The 11th International workshop on OpenCL and SYCL

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A SYCL Extension for User-Driven Online Kernel Fusion

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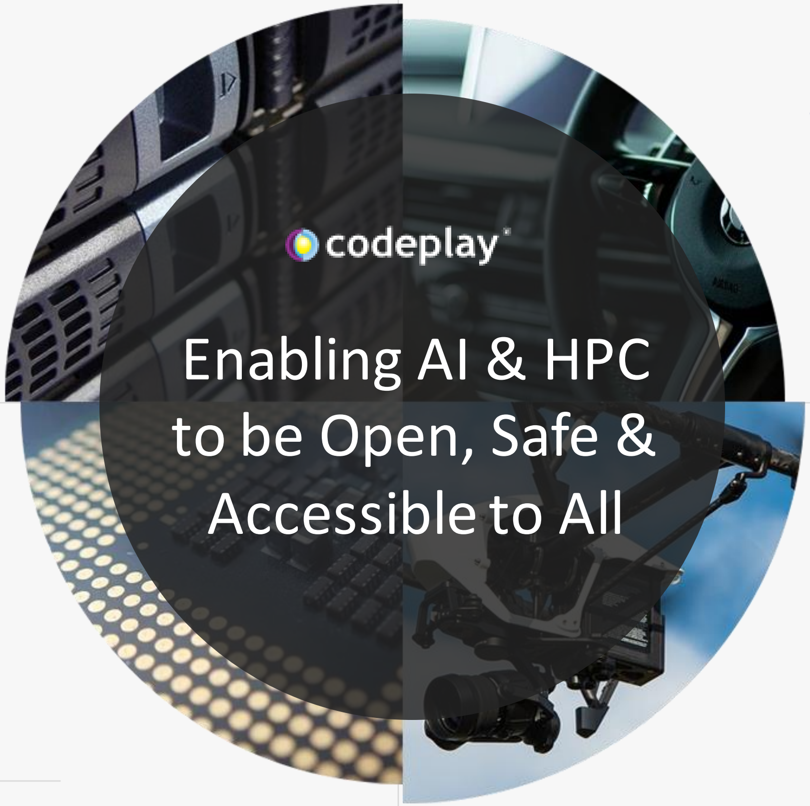

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Markets

High Performance Compute (HPC)
Automotive ADAS, IoT, Cloud Compute
Smartphones & Tablets
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Technologies: Artificial Intelligence
Vision Processing
Machine Learning
Big Data Compute

Disclaimer

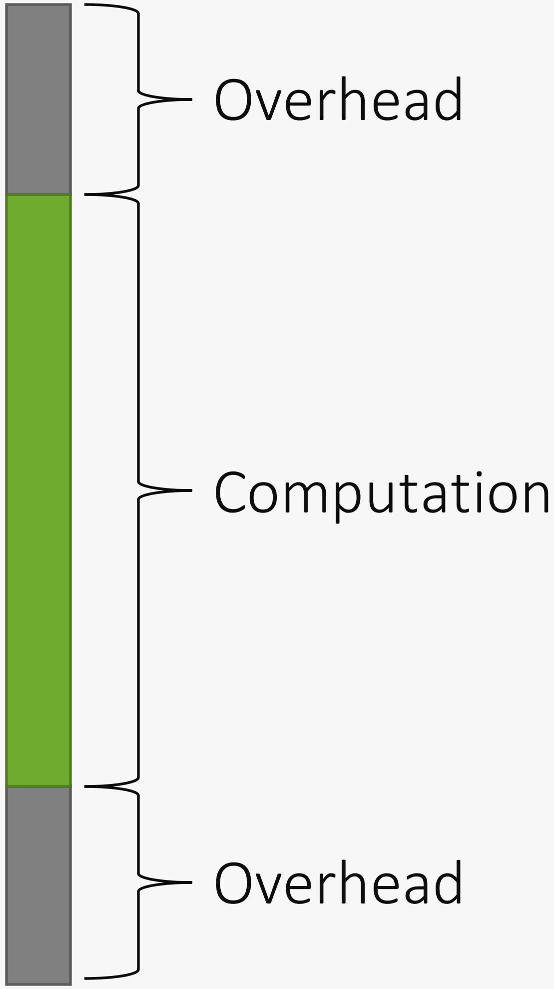
Agenda

- Motivation
- SYCL extension design
- Implementation
- Evaluation
- Conclusion

Motivation

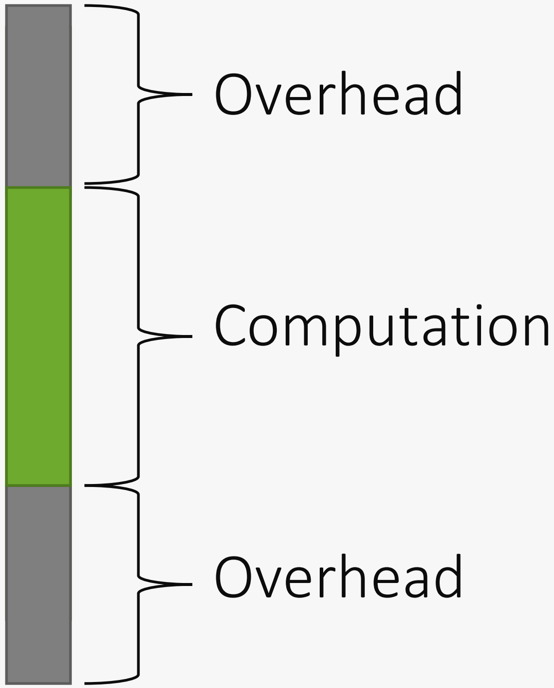
Motivation

- Every SYCL kernel launch carries cost



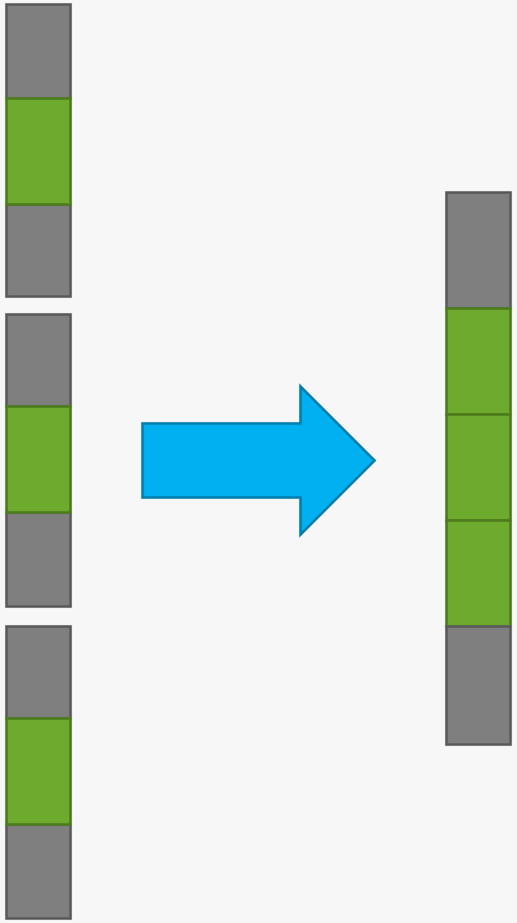
Motivation

- Every SYCL kernel launch carries cost
- Short running kernels problematic
    - High ratio of overhead to actual computation
- Can occur in different domains
    - Example: Machine learning
        - Each neural network operator maps to one kernel
        - Many operators in one network



