

Dive into GPGPU programming

Ashot Vardanian

github.com/ashvardanian/SandboxGPUs



Who am I?

Ashot Vardanian, 24 yo, SPb
First OpenGL line at the age of 15

Worked on:

- Web
- Mobile
- Desktop
- Scientific Computing

Working on:

- High Performance Computing
- Artificial Intelligence Research

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Who is this talk for?

You are familiar with C/C++.

You know what a GPU is.

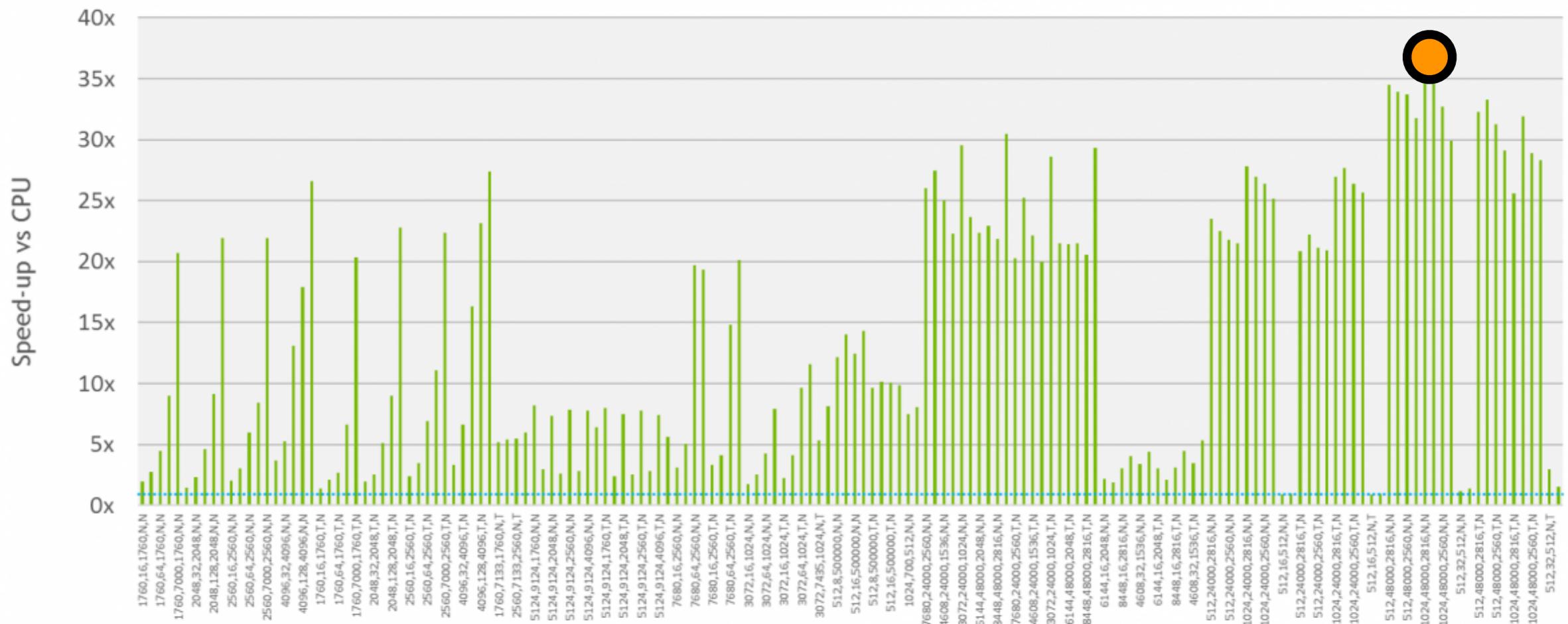
You want to do number-crunching:

- AI & Datascience,
- Video Processing,
- Physics & Bio Simulations.

Not about benchmarking,
but about architecture!

Why GPUs?

...I have heard we can get a 35x performance increase...



What we want ?

Write code once ,

but deploy everywhere!

Optimise performance ,

but avoid boilerplate!

What we want ?

Write code once ,

.cpp

but deploy everywhere!

Intel, Nvidia GPUs, AMD, Xilinx FPGA

Optimise performance ,

but avoid boilerplate!

What we want ?

Unified Language
Write code once ,
Modular Compilers
but deploy everywhere!

Tune code without rewriting logic
Optimise performance ,
but avoid boilerplate!
Clean APIs

Comparison of recipes

...we will fill this table:

	Simple	Unified	Flexible	Clean
Technology	?	?	?	?
Write code once	?	?	?	?
Deploy everywhere	?	?	?	?
Optimise performance	?	?	?	?
Avoid boilerplate	?	?	?	?

We
have
a plan!

The Plan

1. Popular APIs:
 1. OpenGL,
 2. OpenCL.
2. Writing Low-level code
3. Existing Libraries & Tools
4. Optimal Recipes

The Plan

1. Popular APIs
2. Writing Low-level code:
 1. OpenCL Language,
 2. CUDA Language,
 3. GLSL.
3. Existing Libraries & Tools
4. Optimal Recipes

The Plan

1. Popular APIs
2. Writing Low-level code
3. **Existing Libraries & Tools:**
 1. **Linear Algebra,**
 2. **Lazy Evaluation,**
 3. **Halide,**
 4. **SyCL.**
4. Optimal Recipes

The Plan

1. Popular APIs
2. Writing Low-level code
3. Existing Libraries & Tools
4. **Optimal Recipes.**

Popular APIs

For CPU-GPU communication

API Support

	OpenGL
Release	1992, SGI
Intel	Yes
AMD	Yes
Nvidia	Yes
Apple	Deprecated
Android	Yes

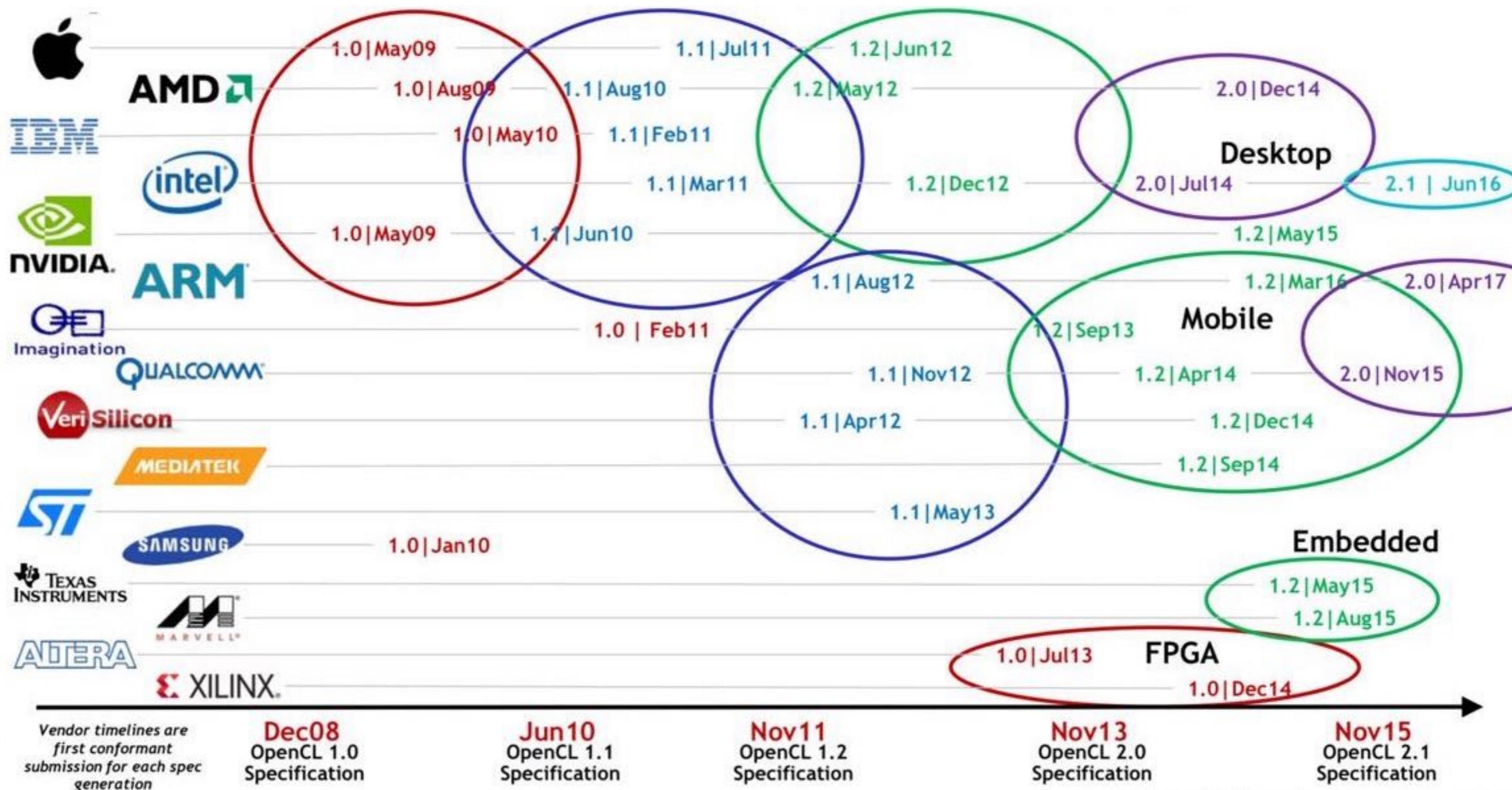
API Support

	OpenGL	CUDA
Release	1992, SGI	2007, Nvidia
Intel	Yes	No
AMD	Yes	No
Nvidia	Yes	Yes
Apple	Deprecated	No
Android	Yes	No

