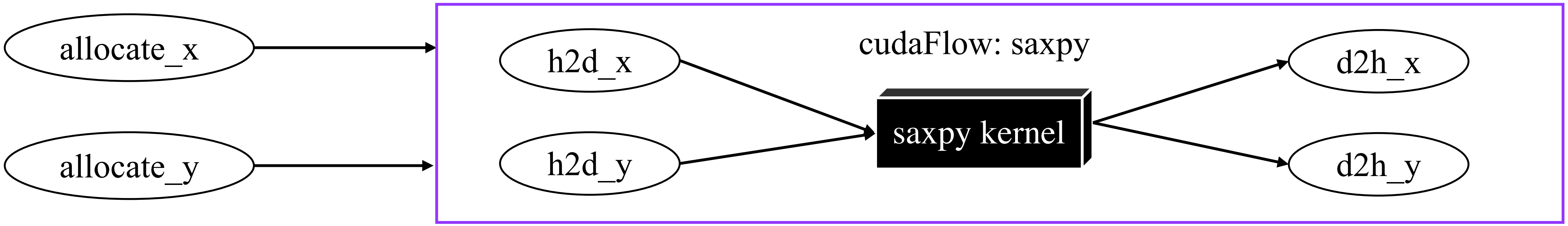
Taskflow defines five tasks:

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



Heterogeneous Tasking (cudaFlow)

- Single Precision AX + Y (“SAXPY”)
  - Get x and y vectors on CPU (allocate_x, allocate_y)
  - Copy x and y to GPU (h2d_x, h2d_y)
  - Run saxpy kernel on x and y (saxpy kernel)
  - Copy x and y back to CPU (d2h_x, d2h_y)



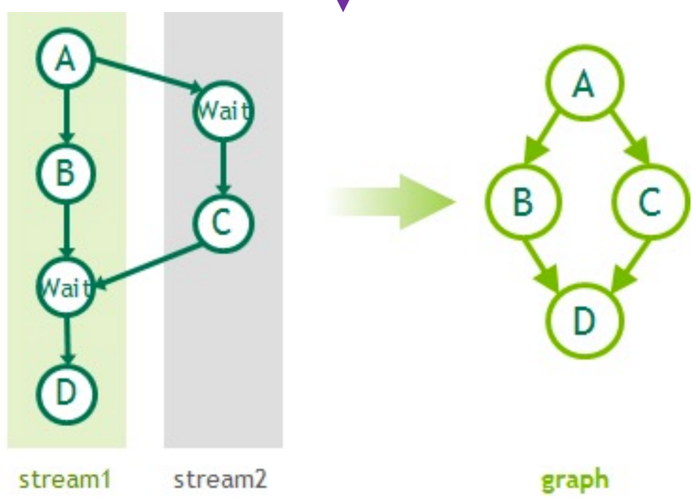
Heterogeneous Tasking (cont'd)

```
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



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 (e.g., SYCL)

```
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)

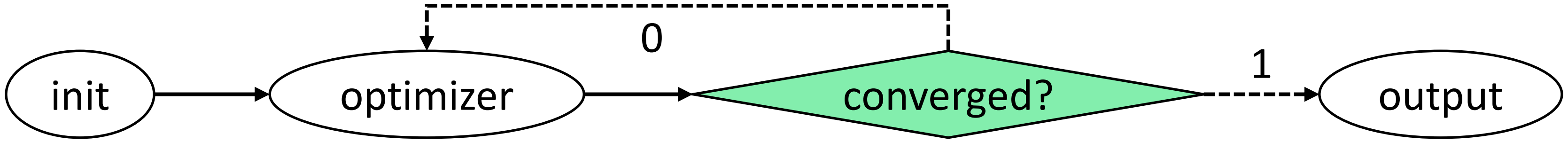
