std::simd

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Outline

Introduction

A Data-Parallel Type

`std::simd`

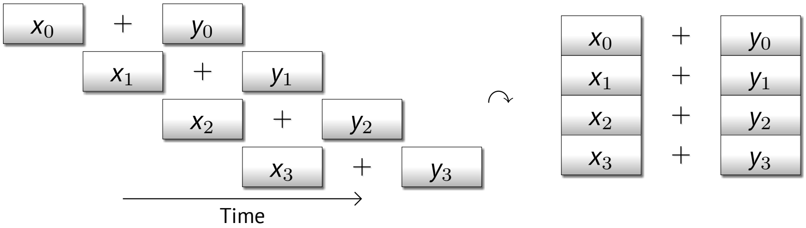
Vector Unit (SIMD)

multiple operations in one instruction

operation often a C++ operator, e.g. +, −, *

instruction one step of machine code
(basic idea: a CPU core executes instructions serially in the specified order)

SIMD – Single Instruction Multiple Data



Data-Parallelism

Data Parallel

- same code
- different data
- may execute in parallel

Example

```
for (auto &x : data) {
  x = transform(x); // transform is a
                    // pure function
}
```

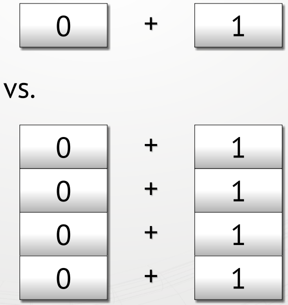
SIMD in the IS

- We have the `unseq` and `par_unseq` execution policies. 👍
- Program-defined code executed from parallel algorithms exposes “vector semantics”:
  - different from C++’s sequenced-before semantics
  - access to globals may have surprising results
  - thread synchronization has undefined behavior
  - exceptions have undefined behavior
  - no I/O (e.g. “printf debugging”)
- Implementations might need all called functions to be `inline` to actually perform vectorization
- Control-flow (`break`, `return`, …) often inhibits vectorization
- Loop based vectorization provides no intuition or support with data structures.

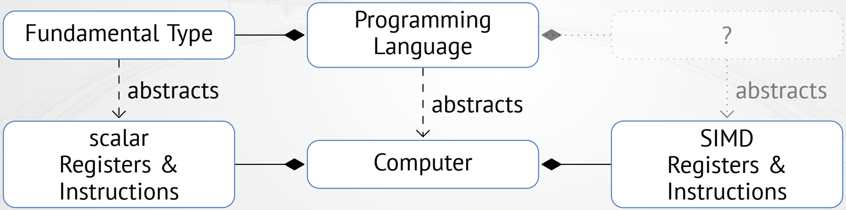
Data-Parallel Types

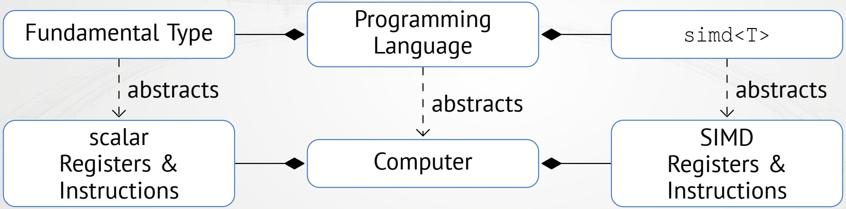
One variable stores $\mathcal{W}_{\mathrm{T}}$ values. ($\mathcal{W}$ for "width")
One operator signifies $\mathcal{W}_{\mathrm{T}}$ operations (element-wise).

```
int x = 0;
x += 1;
```




```
std::simd<int> x = 0;
x += 1;
```


Fundamental Type
Programming Language
?
abstracts
abstracts
abstracts
scalar Registers & Instructions
Computer
SIMD Registers & Instructions


Fundamental Type
Programming Language
simd<T>
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SIMD Registers & Instructions

- In contrast to SIMT and vector loops, `std::simd` makes the chunk size a constant expression.
- Operation on a larger index space than $\mathcal{W}_{\mathrm{T}}$ requires a loop and/or multiple threads.
- Clear separation of serial, SIMD-parallel, and thread parallel execution.
- No restriction on I/O, exceptions, function calls, and synchronization.
- API & ABI for vectorization across multiple translation units (and library boundaries).
  - The `std::simd` ABI could be the ABI for function calls from `unseq` loops.