API Support

	OpenGL	CUDA	OpenCL
Release	1992, SGI	2007, Nvidia	2009, Apple
Intel	Yes	No	Yes
AMD	Yes	No	Yes
Nvidia	Yes	Yes	Yes
Apple	Deprecated	No	MacOS
Android	Yes	No	Depends

OpenCL support (2015)



API Support

	OpenGL	CUDA	OpenCL	Metal
Release	1992, SGI	2007, Nvidia	2009, Apple	2014, Apple
Intel	Yes	No	Yes	No
AMD	Yes	No	Yes	No
Nvidia	Yes	Yes	Yes	No
Apple	Deprecated	No	MacOS	Yes
Android	Yes	No	Depends	No

API Support

	OpenGL	CUDA	OpenCL	Metal	Vulkan
Release	1992, SGI	2007, Nvidia	2009, Apple	2014, Apple	2016, AMD
Intel	Yes	No	Yes	No	Yes
AMD	Yes	No	Yes	No	Yes
Nvidia	Yes	Yes	Yes	No	Yes
Apple	Deprecated	No	MacOS	Yes	MoltenVK
Android	Yes	No	Depends	No	Yes

API Comparison

	OpenGL	CUDA	OpenCL	Metal	Vulkan
Primary Purpose	Graphics	Compute	Compute	Graphics	Graphics
Base Input Language	C	C++	C	C++	Any
Complexity	Hard ...on Device	Easy	Easy	Average	Very Hard
Targets Flexibility	Average	Low ...only Nvidia	Extreme ...FPGA	Low ...only Apple	High
API Flexibility*	Average	High**	Average	Average	High

API Comparison

		CUDA	OpenCL		Vulkan
Primary Purpose		Compute	Compute		Graphics
Base Input Language		C++	C		Any SPIR-V
Complexity		Easy	Easy		Very Hard
Targets Flexibility		Low ...only Nvidia	Extreme ...FPGA		High
API Flexibility*		High**	Average		High

Language Syntax

CUDA vs OpenCL. More or less the same.

Parallelism in Language

Which keywords and features must a language have to make parallel programming easy?

Synchronization
Primitives

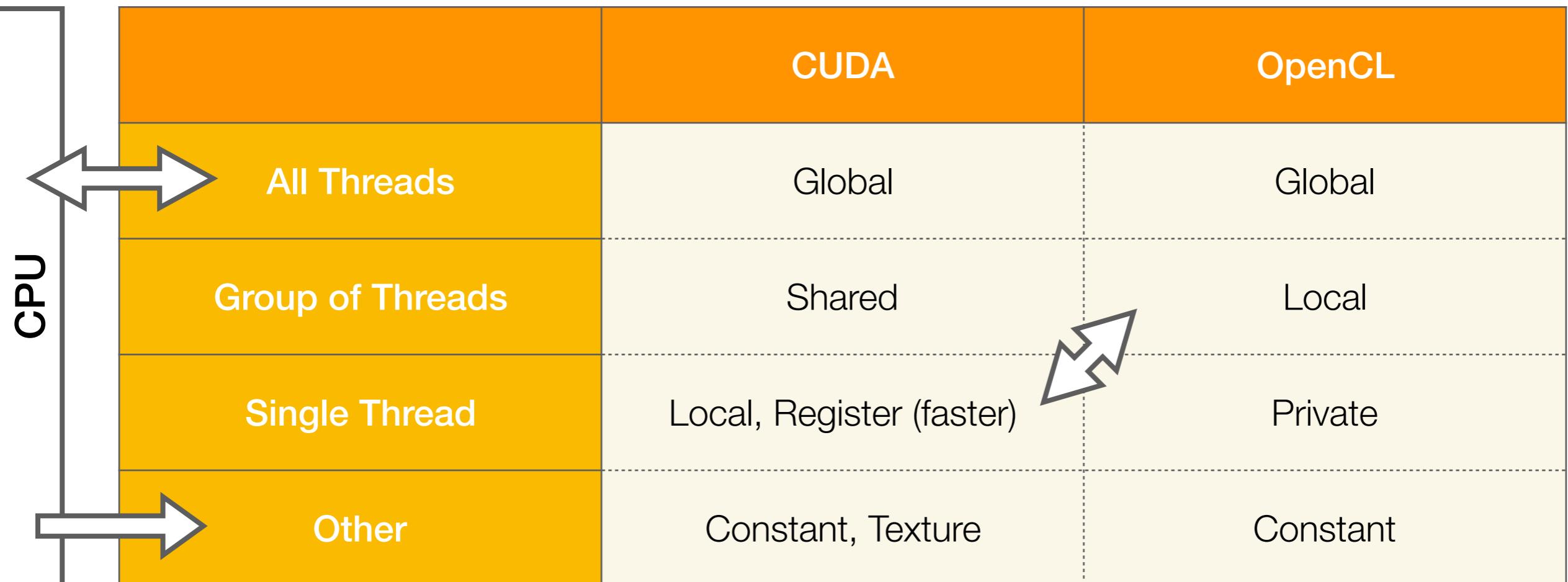
To help threads
understand their role

Memory
Qualifiers

To limit data
visibility

?

Memory Types



Actual Memory Types

...have little to do with physical capabilities of the device! At least from OpenCL perspective!

	i7-7820HQ	Titan V	Radeon Pro 560
Compute Units	8 cores	80 cores	16 cores
Sync-able Group	<1024 threads N¹	<1024 threads N³	< 256 threads N³
Constant Buffer	64 Kb	? Kb	64 Kb
Local Memory	32 Kb	? Kb	32 Kb 1 Mb L2 16 Kb L1 per CU

Actual Memory Types

...have little to do with physical capabilities of the device! At least from OpenCL perspective!

	i7-7820HQ	Titan V	Radeon Pro 560			
Compute Units	8 cores	80 cores	16 cores			
Sync-able Group	<1024 threads	N ¹	<1024 threads	N ³	< 256 threads	N ³
Constant Buffer	64 Kb	"In Volta the L1 cache, texture cache, and shared memory are backed by a combined 128 KB data cache."		64 Kb	1 Mb L2 16 Kb L1 per CU	
Local Memory	32 Kb			32 Kb		

Nvidia GPUs have one real "constant" buffer (64-128 Kb) and allocate rest in global memory.

AMD GPUs often have multiple "constant" buffers (64 Kb each) and allocate rest in global memory.

Memory Qualifiers

	CUDA	OpenCL
All Threads	<code>__device__</code>	<code>__global</code>
Group of Threads	<code>__shared__</code>	<code>__local</code>
Single Thread	~	~
Other	<code>__constant__</code>	<code>__constant</code>