Heterogeneous Tasking (syclFlow)

```
auto syclflow = taskflow.emplace_on([&](tf::syclFlow& sf) {
  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.parallel_for(sycl::range<1>(N), [=](sycl::id<1> id){
    dx[id] = 2.0f * dx[id] + dy[id];
  });
  kernel.succeed(h2d_x, h2d_y)
          .precede(d2h_x, d2h_y);
}, queue);
```

Create a syclFlow from a SYCL queue on a SYCL device

Conditional Tasking (Simple if-else)

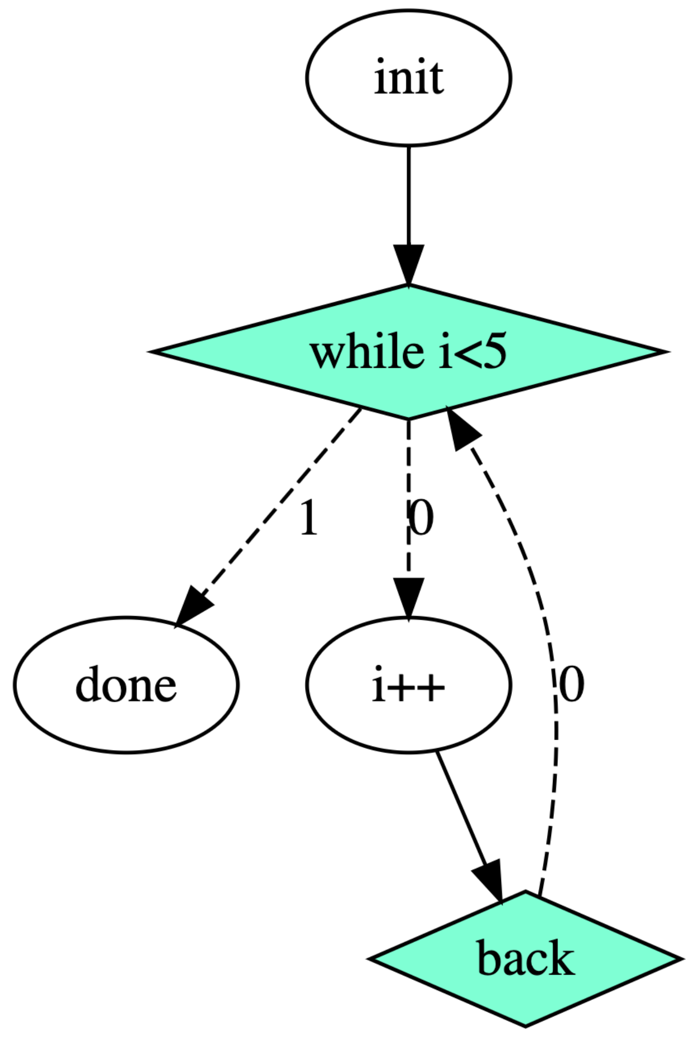
```
auto init          = taskflow.emplace([&](){ initialize_data_structure(); } )
                              .name(”init");
auto optimizer     = taskflow.emplace([&](){ matrix_solver(); } )
                              .name(”optimizer");