Example

One multiplication:

```
float f(float x) {
  return x * 2.f;
}
```

https://godbolt.org/z/1TY9jbqqj

$\mathcal{W}_{\mathrm{T}}$ multiplications in parallel:

```
std::simd<float> f(std::simd<float> x) {
  return x * 2.f;
}
```

Data-Parallel Conditionals

Example

One compare and 0 or 1 assignment:

```
float f(float x) {
  if (x > 0.f) { x *= 2.f; }
  return x;
}
```

$\mathcal{W}_\mathrm{T}$ compares and $0-\mathcal{W}_\mathrm{T}$ assignments in parallel:

```
std::simd<float> f(std::simd<float> x) {
  x = std::conditional_operator(
        x > 0.f, x * 2.f, x);
  return x;
}
```

`https://godbolt.org/z/8Ex6obEfx`

- Compares yield $\mathcal{W}_\mathrm{T}$ boolean answers
- Return type of compares: `std::simd_mask<T, Abi>`
- Reduction functions: `all_of`, `any_of`, `none_of`
- `simd` code typically uses no/few branches, relying on masked assignment instead

Conditional Operator (P2600 and P0917)

Example

TS syntax

```
template <typename T> T f(T x) {
  stdx::where(x > 0.f, x) *= 2.f;
  return x;
}
```

`f` is “vectorizable” in the sense that it can be specialized for `float` and `stdx::simd<float>`.

Preferred C++26 syntax

```
template <typename T> T f(T x) {
  return x > 0.f ? x * 2 : x;
}
```

So much simpler and clearer. Easy to write `simd`-compatible code before ever using `simd`.

Generic code! 🔥 (My GCC can do it 😉.)

**The semantics of data-parallel types
teach developers to design scalable and portable parallelization.**

Target-dependent $\mathcal{W}_T$
Conversions between scalar and vector objects
Conditional assignment instead of branching

- It becomes clear that data structures are the main challenge
  - Translating an inherently data-parallel algorithm to data-parallel types is often trivial
  - However, where do `simd` objects come from, and where can you put them?
  - With vector loops and SIMT it is easy … to write inefficient memory access patterns.
- Using SIMD types makes the design challenges wrt. efficient vectorization obvious
- Subsequent designs can profit from this experience

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Abstract

- Conceptually: SIMD types express data-parallelism.
- Wrong mindset: SIMD types are specific SIMD registers.

Which is why I like to call them “data-parallel types”.

There are implementations

...and lots of existing practice

- `std::experimental::simd` in libstdc++ since GCC 11
- `vir::stdx::simd` at `https://github.com/mattkretz/vir-simd/`
- `std::(experimental::)simd` implementation from Intel in progress
- `std::simd` prototyping `https://github.com/mattkretz/simd-prototyping/`

more existing practice

- Agner Fog's Vector Types
- E.V.E.
- xsimd
- Vc
- ...

Overview

```
template <typename T, typename Abi = ...>
  class simd;

template <typename T, typename Abi = ...>
  class simd_mask;
```

- `T` must be a "vectorizable" type (arithmetic except bool)
  Note: Daniel Towner wants to add `std::complex`, I plan to add enums, and with reflection I'll look into UDTs.
- `simd<T>` behaves just like `T` (as far as is possible)
- `simd_mask<T>` behaves like `bool`
  In contrast to `bool`, there are many different mask types:
  - storage: bit-masks vs. element-sized masks (and `vir-simd` uses array of `bool`),
  - SIMD width `simd::size`
- `Abi` determines width and ABI (i.e. how parameters are passed to functions)

ABI tag default

- The TS uses the wrong default for the ABI tag (my strong opinion, to be fixed for C++26).
- The TS gives you the lowest common denominator for all possible implementations of the target architecture.
- So you want to always use `stdx::native_simd<T>` instead. (This will be `std::simd<T>`).
- `native_simd` sets the ABI tag to the widest efficient $\mathcal{W}_\mathrm{T}$ for your `-march=` setting. It also influences the representation of `simd_mask` (i.e. the `sizeof` may be very different).
- Note that therefore `std::simd` ABI depends on `-m` flags!