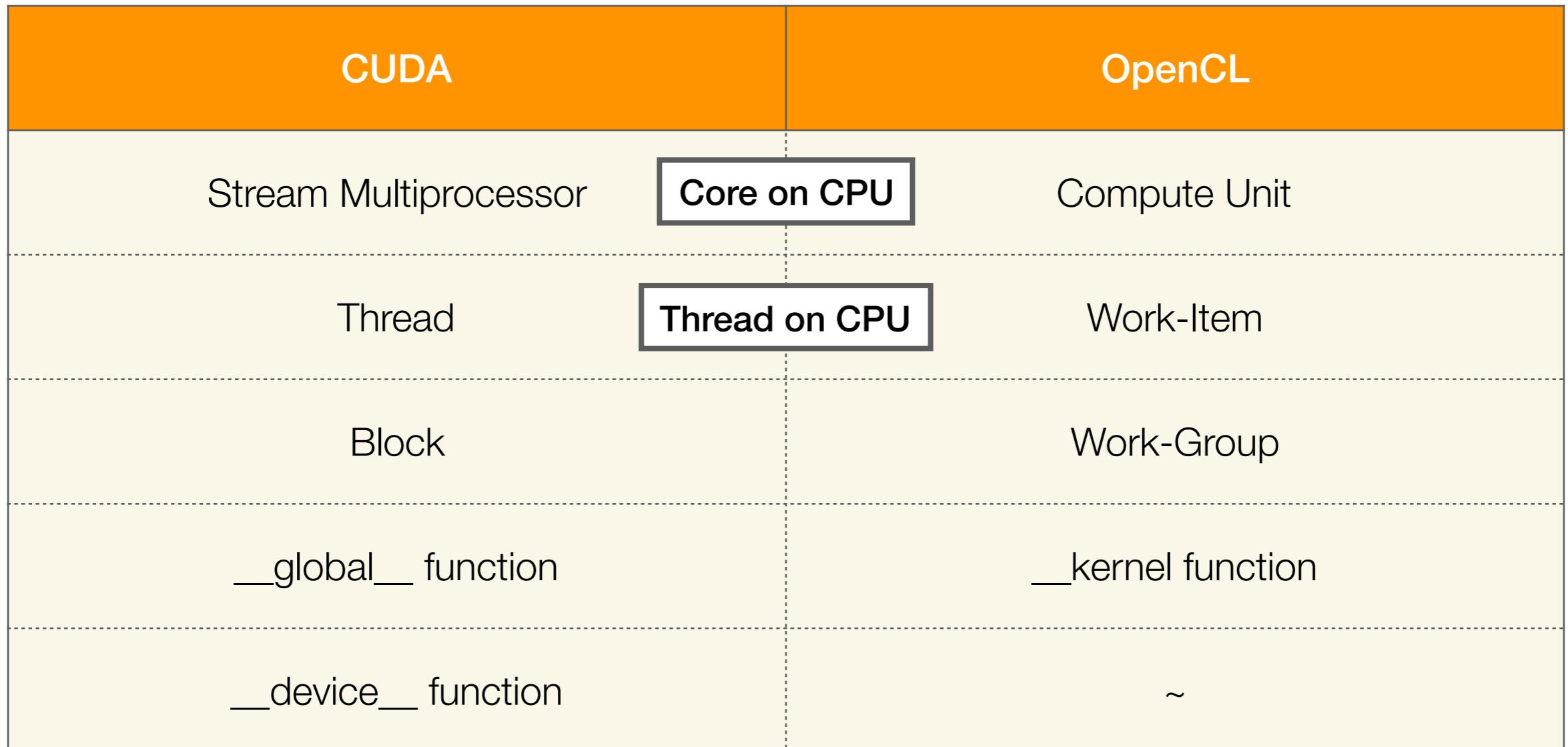
`void sum_2_vecs(float const * xA,
float const * xB,
float * y,
int const xLen);`

CPU

`kernel
void sum_2_vecs(global float const * xA,
global float const * xB,
global float * y);`

GPU version

Terminology



Kernels Indexing

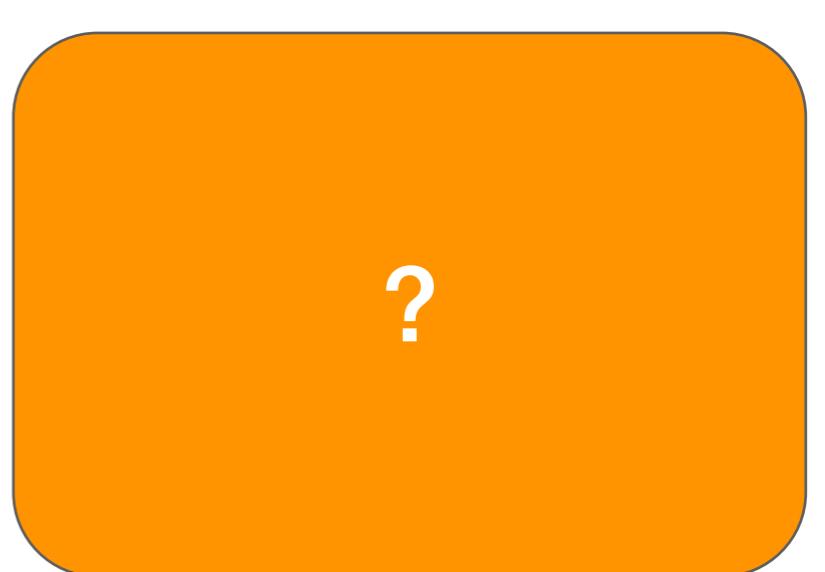
CUDA	OpenCL
gridDim	get_num_groups()
blockDim	get_local_size()
blockIdx	get_group_id()
threadIdx	get_local_id()
Ugly blockIdx * blockDim + threadIdx	get_global_id()
Ugly gridDim * blockDim	get_global_size()

Kernels Synchronization

	CUDA	OpenCL
Group	<code>__syncthreads()</code>	<code>barrier(...)</code>
All	<code>__threadfence()</code>	<code>~</code>
Group Memory	<code>__threadfence_block()</code>	<code>mem_fence(...)</code>
	<code>~</code>	<code>read_mem_fence(...)</code>
	<code>~</code>	<code>write_mem_fence(...)</code>

Parallelism in Language

Which keywords and features must a language have to make parallel programming easy?



Code Examples

Why would you want to write low-level kernels?

Data-Parallel Tasks

...brute-force scaling of simple
non-concurrent problems

Data-Parallel Tasks

...brute-force scaling of simple
non-concurrent problems

Vector Sum: C

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {
    for (int i = 0; i < xLen; i++)
        y[i] = xA[i] + xB[i];
}
```

Vector Sum: OpenCL

```
kernel void sum_2_vectors(global float const * xA,  
                          global float const * xB,  
                          global float * y) {  
    int i = get_global_id(0);  
    y[i] = xA[i] + xB[i];  
}
```

Vector Sum: GLSL

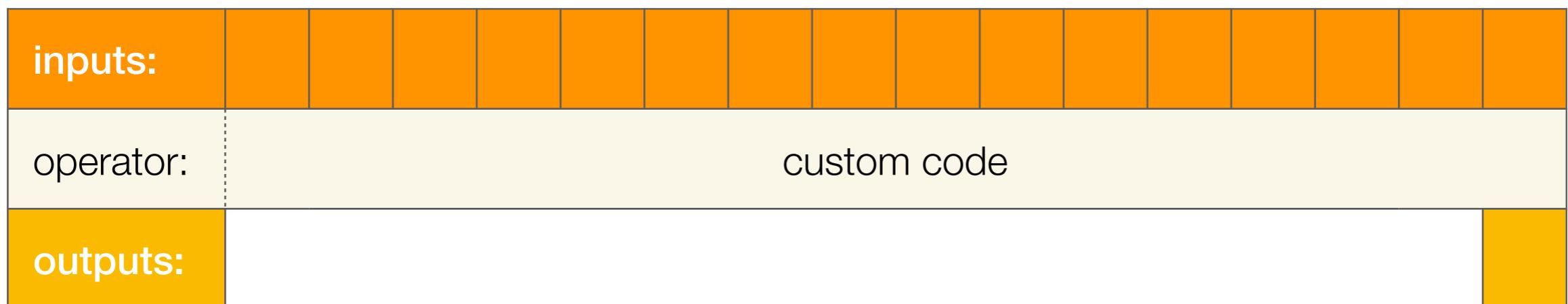
```
#version 450

layout(binding = 0) in buffer lay0 { float xA[]; };
layout(binding = 1) in buffer lay1 { float xB[]; };
layout(binding = 2) out buffer lay2 { float y[]; };

void main() {
    uint const i = gl_GlobalInvocationID.x;
    y[i] = xA[i] + xB[i];
}
```

Concurrent Tasks

...synchronization nightmare
and benchmarks heaven!

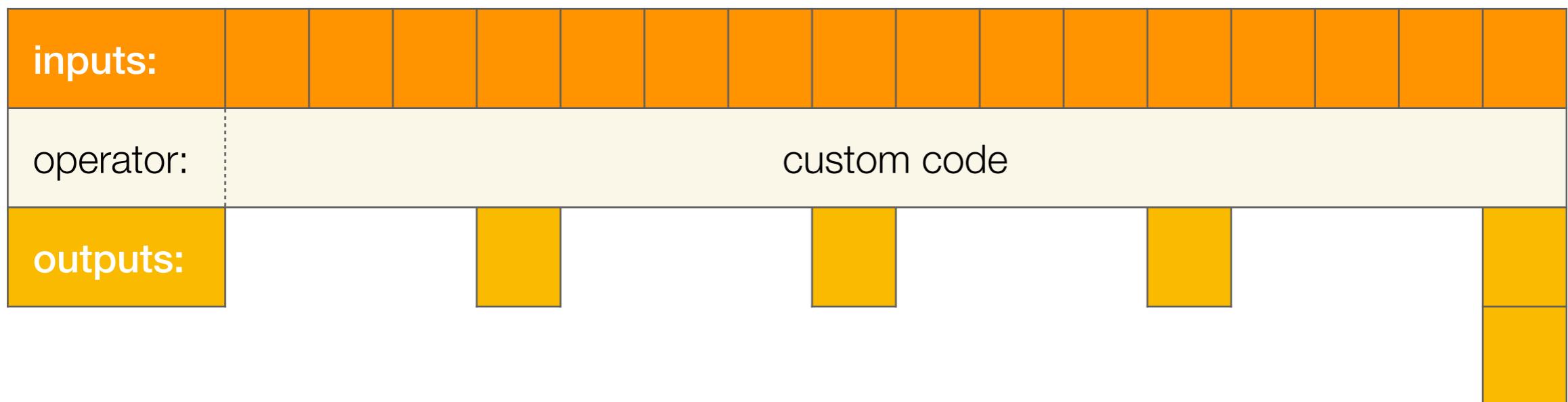


Reduction: C