auto converged     = taskflow.emplace([&](){ return converged() ? 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*

Conditional Tasking (While/For Loop)

```
tf::Taskflow taskflow;
int i;
auto [init, cond, body, back, done] = taskflow.emplace(
  [&](){ std::cout << “i=0”; i=0; },
  [&](){ std::cout << "while i<5\n"; return i < 5 ? 0 : 1; },
  [&](){ std::cout << "i++=" << i++ << '\n'; },
  [&](){ std::cout << "back\n"; return 0; },
  [&](){ std::cout << "done\n"; }
);
init.precede(cond);
cond.precede(body, done);
body.precede(back);
back.precede(cond);
```



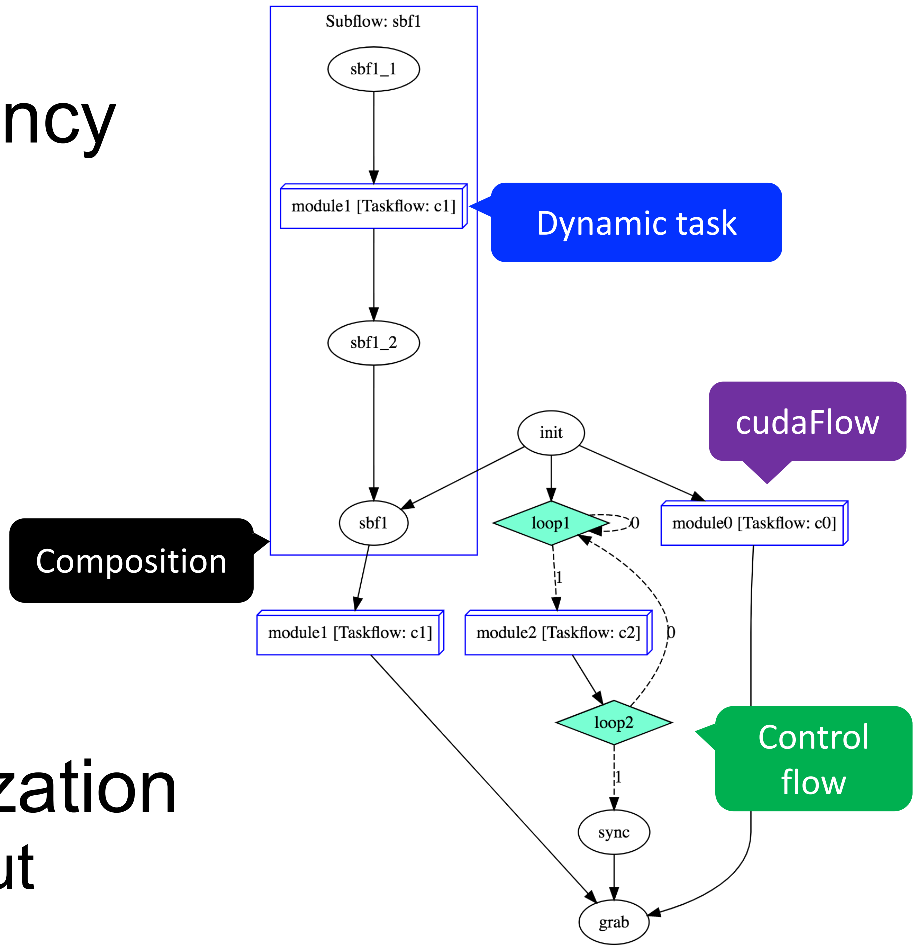
Existing Frameworks on Control Flow?