Constructors (simplified)

```
template <typename T, typename Abi = ...>
class simd {
  simd() = default;
  simd(T);
  simd(contiguous_iterator auto const&, Flags);
  simd(Generator);
}
```

- The defaulted *default* constructor allows uninitialized and zero-initialized objects.
- The *broadcast* constructor initializes all elements with the given value.
  - Requires value-preserving conversion (P2509R0)
- The *load* constructor reads $\mathcal{W}_{\mathrm{T}}$ elements starting from the given address.
  - `Flags` provides a hint about alignment (and can be extended to do more: in Vc it controls streaming loads & stores, prefetching; P1928R3 suggests control over conversions)
- The *generator* constructor initializes each element via the generator function.
  - The generator function is called with `std::integral_constant<std::size_t, i>`, where `i` is the index of the element to be initialized.

Constructor examples

```
stdx::native_simd<int> x0; // uninitialized

stdx::native_simd<int> x1{}; // zero-initialized

stdx::native_simd<int> x2 = 1; // all elements are 1

stdx::native_simd<int> x3(addr, stdx::vector_aligned); // load from aligned address

stdx::native_simd<int> iota([](int i) { return i; }); // [0, 1, 2, 3, 4, ...]
```

Loads & stores

You need to interact with the world somehow…

```
void f(std::vector<float>& data) {
  using V = stdx::native_simd<float>;
  for (std::size_t i = 0; i < data.size(); i += V::size()) {
    V v(&data[i], stdx::element_aligned);
    v = sin(v);
    v.copy_to(&data[i], stdx::element_aligned);
  }
}
```

- The member functions `copy_from` and `copy_to` allow "conversion" from/to arrays of `T`.
- The above applies the sine to all values in `data`.
- Don't be afraid that this copy costs performance.
  - Consider loading from memory into a register / storing from register into memory.
  - This is a necessary cost that always happens anyway.
- There's a bug, though…

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Loads & stores (fixed)

You often need an “epilogue”:

```
void f(std::vector<float>& data) {
  using V = stdx::native_simd<float>;
  std::size_t i = 0
  for (; i + V::size() <= data.size(); i += V::size()) {
    V v(&data[i], stdx::element_aligned);
    v = sin(v);
    v.copy_to(&data[i], stdx::element_aligned);
  }
  for (; i < data.size(); ++i) {
    data[i] = std::sin(data[i]);
  }
}
```

- Having to write the epilogue every time is *error prone.*
- The TS does not come with supporting code, but P0350 proposes useful higher-level API.

Subscripting

Loads & stores are great, but sometimes you just want to access it like an array.

```
void f(stdx::native_simd<float> x) {
  for (std::size_t i = 0; i < x.size(); ++i) {
    x[i] = foo(x[i]);
    auto ref = x[i];
    ref = foo(x[i]); // ERROR doesn't compile
    x[i] = float(ref); // OK
  }
}
```

- non-`const` subscripting returns a `simd::reference`
- this type implements all non-const operators, i.e. (compound) assignment, increment and decrement, and also `swap`.
- all of the above functions are rvalue-ref qualified, i.e. are only allowed on temporaries
- What we all actually expect would be a *decay* of the reference proxy to the element type. Another paper I still have to write and defend in the committee.
- the conversion operator is not ref qualified

Arithmetic & math

This is what you all came for, I guess

```
void f(stdx::native_simd<float> x, stdx::native_simd<float> y) {
  x += y; // 𝒲float additions
  x = sqrt(x); // 𝒲float square roots
  ... // etc. all operators and <cmath>
}
```

- Operations act element-wise
- Speed-up is often a factor of $\mathcal{W}_{\mathrm{T}}$, but may be less, depending on hardware details.

Same for compares

```
void f(stdx::native_simd<float> x, stdx::native_simd<float> y) {
  if (x < y) {} // nonono, you don't write 'if (truefalsetruetrue)' either
  where(x < y, x) = y; // x = y but only for the elements where x < y
  if (all_of(x < y)) {} // this makes sense, yes
}
```

- Comparisons return a `simd_mask`.
- `simd_mask` is not convertible to `bool`.
- `simd_mask` can be *reduced* to `bool` via `all_of`, `any_of`, or `none_of`.
- The SIMT model does not expose the nature of its `if` statements in code. It seems like branching but it isn't really. With `std::simd` it is explicit.