Motivation

- Applications often use multiple kernels
  - Leads to sequence of short-running kernels
- Fusing multiple kernels into one yields better overhead/computation ratio
- Manual fusion possible but...
  - Time-consuming for developers
  - Error-prone
  - Not possible for kernels coming from libraries



SYCL Extension

SYCL Extension

- Allow the user to instruct SYCL runtime to fuse multiple kernels
- Easy-to-use API
- User in the driver seat
  - Correctness and profitability hard to assess with compiler methodology
  - User triggers fusion and takes responsibility
- SYCL runtime automates creation of fused kernel
  - User does not need to manually implement fused version of the kernel

Extension API

- Create queue with fusion property

```
queue q{gpu_selector_v,
      property::queue::enable_fusion{}};
```

- Start fusion mode

```
q.start_fusion();
```

- Submit kernels
  - Not executed on the device right away
  - Stored in a list of kernels to fuse

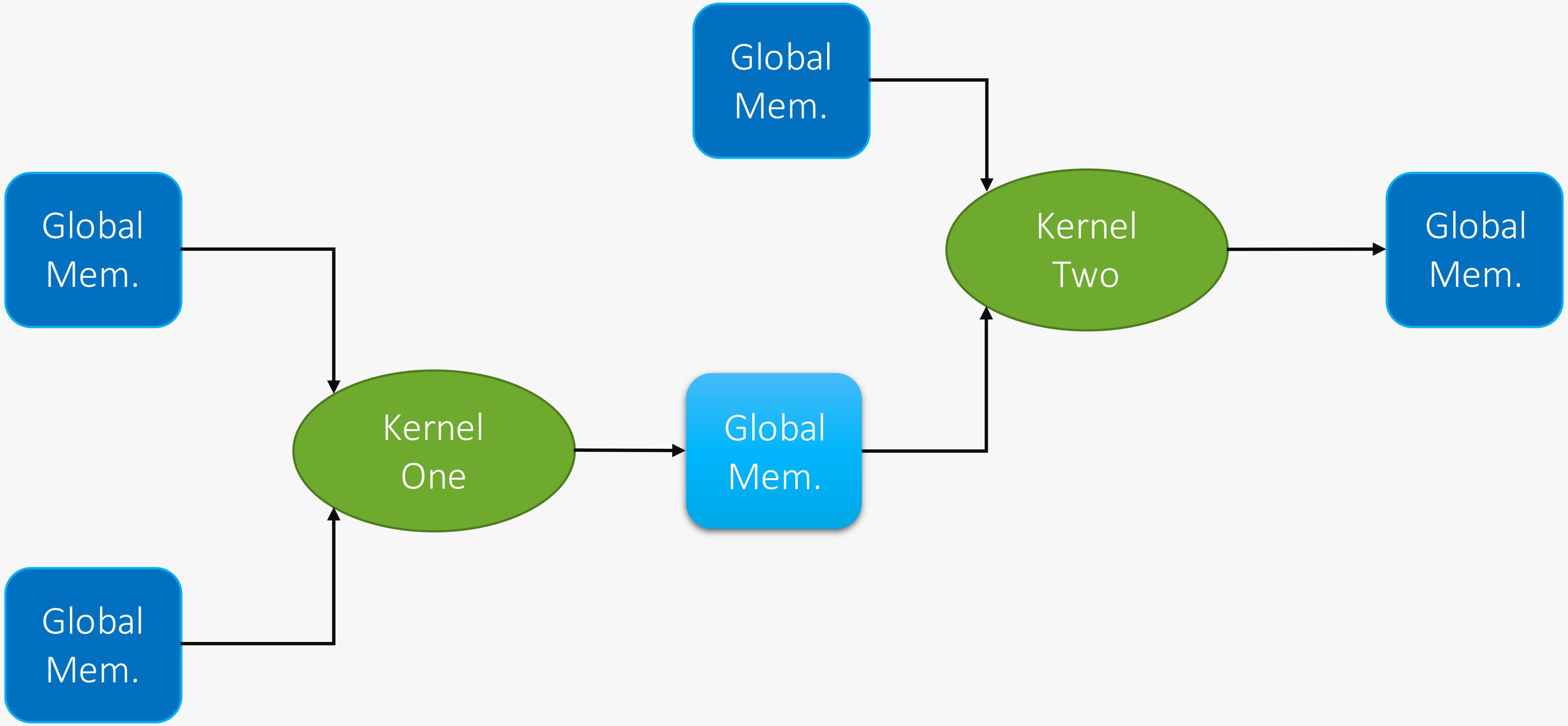
```
q.submit(…);

...

q.submit();
```

- Complete fusion
  - Leaves fusion mode
  - Creates fused kernel and schedules for execution