- 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-flow tasks?
- … (resort to client-side decision)

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

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



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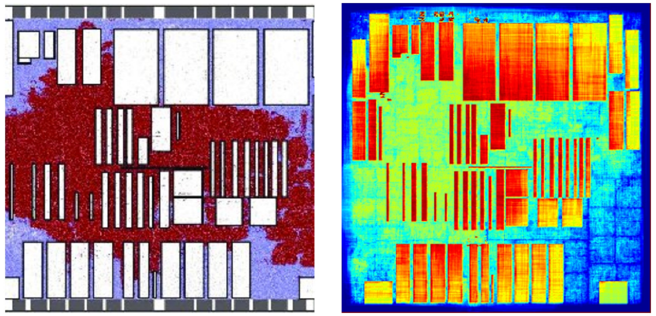
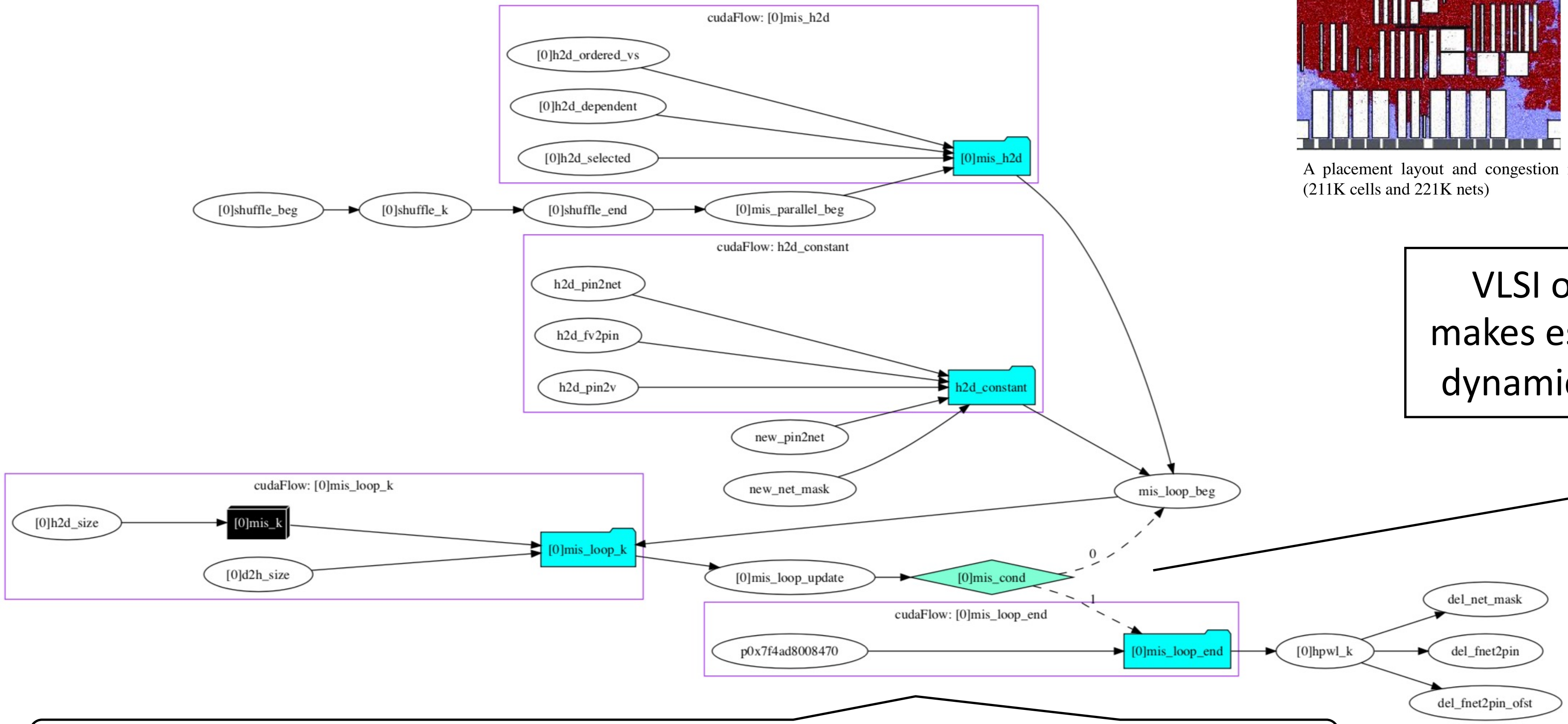
Application 1: VLSI Placement

- Optimize cell locations on a chip



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

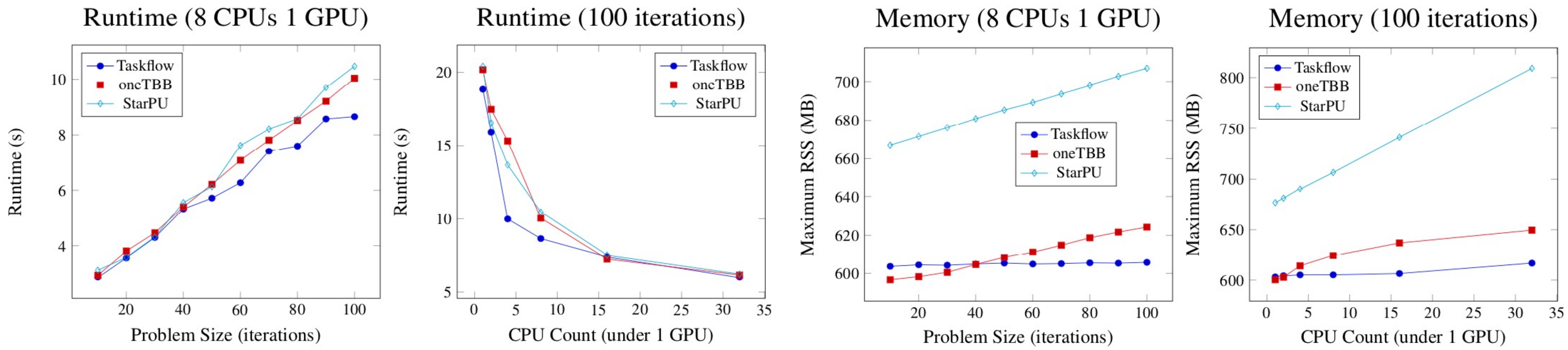


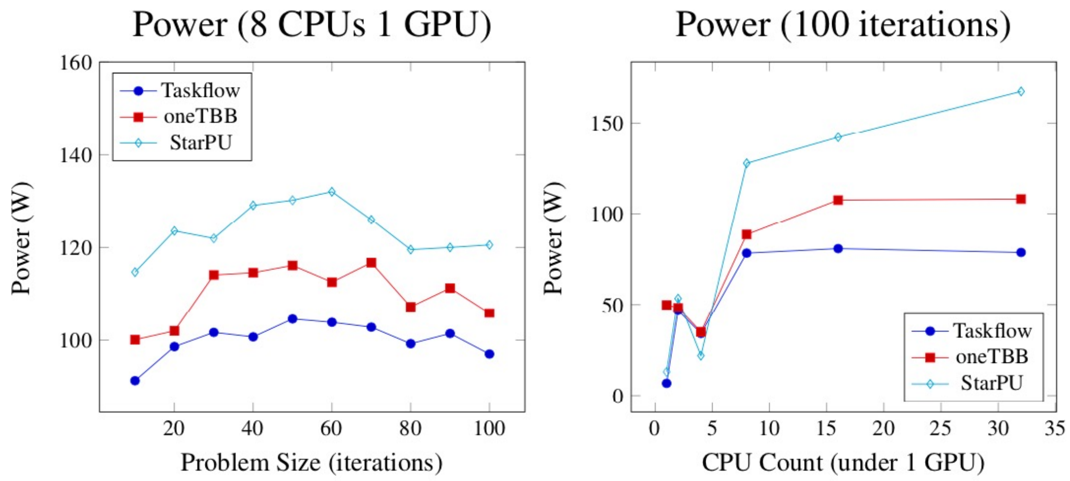
VLSI optimization makes essential use of dynamic control flow

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

Application 1: VLSI Placement (cont'd)