```
void reduce(float const * x,
           float * y,
           int const xLen) {
    *y = 0;
    for (int i = 0; i < xLen; i++)
        *y += x[i];
}
```

Concurrent Tasks

...force us to inject memory synchronization
barriers and loops, that compiler won't unroll!



Reduction: OpenCL (1)

```
__kernel
void reduce_simple(__global float const * xArr, __global float * yArr,
                   int const xLen, __local float * mBuffer) {
    int const lIdxGlobal = get_global_id(0);
    int const lIdxInBlock = get_local_id(0);
    mBuffer[lIdxInBlock] = (lIdxGlobal < xLen) ? xArr[lIdxGlobal] : 0;

     barrier(CLK_LOCAL_MEM_FENCE);
    int lBlockSize = get_local_size(0);
    int lBlockSizeHalf = lBlockSize / 2;
    while (lBlockSizeHalf > 0) {
        if (lIdxInBlock < lBlockSizeHalf) {
            mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + lBlockSizeHalf];
            if ((lBlockSizeHalf * 2) < lBlockSize) {
                if (lIdxInBlock == 0)
                    mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + (lBlockSize - 1)];
            }
        }
         barrier(CLK_LOCAL_MEM_FENCE);
        lBlockSize = lBlockSizeHalf;
        lBlockSizeHalf = lBlockSize / 2;
    }

    if (lIdxInBlock == 0) yArr[get_group_id(0)] = mBuffer[0];
}
```

Reduction: OpenCL (2)

```
__kernel
void reduce_unrolled(__global float const * xArr, __global float * yArr,
                     int const xLen, __local float * mBuffer) {
    int const lIdxInBlock = get_local_id(0);
    int const lIdxGlobal = get_group_id(0) * (get_local_size(0) * 2) + get_local_id(0);
    int const lBlockSize = get_local_size(0);
    mBuffer[lIdxInBlock] = (lIdxGlobal < xLen) ? xArr[lIdxGlobal] : 0;

    if (lIdxGlobal + get_local_size(0) < xLen)
        mBuffer[lIdxInBlock] += xArr[lIdxGlobal + get_local_size(0)];
→ barrier(CLK_LOCAL_MEM_FENCE);

→ #pragma unroll 1
    for (int lTemp = get_local_size(0) / 2; lTemp > 32; lTemp >>= 1) {
        if (lIdxInBlock < lTemp)
            mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + lTemp];
→ barrier(CLK_LOCAL_MEM_FENCE);

→ if (lIdxInBlock < 32) {
        if (lBlockSize >= 64) { mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + 32]; }
        if (lBlockSize >= 32) { mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + 16]; }
        if (lBlockSize >= 16) { mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + 8]; }
        if (lBlockSize >= 8) { mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + 4]; }
        if (lBlockSize >= 4) { mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + 2]; }
        if (lBlockSize >= 2) { mBuffer[lIdxInBlock] += mBuffer[lIdxInBlock + 1]; }
→ }

→ if (lIdxInBlock == 0) yArr[get_group_id(0)] = mBuffer[0];
}
```

Existing Libs & Tools

The complexity of Choice

Linear Algebra

	Intel MKL	cuBLAS	CLBlast
Types	Basic	Basic, FP16, INT8	Basic, FP16
Performance	+	+++	++
APIs	BLAS, LAPACK...	BLAS +	BLAS
BLAS Levels	Vector-Vector	Matrix-Vector	Matrix-Matrix
LAPACK	Least Squares	Eigenvalues	Factorization

Optimized kernels are chained into slow pipelines!

Linear Algebra

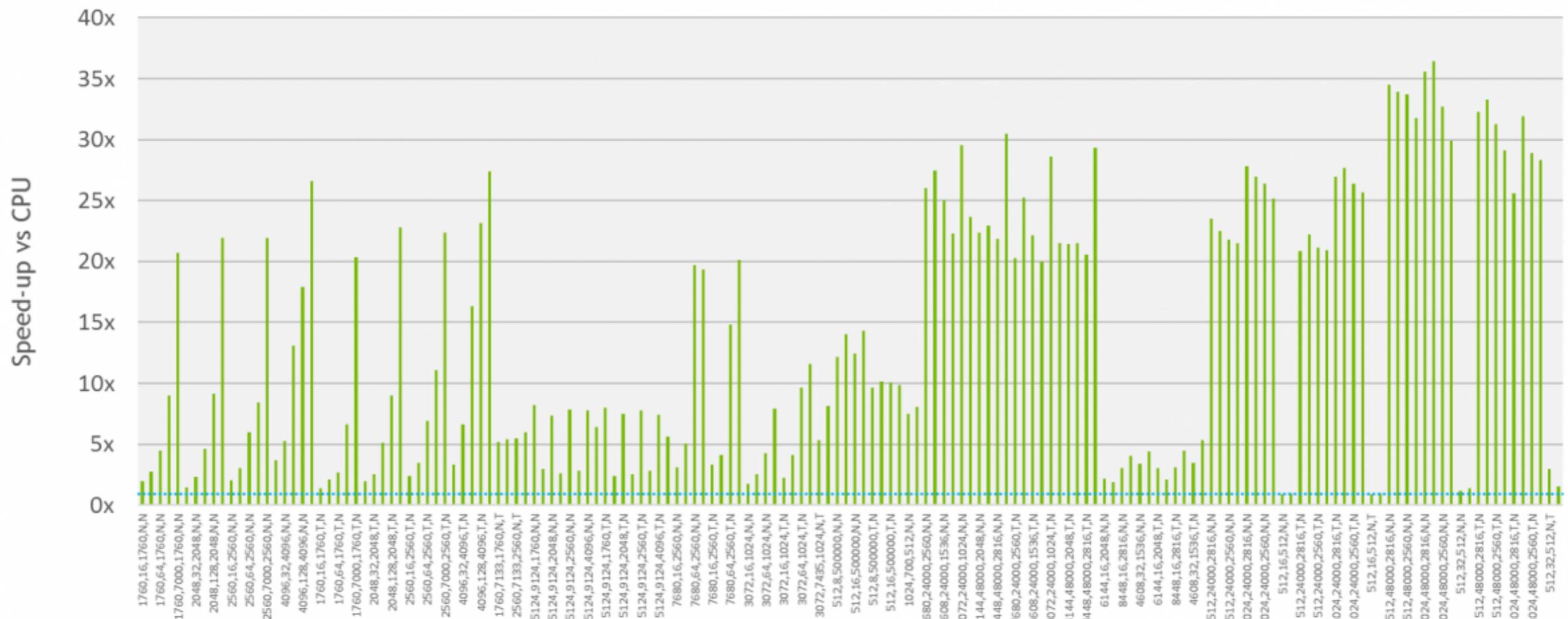
	Intel MKL	cuBLAS	CLBlast		
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Performance	+	+++	++		
APIs	BLAS, LAPACK...	BLAS +	BLAS		
BLAS Levels	Vector-Vector	Matrix-Vector	Matrix-Matrix	152 Ops!	
LAPACK	Least Squares	Eigenvalues	Factorization	Vectors Sum?	Array Sum Reduction?

Optimized kernels are chained into slow pipelines!

Linear Algebra

	Intel MKL	cuBLAS	CLBlast	
Types	Basic	Basic, FP16, INT8	Basic, FP16	
Performance	+	+++	++	
APIs	BLAS, LAPACK...	BLAS +	BLAS	
BLAS Levels	Vector-Vector Vectors Sum? SAXPY with a=1	Matrix-Vector Array Sum Reduction? SDOT with unit vector	Matrix-Matrix Factorization	152 Ops!
LAPACK	Least Squares	Eigenvalues		

Optimized kernels are chained into slow pipelines!



	E5-2690v4	Gold 6262V	V100
Float Performance	+	++	+++
Cores	14	24	14
Year	2016	2019	2017
Price	2,000-2,500 USD	3,000 USD	8,000 USD

Lazy Evaluation Graph

Lazy	Eigen	ArrayFire	Boost. Compute	Thrust	VexCL
Stars	10k	2.8k	1K	2.5k	565
Type-Safe	Yes	No	Yes	Yes	Yes
Backends	OpenMP, CUDA?	OpenCL, CUDA, etc.	OpenCL	CUDA, OpenMP	OpenCL, CUDA, OpenMP

Very different functionality and inconsistent APIs.
Potential Licensing issues.

Data-Parallel Tasks

...again, but now with higher level
heterogeneous computing tools!

Cost of Memory Access

...is much higher, than cost of compute, so we need **kernel fusion!**

	Power
ALU	1 pJ
Load from SRAM	3 pJ
Move 10 mm on-chip	30 pJ
Send off-chip	500 pJ
Send to DRAM	1 nJ
Send over LTE	10 µJ

1,000x more

10,000,000x more

Parallelism in Language

...we want to separate the inner part of the "for" loop and the enumeration order

Synchronization
Primitives

To help threads
understand their role

Memory
Qualifiers

To limit data
visibility

Order
Descriptors

To simplify loops
optimization

How Halide works?

...by separating the inner loop logic!