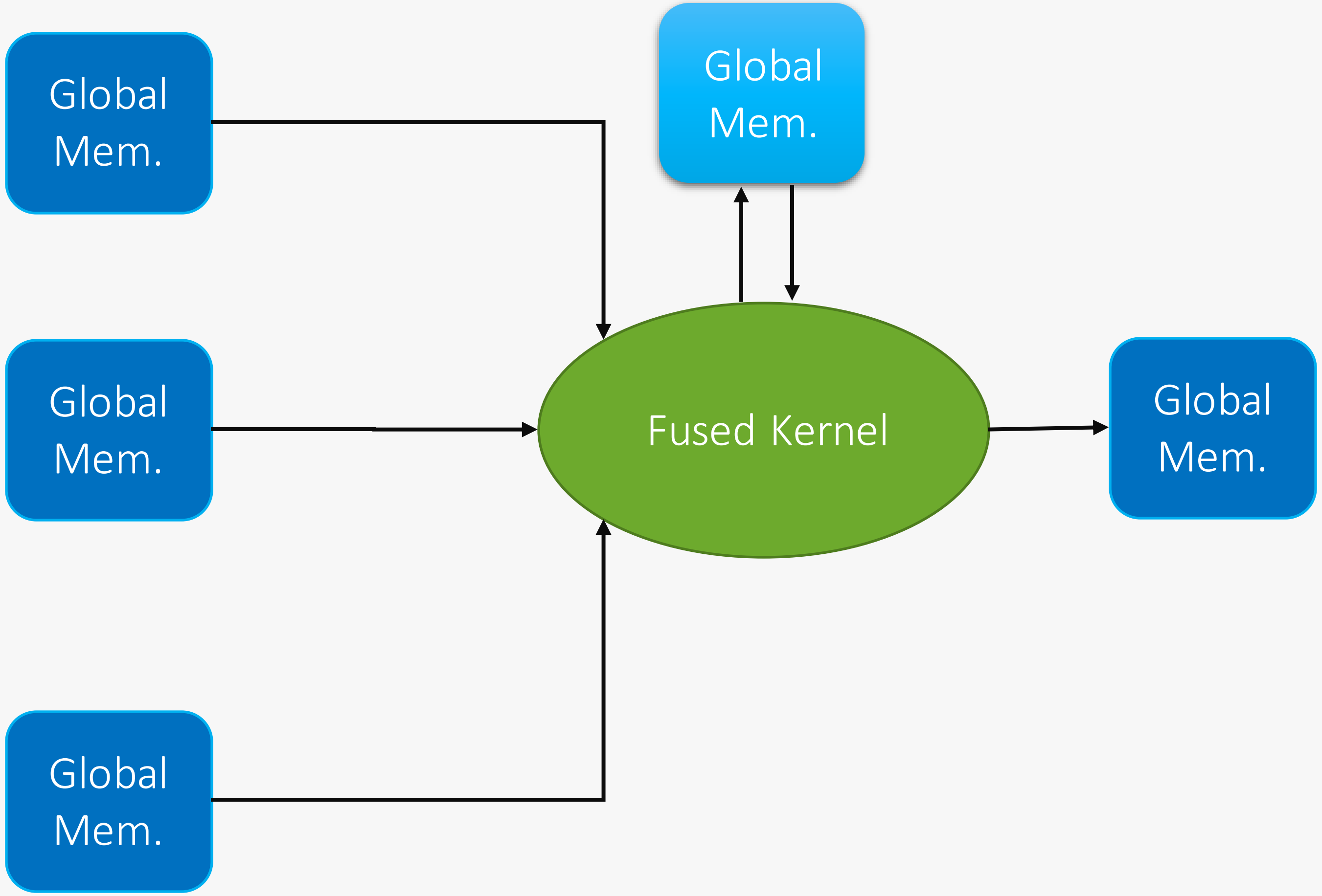
```
q.complete_fusion();
```

Dataflow Internalization

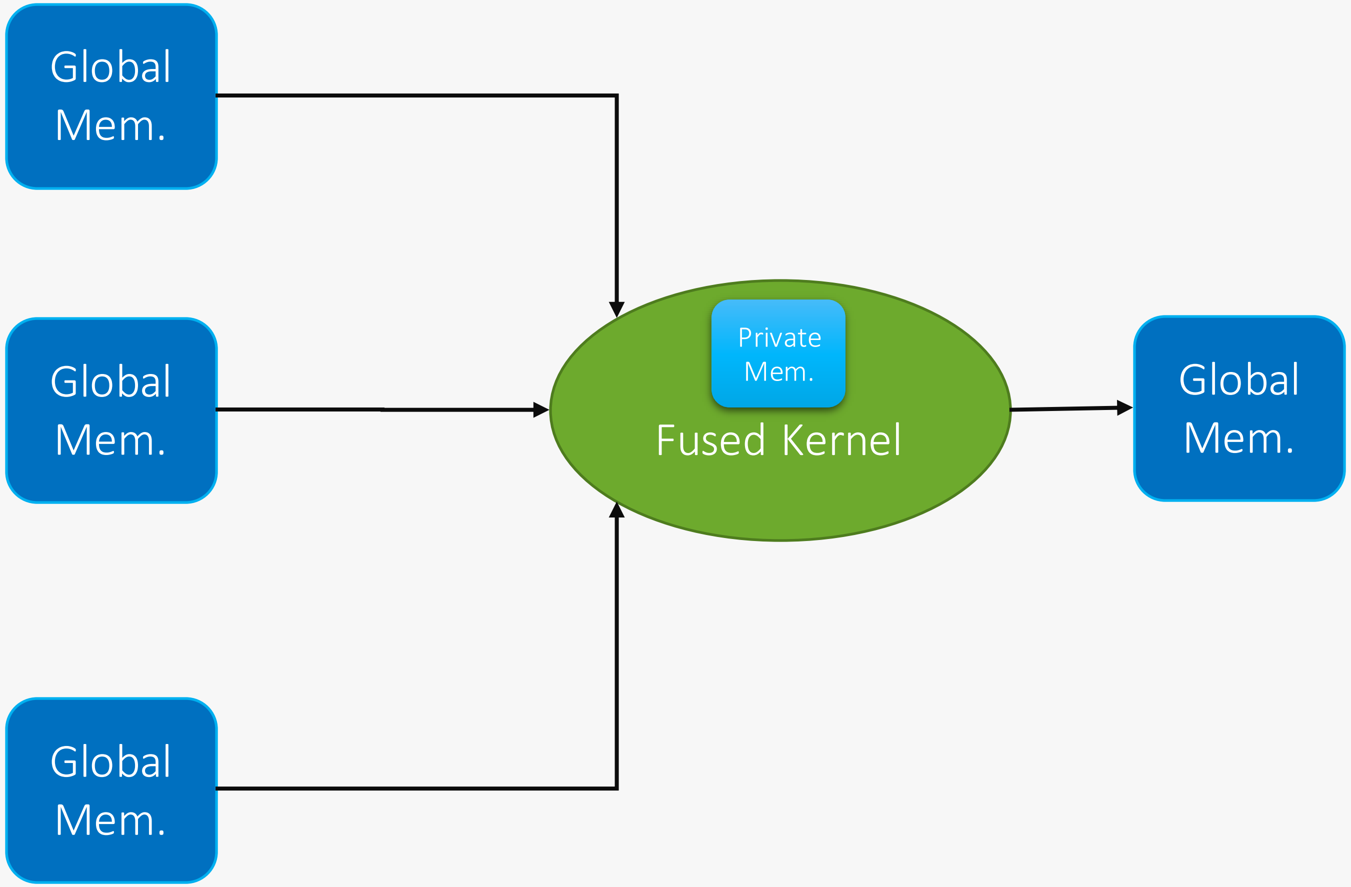
Unfused Kernels Dataflow



Fused Kernels Dataflow



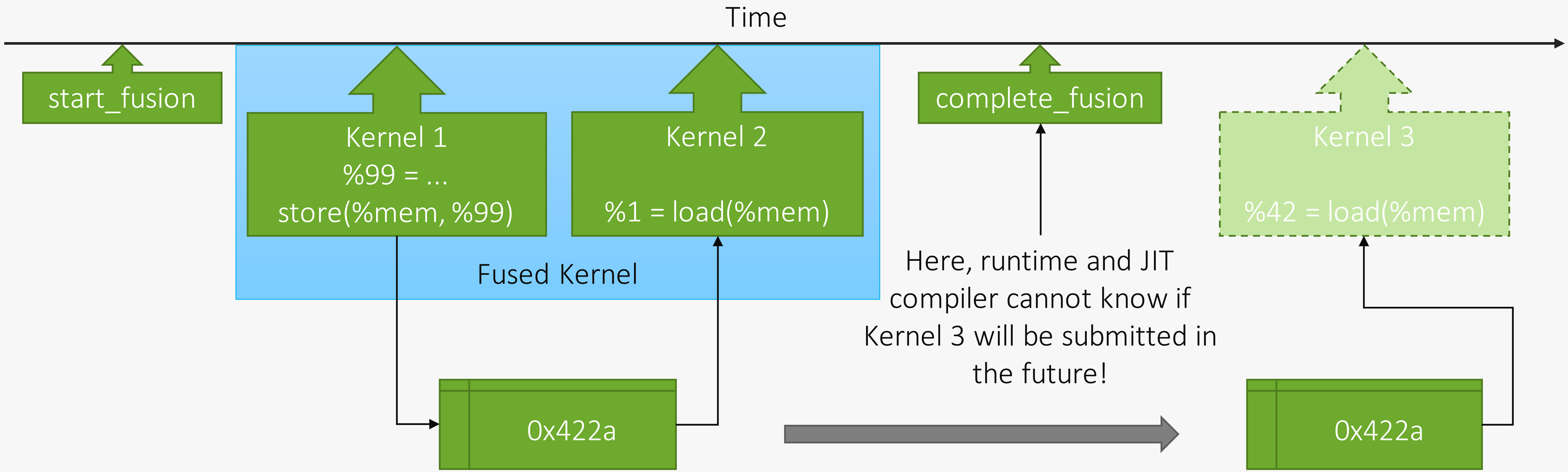
Internalized Dataflow



Internalization Extension API

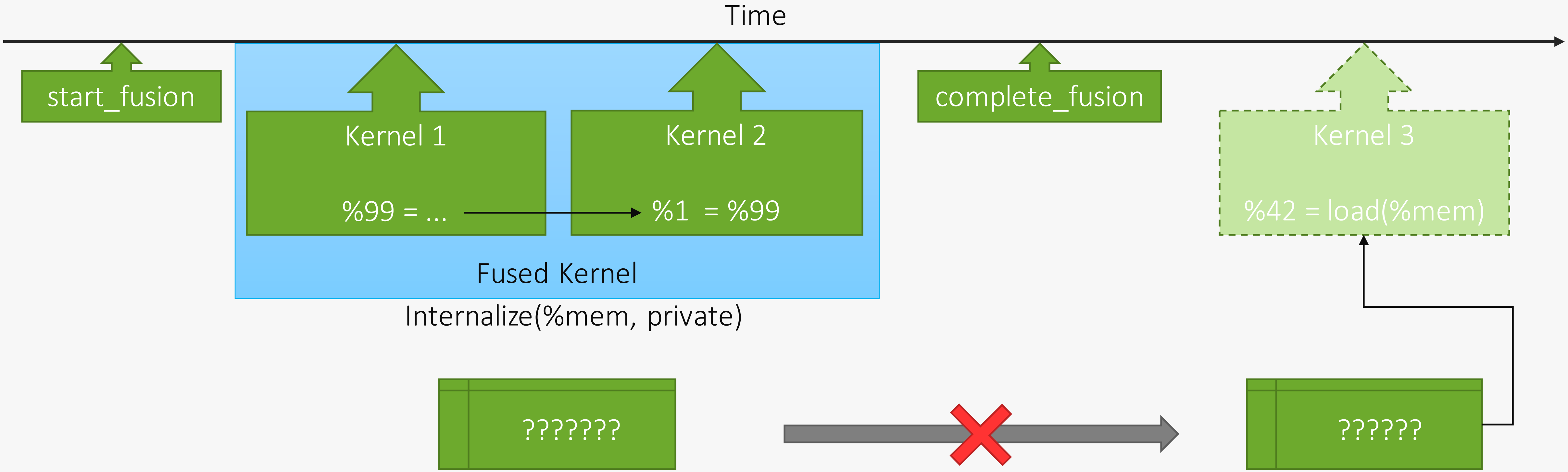
- Two properties:
  - `property::promote_local`
    - Promote to local memory