- Runtime, memory, power, and throughput

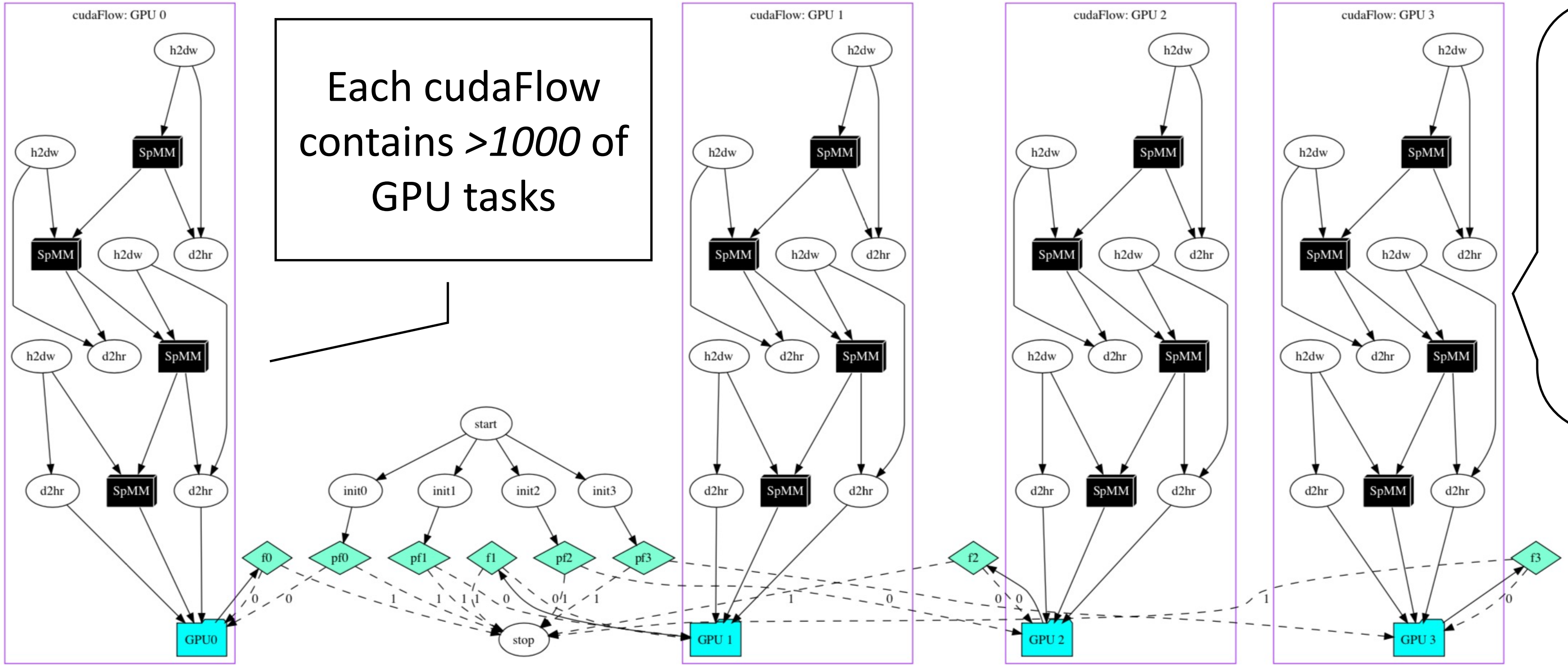




Performance improvement comes from the *end-to-end* expression of CPU-GPU dependent tasks using condition tasks

Application 2: Machine Learning

- IEEE HPEC/MIT/Amazon Sparse DNN Challenge
  - Compute a 1920-layer DNN each of 65536 neurons



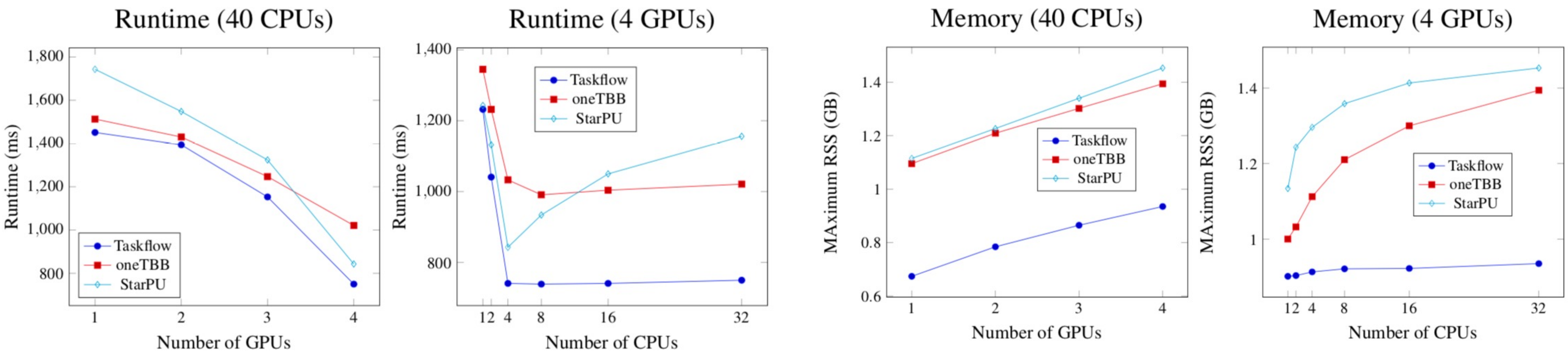
Each cudaFlow contains *>1000* of GPU tasks

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

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

Application 2: Machine Learning (cont'd)

- Comparison with TBB and StarPU



- Taskflow's runtime is up to 2x faster
  - Adaptive work stealing balances the worker count with task parallelism
- Taskflow's memory is up to 1.6x less
  - Conditional tasking allows efficient reuse of tasks

<u>Parallel programming infrastructure matters</u>

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

Conclusion

- Taskflow is a lightweight parallel task programming system
  - 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 provide more higher-level algorithms
  - We want to broaden real use cases
  - We want to enhance the core functionalities (e.g., pipeline)

Thank You All Using Taskflow!

Use the right tool for the right job

Taskflow: https://taskflow.github.io

Thank You

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