```
func(i) = lA(i) + lB(i);
```

How Halide works?

...and by making loops implicit!

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {
    Halide::Buffer<bFlt32> lA { const_cast<float *>(xA), xLen, "xA" };
    Halide::Buffer<bFlt32> lB { const_cast<float *>(xB), xLen, "xB" };
    Halide::Var i { "i" };
    Halide::Func func;

    func(i) = lA(i) + lB(i);
    Halide::Buffer<bFlt32> l0ut = func.realize(xLen);
    std::copy_n(l0ut.data(), xLen, y);
}
```

The diagram illustrates the execution flow of the provided C++ code. It consists of two horizontal arrows pointing from left to right. The top arrow originates from the assignment statement `func(i) = lA(i) + lB(i);` and points to a rectangular box labeled "Function body". The bottom arrow originates from the final statement `Halide::Buffer<bFlt32> l0ut = func.realize(xLen);` and points to another rectangular box labeled "The 'for' loop".

How Halide works?

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {
    Halide::Buffer<bFlt32> lA { const_cast<float *>(xA), xLen, "xA" };
    Halide::Buffer<bFlt32> lB { const_cast<float *>(xB), xLen, "xB" };
    Halide::Var i { "i" };
    Halide::Func func;

    func(i) = lA(i) + lB(i);

    Halide::Buffer<bFlt32> l0ut = func.parallel(i).realize(xLen);
    std::copy_n(l0ut.data(), xLen, y);
}
```



Parallel "for" loop

How Halide works?

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {
    Halide::Buffer<bFlt32> lA { const_cast<float *>(xA), xLen, "xA" };
    Halide::Buffer<bFlt32> lB { const_cast<float *>(xB), xLen, "xB" };
    Halide::Var i { "i" };
    Halide::Func func;

    func(i) = lA(i) + lB(i);

    Halide::Buffer<bFlt32> l0ut = func.vectorize(i, 8).realize(xLen);
    std::copy_n(l0ut.data(), xLen, y);
}
```



Vectorized "for" loop with "float8"

How Halide works?

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {
    Halide::Buffer<bFlt32> lA { const_cast<float *>(xA), xLen, "xA" };
    Halide::Buffer<bFlt32> lB { const_cast<float *>(xB), xLen, "xB" };
    Halide::Var i { "i" }, j { "j" }, k { "k" };
    Halide::Func func;

    func(i) = lA(i) + lB(i);
    func.vectorize(i, j, k, 8);
    Halide::Buffer<bFlt32> l0ut = func.parallel(j).unroll(k).realize(xLen);
    std::copy_n(l0ut.data(), xLen, y);
}
```

Transforming a 1 dimensional
"for"-loop into 2D loop

Unroll the inner loop!

Blur Filter: C++

...the baseline for comparison!

```
void box_filter_3x3(const Image &in, Image &blury) {  
    Image blurx(in.width(), in.height()); // allocate blurx array  
  
    for (int y = 0; y < in.height(); y++)  
        for (int x = 0; x < in.width(); x++)  
            blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;  
  
    for (int y = 0; y < in.height(); y++)  
        for (int x = 0; x < in.width(); x++)  
            blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;  
}
```

Slow

Fast

Blur Filter: Halide

Halide

0.9 ms/megapixel

```
Func box_filter_3x3(Func in) {
    Func blurx, blury;
    Var x, y, xi, yi;

    // The algorithm - no storage, order
    blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
    blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;

    // The schedule - defines order, locality; implies storage
    blury.tile(x, y, xi, yi, 256, 32)
        .vectorize(xi, 8).parallel(y);
    blurx.compute_at(blury, x).store_at(blury, x).vectorize(x, 8);

    return blury;
}
```

Sugar: tiling!

C++

0.9 ms/megapixel

```
void box_filter_3x3(const Image &in, Image &blury) {
    __m128i one_third = _mm_set1_epi16(21846);
    #pragma omp parallel for
    for (int yTile = 0; yTile < in.height(); yTile += 32) {
        __m128i a, b, c, sum, avg;
        __m128i blurx[(256/8)*(32+2)]; // allocate tile blurx array
        for (int xTile = 0; xTile < in.width(); xTile += 256) {
            __m128i *blurxPtr = blurx;
            for (int y = -1; y < 32+1; y++) {
                const uint16_t *inPtr = &(in[yTile+y][xTile]);
                for (int x = 0; x < 256; x += 8) {
                    a = _mm_loadu_si128((__m128i*)(inPtr-1));
                    b = _mm_loadu_si128((__m128i*)(inPtr+1));
                    c = _mm_load_si128((__m128i*)(inPtr));
                    sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
                    avg = _mm_mulhi_epi16(sum, one_third);
                    _mm_store_si128(blurxPtr++, avg);
                    inPtr += 8;
                }
            }
            blurxPtr = blurx;
            for (int y = 0; y < 32; y++) {
                __m128i *outPtr = (__m128i *)(&(blury[yTile+y][xTile]));
                for (int x = 0; x < 256; x += 8) {
                    a = _mm_load_si128(blurxPtr+(2*256)/8);
                    b = _mm_load_si128(blurxPtr+256/8);
                    c = _mm_load_si128(blurxPtr++);
                    sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
                    avg = _mm_mulhi_epi16(sum, one_third);
                    _mm_store_si128(outPtr++, avg);
                }
            }
        }
    }
}
```

With platform-specific SIMD!

Laplacian Filter

...real life example!

	Reference C++
LOC	300
Time	?
Performance	1x

Laplacian Filter

...real life example!

	Reference C++	Adobe CPU
LOC	300	1,500
Time	?	3 months
Performance	1x	10x

Laplacian Filter

...real life example!

	Reference C++	Adobe CPU	Halide CPU
LOC	300	1,500	60
Time	?	3 months	1 day
Performance	1x	10x	20x

Laplacian Filter

...real life example!

	Reference C++	Adobe CPU	Halide CPU	Halide GPU
LOC	300	1,500		60
Time	?	3 months		1 day
Performance	1x	10x	20x	70x

Vector Sum: SyCL Today

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {

    cl::sycl::queue q;
    cl::sycl::buffer<float, 1> lA { xA, xLen };
    cl::sycl::buffer<float, 1> lB { xB, xLen };
    cl::sycl::buffer<float, 1> lOut { y, xLen };

    q.submit([&](cl::sycl::handler & h) {
        auto hA = lA.get_access<cl::sycl::access::mode::read>(h);
        auto hB = lB.get_access<cl::sycl::access::mode::read>(h);
        auto hOut = lOut.get_access<cl::sycl::access::mode::write>(h);
        h.parallel_for<class kernel_name>(xLen, [=] (cl::sycl::id<1> i) {
            hOut[i] = hA[i] + hB[i];
        });
    });
    q.wait();
}
```