    - Requires *work-group* exclusive access
  - `property::promote_private`
    - Promotes to private memory (registers)
    - Requires *work-item* exclusive access
- Property can be applied to buffers or accessors

Why Properties for Internalization?



Here, runtime and JIT compiler cannot know if Kernel 3 will be submitted in the future!

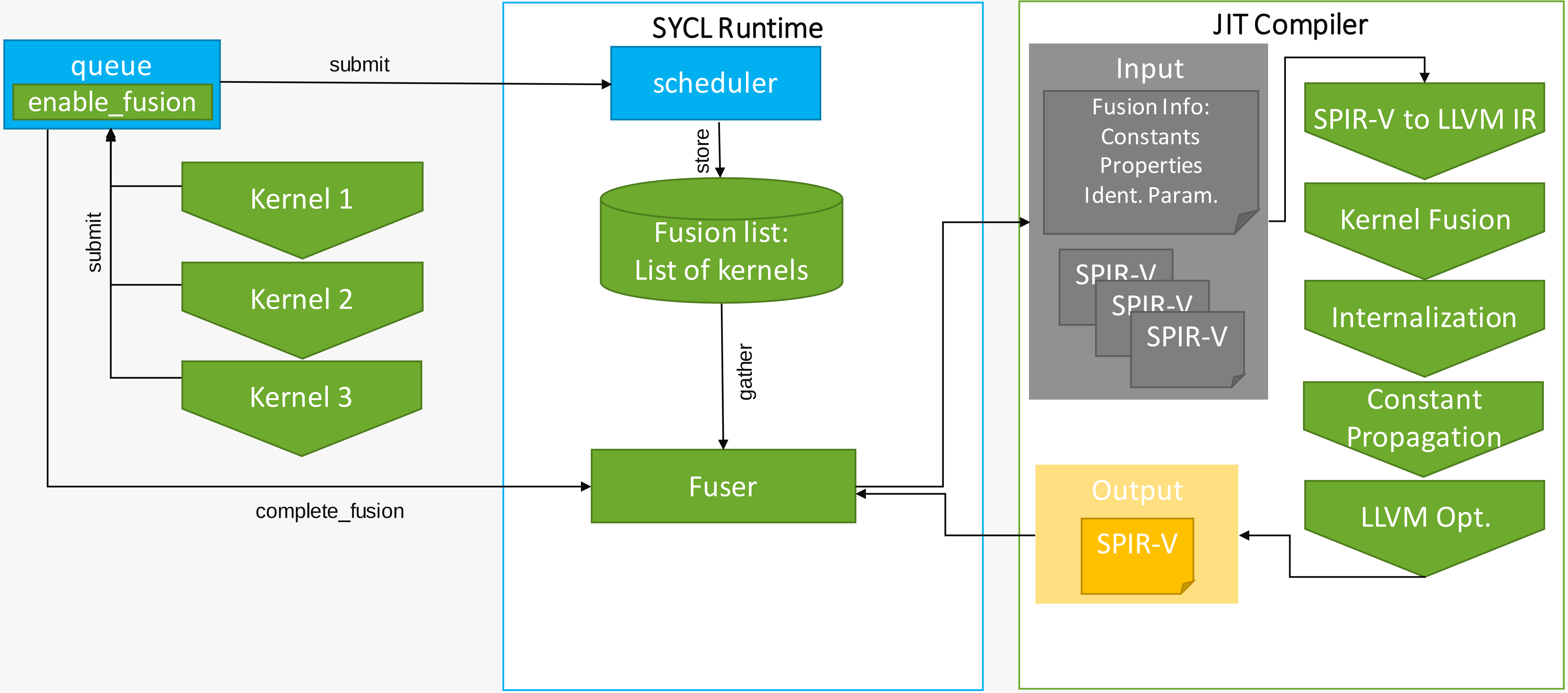
Why Properties for Internalization?



- Property specifies two things
  - JIT compiler should try to replace store & load with register/dataflow
  - **No future kernel will need access to results written by Kernel 1**
    - Kernel 3 can still use the same buffer, but cannot access results of Kernel 1

Implementation

Implementation overview



Fusion Steps – Defining fused kernel

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}


void input_kernel2(accessor%4, scalar%5, accessor%6){...}


void fused_kernel(accessor%1, scalar%2, accessor%3, accessor%4, scalar%5,
                      accessor%6){
  call input_kernel1(accessor%1, scalar%2, %accessor%3);
  work_group_barrier()
  call input_kernel2(accessor%4, scalar%5, accessor%6);
}
```

Fusion Steps – Omitting Barriers

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}


void input_kernel2(accessor%4, scalar%5, accessor%6){...}


void fused_kernel(accessor%1, scalar%2, accessor%3, accessor%4, scalar%5, accessor%6)
!2 {
  call input_kernel1(accessor%1, scalar%2, %accessor%3);
  work_group_barrier()
  call input_kernel2(accessor%4, scalar%5, accessor%6);
}


LLVM Metadata:
!2 property_no_barrier ← Specified by the user through no_barriers property
...
```

Fusion Steps – Omitting Barriers

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}


void input_kernel2(accessor%4, scalar%5, accessor%6){...}


void fused_kernel(accessor%1, scalar%2, accessor%3, accessor%4, scalar%5,
accessor%6){
  call input_kernel1(accessor%1, scalar%2, %accessor%3);
  call input_kernel2(accessor%4, scalar%5, accessor%6);
}


LLVM Metadata:
!2 property_no_barrier
...
```

Fusion Steps – Removing Identical Arguments

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}


void input_kernel2(accessor%4, scalar%5, accessor%6){...}


void fused_kernel(accessor%1, scalar%2, accessor%3, ~~accessor%4~~, scalar%5,
accessor%6) !1 {
  call input_kernel1(accessor%1, scalar%2, %accessor%3);
  call input_kernel2(accessor%4, scalar%5, accessor%6);
}
```

```
LLVM Metadata:
!1 identical(%accessor3, %accessor4)
...
```

← Can be determined by SYCL runtime

Fusion Steps – Removing Identical Arguments

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}

void input_kernel2(accessor%4, scalar%5, accessor%6){...}

void fused_kernel(accessor%1, scalar%2, accessor%3, scalar%5, accessor%6) !1 {
  call input_kernel1(accessor%1, scalar%2, %accessor%3);
  call input_kernel2(accessor%3, scalar%5, accessor%6);
}

LLVM Metadata:
!1 identical(%accessor3, %accessor4)
...
```

Fusion Steps – Constant Propagation

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}

void input_kernel2(accessor%4, scalar%5, accessor%6){...}

void fused_kernel(accessor%1, scalar%2, accessor%3, scalar%5, accessor%6) !3 {
  call input_kernel1(accessor%1, scalar%2, %accessor%3);
  call input_kernel2(accessor%3, scalar%5, accessor%6);
}

LLVM Metadata:
!3 list((scalar%2, value=5), (scalar%5, value=17))
...
```

← Can be determined by SYCL runtime

Fusion Steps – Constant Propagation

```
void input_kernel1(accessor%1, scalar%2, accessor%3){...}

void input_kernel2(accessor%4, scalar%5, accessor%6){...}

void fused_kernel(accessor%1, accessor%3, accessor%6) {
  call input_kernel1(accessor%1, 5, %accessor%3);
  call input_kernel2(accessor%3, 17, accessor%6);
}
```

Fusion Steps – Inline Fused Kernel Functions

```
void input_kernel1(accessor%1, scalar%2, accessor%3){ <body_kernel1> }


void input_kernel2(accessor%4, scalar%5, accessor%6){ <body_kernel2> }


void fused_kernel(accessor%1, accessor%3, accessor%6) {
  <body_kernel1>
  <body_kernel2>
}
```

Fusion Steps – Internalization

```
void fused_kernel(accessor%1, ~~accessor%3,~~ accessor%6) !4 {
  ...
  <kernel1>
    value%99 = mul ...
    ~~store value%99, accessor%3~~
  </kernel1>
  <kernel2>
    ~~value%1337 = load %accessor3~~
    value%1338 = add %value1337, ...
  </kernel2>
}
```

```
LLVM Metadata:
!4 internalize(accessor%3, private)
```

← Specified by the user through SYCL property

Fusion Steps – Internalization

```
void fused_kernel(accessor%1, accessor%6) !4 {
  ...
  <kernel1>
    value%99 = mul ...
  </kernel1>
  <kernel2>
    value%1338 = add %value99, ...
  </kernel2>
}
LLVM Metadata:
!4 internalize(accessor%3, private)
```

Evaluation

Evaluation Setup

Device type	Model	OpenCL driver Version	OS	SYCL Compiler Version
CPU	Intel i7-6700K	2022.13.3.0.16_160000	Ubuntu 18.04.6 Kernel 4.15.0	ComputeCpp-PE 2.10.0
GPU	Intel Gen9 HD Graphics NEO	21.38.21026		