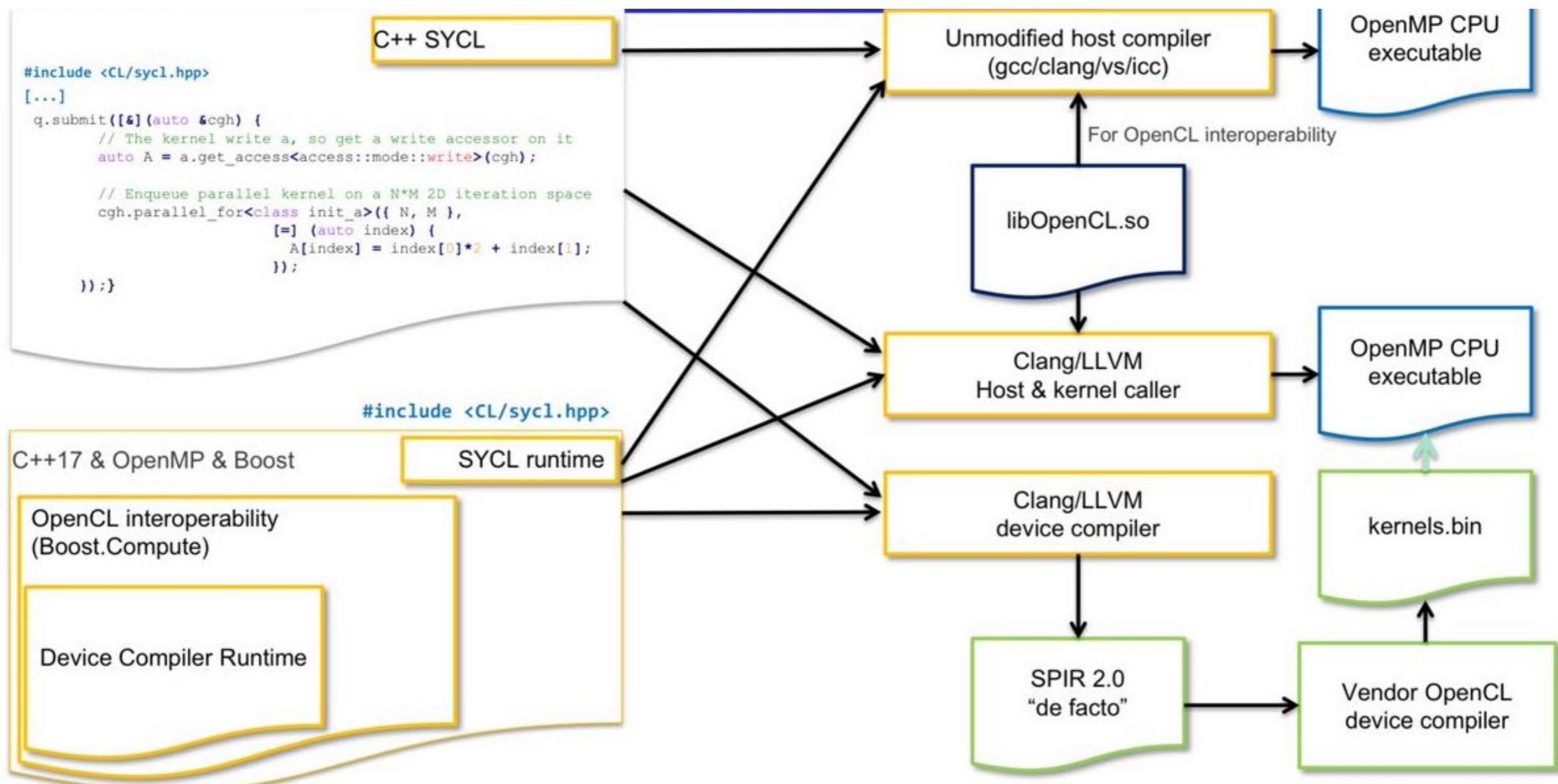
A lonely meaningful line, surrounded by boilerplate!

Vector Sum: SyCL STL

```
void sum_2_vectors(float const * xA,
                    float const * xB,
                    float * y,
                    int const xLen) {

    std::transform(cl::sycl::uniform_policy,
                  std::span(xA, xLen), std::span(xB, xLen),
                  std::span(y, xLen),
                  std::plus<float> { });
}
```

How SyCL works?



How SyCL works?

...here is what you actually
need to know

It's not a language!

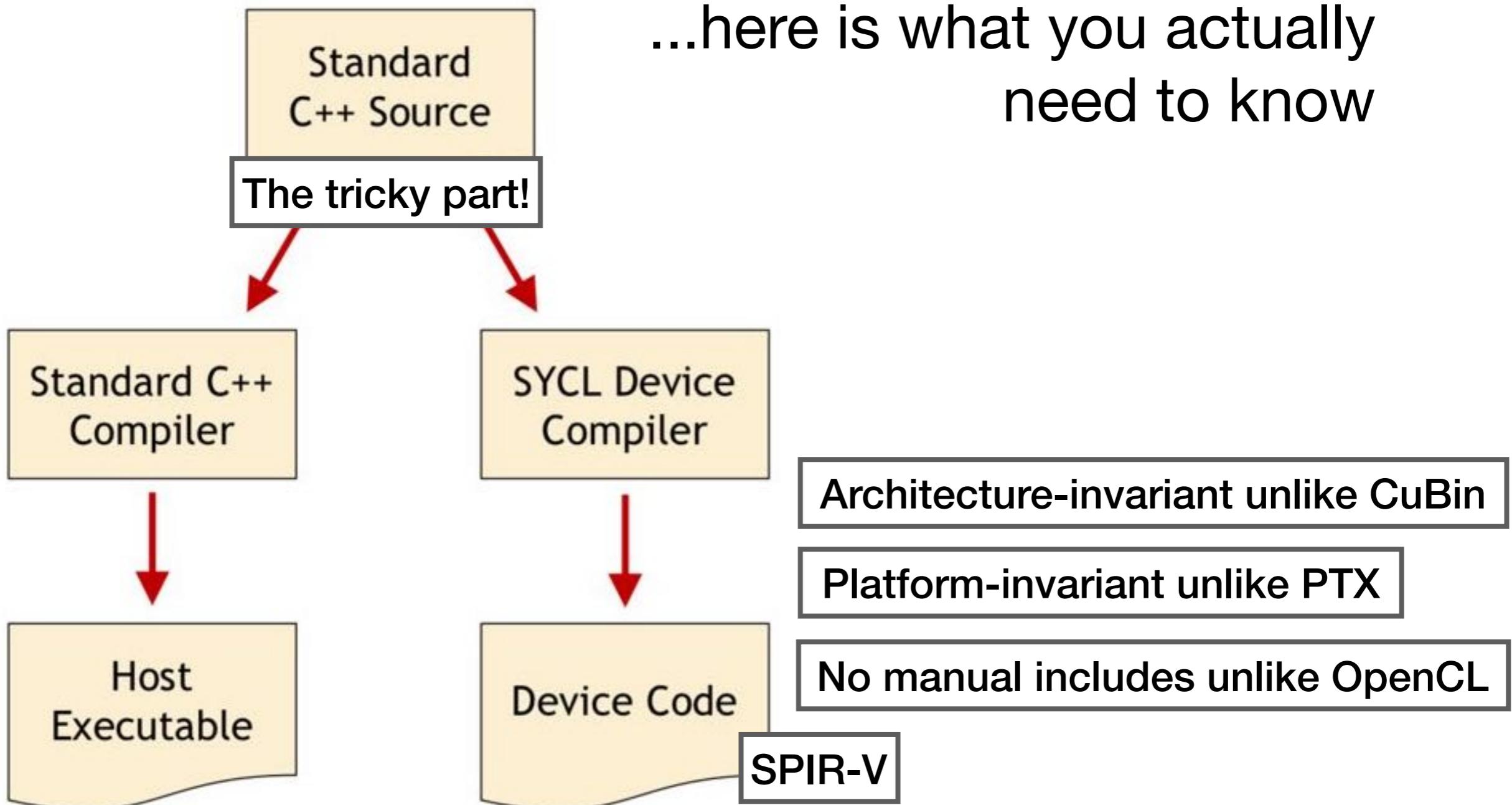
It's not a library!

It's not a compiler!