Case Study – SYCL-DNN

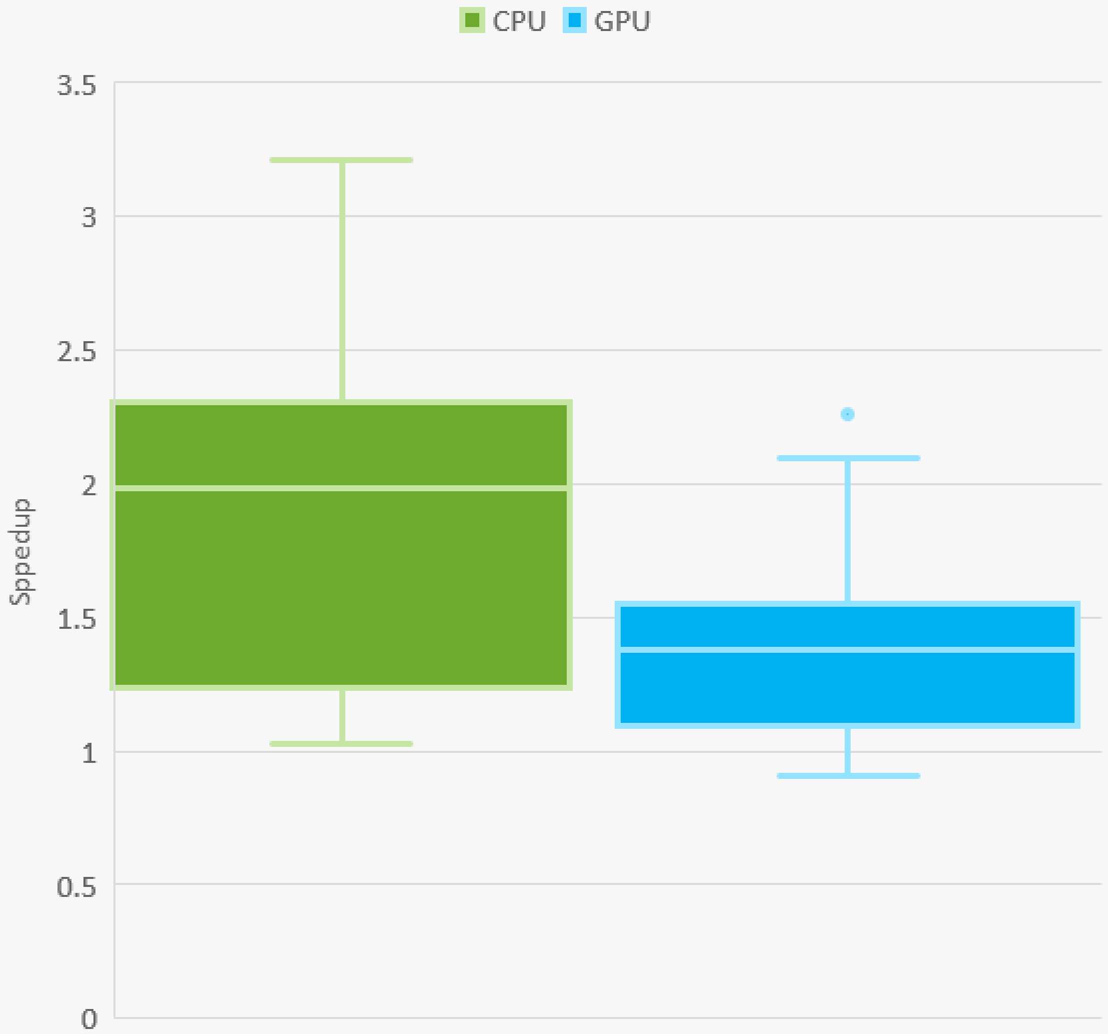
SYCL-DNN

- Open-source SYCL library for neural network operators
- Two types of workloads
  - Microbenchmarks
    - Sequences taken from actual neural network models (e.g. GPT-2)
    - Fusion of arithmetic-heavy kernels
    - Example: BatchNormalization + ReLu
  - End-to-end neural networks
    - VGG16 & ResNet-50
    - Alternative version using a more "fusion-friendly" convolution algorithm

Microbenchmarks Results - Distribution

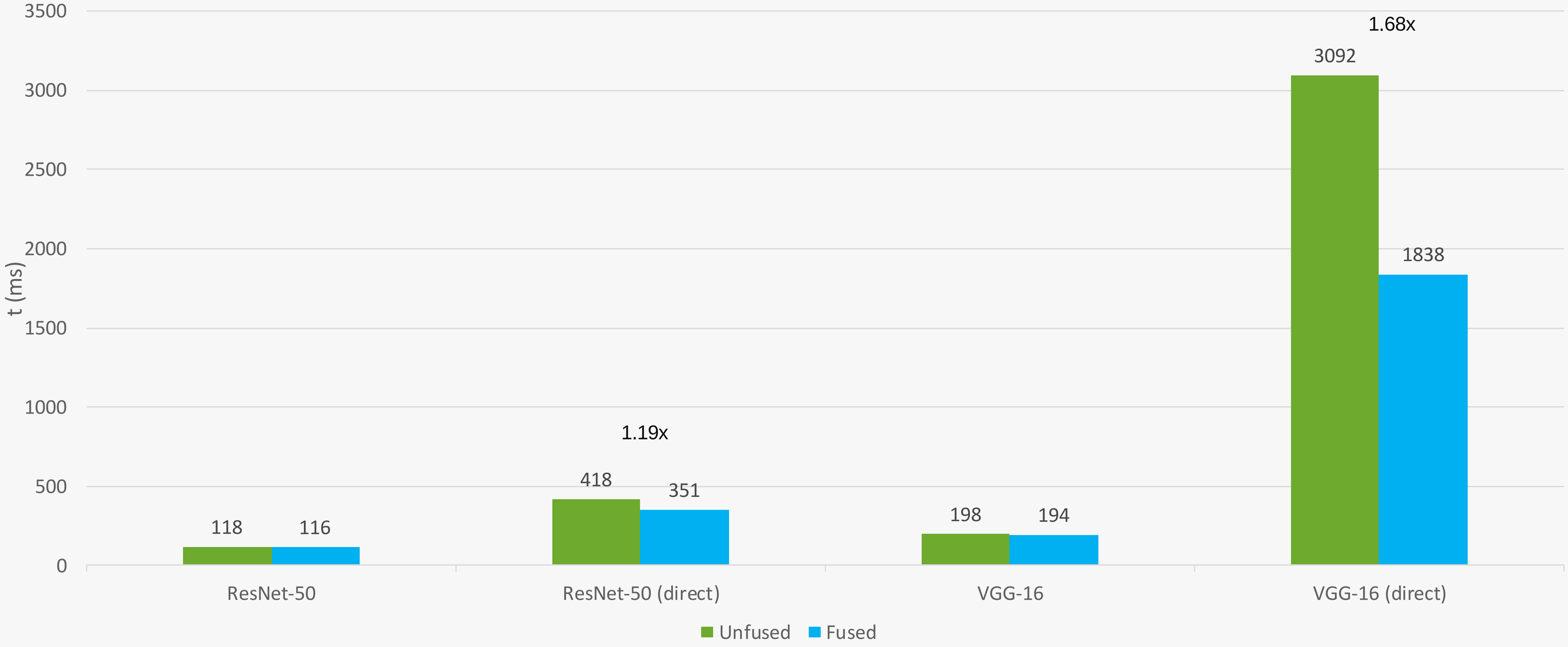
- CPU:
  - 100 %: >1x
  - 75 %: >1.25x
  - 50 %: >1.78x
  - Max: 3.21x