It's a combination of:

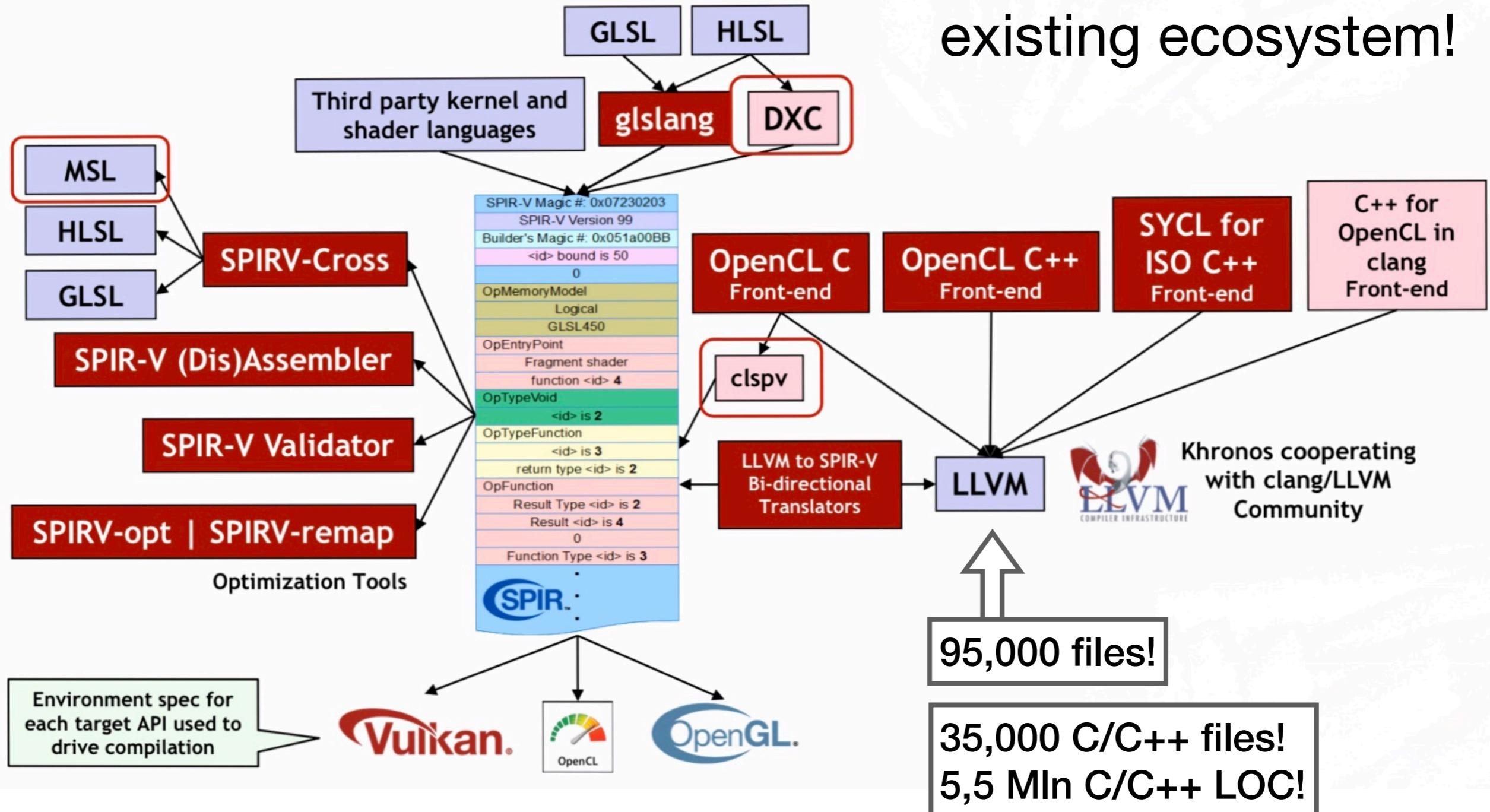
- library,
- compiler extensions!

How SyCL works?



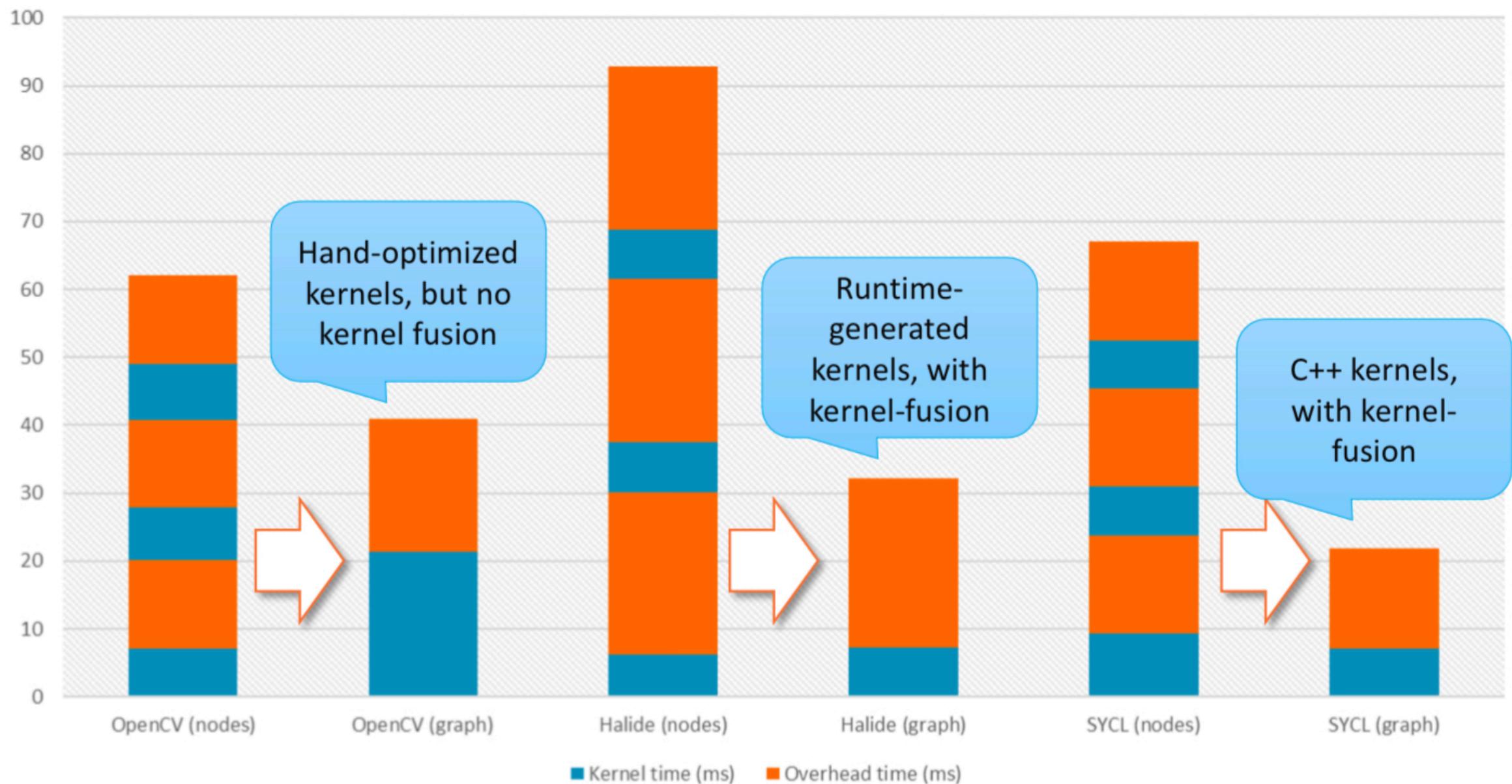
How SyCL works?

...it grows on top of the existing ecosystem!



Kernel Fusion

...impact on pipeline performance!



What to choose?

Compromises

Unified solution

...if you want cross platform binaries for your
custom hand-made kernels!

OpenCL
Source

SPIR-V
Binary

Google/clspv

Vulkan
Pipeline

OpenCL Source

SPIR-V Binary

Vulkan Pipeline

Pros

**Same binary runs everywhere,
easy to debug**

Concurrent queues

**Logical devices can represent
SLI groups**

**Same ecosystem for both
graphics and compute**

Cons

Separate CL/C++ codebases

Experimental stage compilers

No support for CUDA features:
warp shuffles,
hardware-specific instructions *,
L1 cache tuning