- GPU:
  - 50 %: >1.35x
  - 25 %: >1.5x
  - Max: 2.36x



See backup for workloads and configurations. Results may vary. See TACO paper for more information: https://tinyurl.com/taco-paper

Full NN Results - CPU



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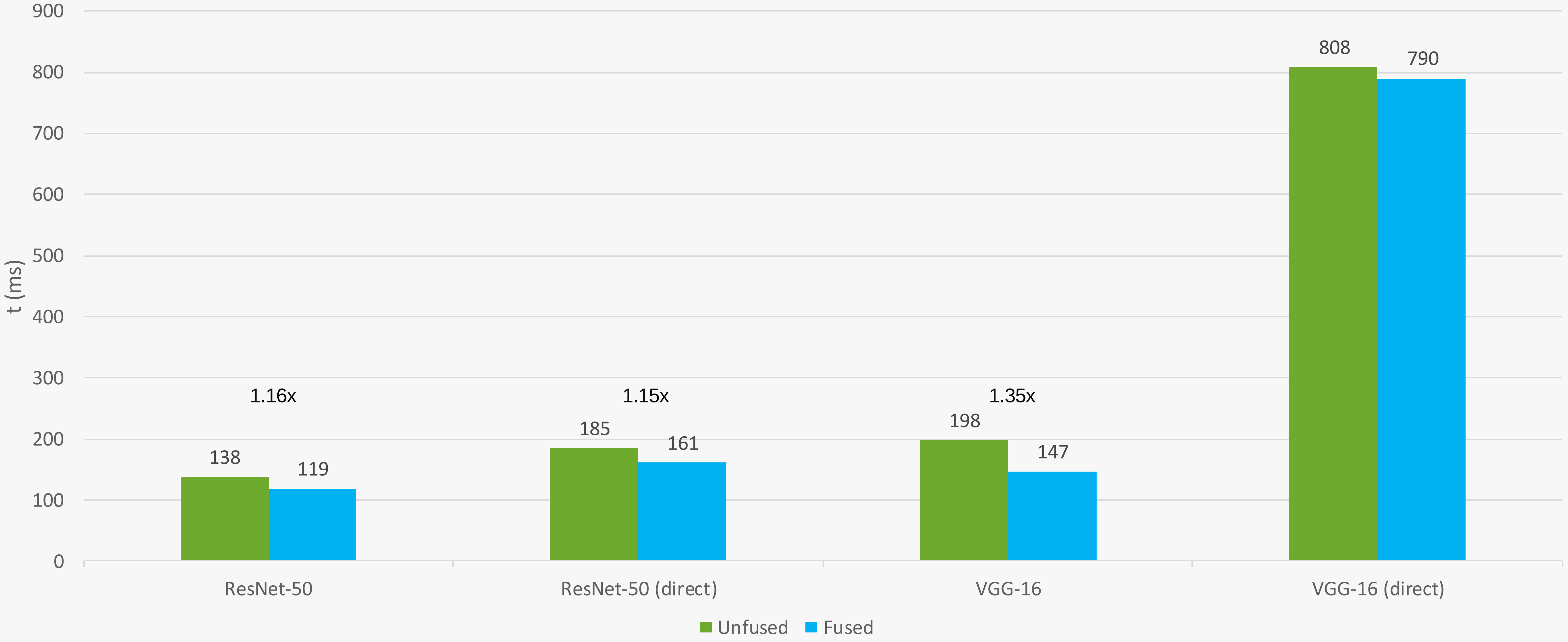
Full NN Results - GPU



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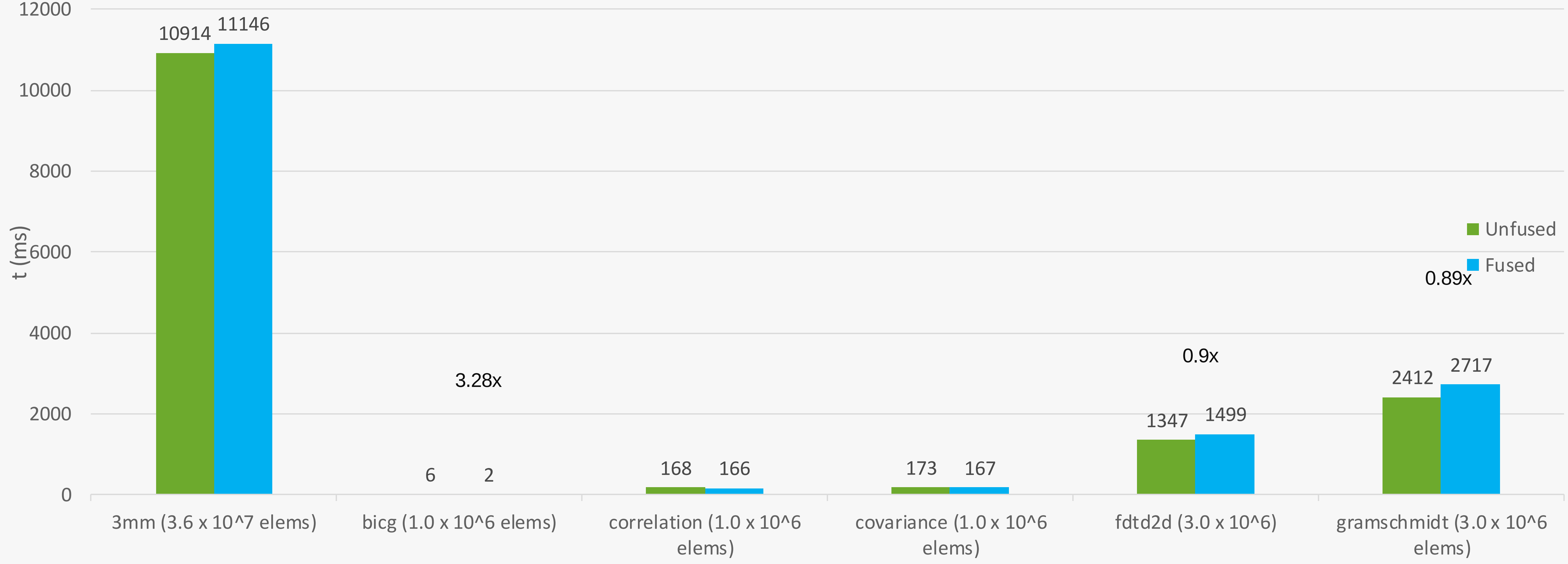
Case Study – SYCL-Bench

SYCL-Bench

- SYCL benchmark-suite
- Focus on `polybench` benchmarks
  - arithmetic-heavy workloads
- Kernel fusion broadly applicable
  - 6 out of 9 polybench benchmarks
  - Internalization applicable to 2 out of 6
- https://github.com/bcosenza/sycl-bench