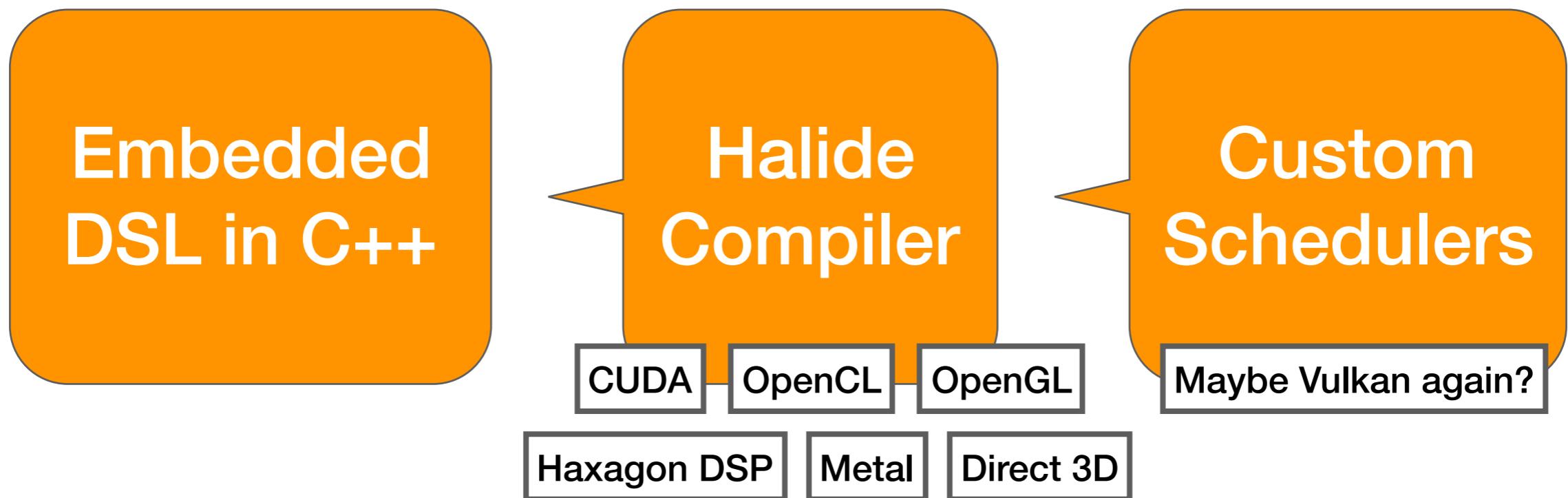
**No work-
arounds?**

100 TFlops?!

No modern C++ support until
version 2.2

Flexible solution

...if you want a flexible tool
here and now!



Embedded DSL in C++

Halide Compiler

Custom Scheduler

Pros

Great for prototyping and benchmarking

Generate binaries for every platform

Easy to export computational graphs into other libs

Easy to debug algorithms

Built-in tools for image processing

Cons

Turing-incomplete

Limited number of supported types

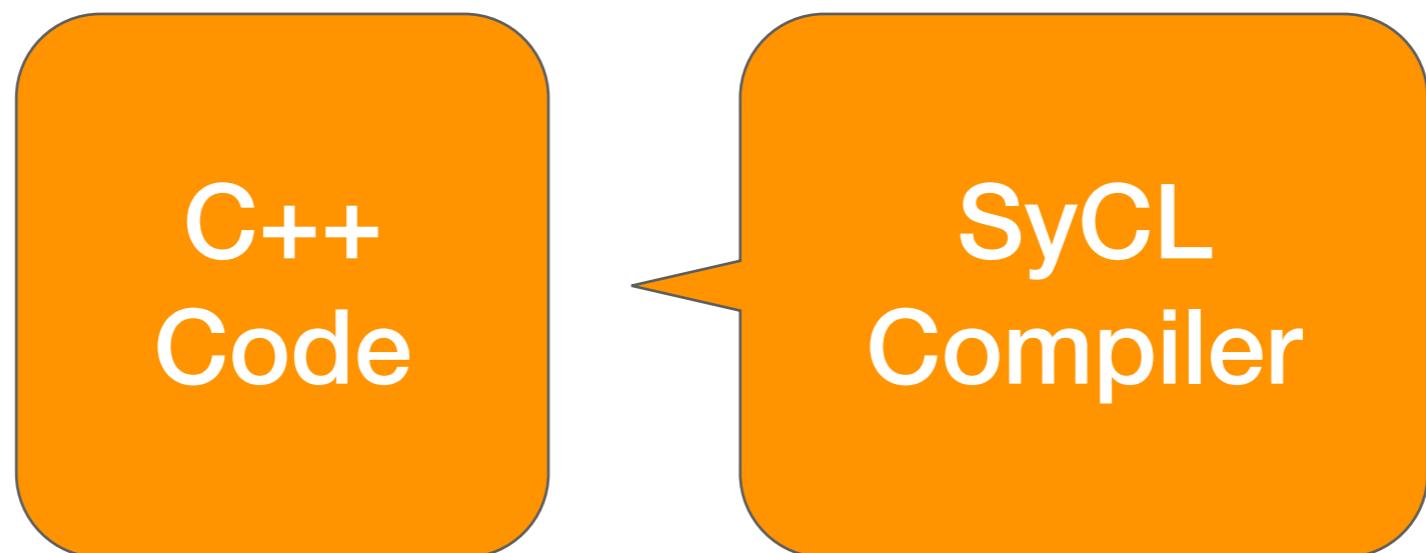
Huge LLVM dependency

Non-standard C++

Bad error messages

Clean solution

...if you want some classical
type-safe C++!



C++
Code

SyCL
Compiler

Pros

Use C++ templates and lambda functions for host & device code - just pass "sycl" policy

SYCL will not create C++ language extensions, but instead add features via C++ library

Does kernel fusion

Layered over OpenCL

Cons

Very immature, stability and C++17 adoption is expected closer to 2020

Underlying implementation requires compiler support

Kernel fusion may be weak

Boost.Compute dependency



Simple solution

...if you want a brute-force accelerator for simple data-parallel number-crunching!

High level GPGPU library
of choice like ArrayFire

High level GPGPU library of choice like ArrayFire

Pros

**Already packed with binaries for
multiple backends**

Minimal coding required

Cons

Weak kernel fusion

Comparison of recipes

...lets summarize our results!

	Simple	Unified	Flexible	Clean
Technology	ArrayFire	CL & SPIR-V	Halide	C++ SyCL
Write code once	Yes	Separate Files	T-Incomplete	Yes
Deploy everywhere	Almost	Yes	Yes	Eventually
Optimise performance	Average	High	Highest	High
Avoid boilerplate	YES!	Depends	Depends	Yes

Comparison of recipes

...lets summarize our results!

		Max Performance Today	
Technology		CL & SPIR-V	Halide
Write code once		Yes	T-Incomplete
Deploy everywhere		Yes	Yes
Optimise performance		High	Highest
Avoid boilerplate		Depends	Depends

Comparison of recipes

...lets summarize our results!

		Sometime in the Future		
Technology				C++ SyCL
Write code once				Yes
Deploy everywhere				Eventually
Optimise performance				High
Avoid boilerplate				Yes

Tips & Tricks

OpenCL Tips

1. Unroll loops & inline functions manually!
2. Violate the IEEE 754 standard:
 - Accuracy: `-cl-unsafe-math-optimizations`, `-cl-mad-enable`
 - Zeroes: `-cl-finite-math-only`, `-cl-no-signed-zeros`
3. **Use special functions:**
 - Work with fractions: `remainder()`, `remquo()`, `fract()`
 - Perform multiple actions: `fma()`, `sincos()`, `expm1()`, `mad()`
 - OpenCL knows Pi: `tanpi()`, `sinpi()`, `atanpi()`, `atan2pi()`
4. Don't create too many command buffers!



CUDA Tips

1. Similarly, use fast math functions:
 - Half precision: `__hadd()`, `__hadd_sat()`, `__hmul()`, `__hneg()`
 - Control rounding: `__fadd_rd()`, `__fadd_rz()`, `__fadd_rn()`
 - Perform multiple actions: `__fmaf_rd()`, `__sincosf()`
2. Use the ecosystem!
 - **Mixed Precision Math libraries.**
 - cuBLAS & cuDNN.
3. Transform CUDA stream code into multi-GPU reusable dependency graph.

Existing Ecosystem

Symbolic Graph	TF, PyTorch, cuDNN, MKL-DNN
Lazy Evaluation	Eigen, TF , VexCL, ArrayFire
Linear Algebra	Eigen, MKL, VexCL, cuBLAS, ArrayFire , Boost.Compute
Scheduling	Intel TBB, Vulkan, OpenMP , SyCL
Language & Extensions*	CUDA, OpenCL , GLSL, OpenMP, OpenACC
Compilers*	LLVM, TVM , GCC

Where to apply?



Unum

Scalable & cheap analytics with modern ML techniques.

Built on top of:

- C++14 since 2015,
- C++17 since 2017,
- OpenCL, LLVM,
- Eigen, ArrayFire.

Working on a new programming language now - **C***.

Why? Existing Problems

Symbolic Graph	TF, PyTorch, Too big to navigate & embed!
Lazy Evaluation	Eigen, TF , VexCL, Limited serialisation beyond ONNX!
Linear Algebra	Eigen, MKL, VexCL, cuBLAS , ArrayFire , Boost.Compute
Scheduling	Intel TBB, Vulkan, OpenMP , SyCL Verbose!
Language & Extensions*	CUDA , OpenCL , Same, but fragmented!
Compilers*	LLVM , Single point of failure!

Goals for C*

Performance higher than in C++.

Kernel fusion > Inlining

As simple as Common LISP.

Interpretable into C, OpenCL, CUDA

Flexible like Halide.

Tuning is separate from logic



Q & A

The talk:

- [github.com/ashvardanian/
SandboxGPUs](https://github.com/ashvardanian/SandboxGPUs)

The project:

- unum.xyz
- github.com/unumxyz

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