SYCL-Bench Results - CPU



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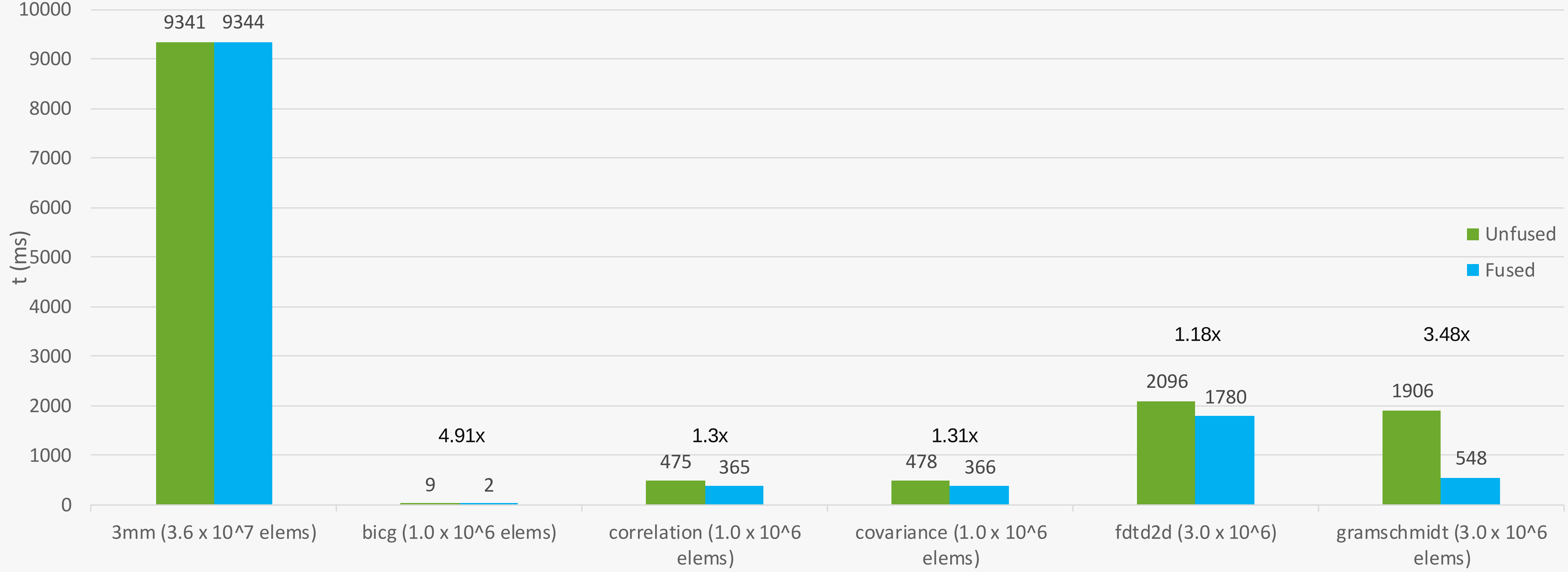
SYCL-Bench Results - GPU



See backup for workloads and configurations. Results may vary. See TACO paper for more information: https://tinyurl.com/taco-paper

Extension Status Update

Current Extension

- Available in DPC++ with some modifications
- Only supporting SPIR-V targets for now
  - Working on PTX/HIP targets support
- Extension proposal: https://tinyurl.com/dpcpp-extension

Kernel Fusion + SYCL Graphs

- Use SYCL graphs to fuse several kernels at runtime
- WIP: *Graph Fusion* extension built on top of SYCL graphs
- Graph Fusion extension proposal:
  - https://tinyurl.com/graph-fusion
- SYCL graphs extension proposal:
  - https://tinyurl.com/sycl-graphs

Graphs Fusion Advantages

- Two different versatile APIs to construct fusion sequence: recording or explicit
- Fine-grained control over execution of JIT compilation through `command_graph::finalize()`
- Unify two similar APIs
- Reusability of fused kernels

Graph Fusion API

Kernel fusion

```
queue q{gpu_selector_v,
      property::queue::enable_fusion{}};
```

```
q.start_fusion();
```

```
q.submit(…);

...

q.submit();
```

```
q.complete_fusion();
```

Graph fusion extension proposal:
https://tinyurl.com/graph-fusion

Graph fusion

```
queue q{gpu_selector_v};
command_graph graph;
```

```
graph.add(…);

...

graph.add();
```

```
auto exec_graph = graph.finalize(q.get_context(),
        {property::perform_fusion});
q.ext_oneapi_graph(exec_graph);
```

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Conclusion

Conclusion

- Kernel fusion can improve SYCL performance significantly
  - Example: >3x for neural network operator sequence
- Extension allows user to instruct SYCL runtime to fuse
  - No need to manually write fused kernel
- Upstreamed to DPC++
  - Working on support for more targets (currently only SPIR-V based)
  - Align with SYCL graphs extension
- Links
  - TACO journal paper: https://tinyurl.com/taco-paper
  - DPC++ extension proposal: https://tinyurl.com/dpcpp-extension
  - SYCL graphs extension proposal: https://tinyurl.com/command-graphs
  - Graph fusion extension proposal: https://tinyurl.com/graph-fusion
  - Kernel fusion tutorial: https://tinyurl.com/kernel-fusion-blogpost

See backup for workloads and configurations. Results may vary. See TACO paper for more information: https://tinyurl.com/taco-paper

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Ask me anything (about kernel fusion)!

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Workloads and Configuration

- System configuration
  - ComputeCpp Professional Edition (PE) 2.10.0
  - OS: Ubuntu 18.04.6 LTS, Kernel 4.15.0
  - CPU: Intel Core i7-6700K, OpenCL driver 2022.13.3.0.16_160000
  - GPU: Intel Gen9 HD Graphics NEO, OpenCL driver 21.38.21026
- Workloads
  - For workloads that measure time, measured time is time spent on the device and time used in the data transfer between host and device
  - Workloads selected include domains such as HPC and ML/DL
  - Each measurement is run 10 times, first measurement is discarded and then average is taken
- Results
  - In most cases, better performance was attributed to reduction in overhead through fusion and less reads and writes to global memory through internalization as part of fusion

Backup

Kernel Fusion: Minimal Overhead

```
queue q{gpu_selector{}, {property::queue::enable_fusion{}}};
{
  buffer<float> buffer1{data1, range};
  buffer<float> buffer2{data2, range, {property::promote_private{}}};
  q.start_fusion();
  q.submit(…);
  q.submit(…);
  …
  q.complete_fusion({property::no_barriers{}});
}
```

Fusion Steps

Adding Metadata

```
void input_kernel1(accessor%1, scalar%2, accessor%3){
<body kernel1>
}

void input_kernel2(accessor%4, scalar%5, accessor%6){
<body kernel2>
}

void fused_kernel() !0 !...

LLVM Metadata:
!0 list(input_kernel1, input_kernel2)
...
```