Wojciech Muła, 0x80.pl January 2021 Thanks to Roman Kurc & Daniel Lemire for valuable feedback

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What do we cover?

What are vector instructions/SIMD instructions

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- ► What are vector instructions/SIMD instructions
- Why are they important

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- What are they good for

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- An array can hold anything, not only bare numbers, but also pixels (images), samples (sound), points (3D models), characters (text)

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$$b = (7, 1, 4, 2, 3, 5, 1, 0)$$

Their sum *c* is:

$$c = a + b = (8, 3, 7, 6, 8, 11, 8, 8)$$

A program that performs vector addition is quite simple:

```
 c[0] = a[0] + b[0] 
 c[1] = a[1] + b[1] 
 c[2] = a[2] + b[2] 
 c[3] = a[3] + b[3] 
 c[4] = a[4] + b[4] 
 c[5] = a[5] + b[5] 
 c[6] = a[6] + b[6] 
 c[7] = a[7] + b[7]
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 c[7] = a[7] + b[7]
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It can be written with a loop:

for (int 
$$i=0$$
;  $i < 8$ ;  $i++$ )  
c[i] = a[i] + b[i];

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for (int i=0; i < 8; i++)
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- ▶ 16 loads from memory (a[0..7] and b[0..7])
- 8 additions (+)
- ▶ 8 stores to memory (c[0..7])

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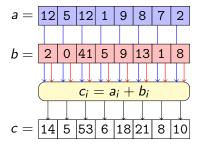
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- GPUs usually have SIMD execution units
- Vector instructions are not the only mean of speeding up vector calculation, there are CPUs having vector architectures built entirely around the concept of arbitrary length vectors

# How vector operations work?

Suppose vectors have 8 elements Operation is c = a + b



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- ► SIMD means: Single Instructions, Multiple Data
- Here "multiple data" means "a vector"
- ► Most **CPU cores** work in SISD model: *Single Instruction, Single Data*

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Va = vector_load(a);  // Va holds 8 elements
Vb = vector_load(b);  // ... likewise Vb
Vc = vector_add(Va, Vb);  // execute 8 additions
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- ► What we pay for are **instuctions**

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- ... but we can expect significant boost over most of regular CPU instructions

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#### What is a hardware vector?

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- ▶ Some CPU architectures support only integer operations

#### Hardware vs software vectors

For instance a 256-bit vector can be used in a program as the following vectors (C/C++ types)

- ▶ int8\_t[32], uint8\_t[32]
- int16\_t[16], uint16\_t[16]
- int32\_t[8], uint32\_t[8]
- int64\_t[4], uint64\_t[4]
- ▶ float[8]
- ▶ double[4]

# Existing SIMD implementations

cryptic name	vendor	year	vector width [bits]
MMX	Intel	1997	64
3DNow	AMD	1998	64
AltiVec	many	1998	128
SSE	Intel	1999	128
_	ARM	2002	32
SSE2	Intel	2001	128
SSE3	Intel	2004	128
SSSE3	Intel	2006	128
SSE4	Intel	2007	128
AVX	Intel	2008	256
XOP	AMD	2010	128
Neon	ARM	2011	64
AVX2	Intel	2013	256
Neon	ARM	2014	128
AVX-512	Intel	2015	512
SVE	ARM	???	1024-4096

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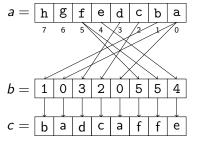
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- blending two vectors (ternary operation s ? a : b)
- integer addition / subtraction / type casts using saturated arithmetic

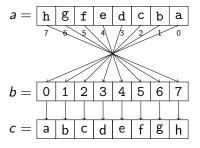
# Example of shuffle — arbitrary order of elements

Operation is c = shuffle(a, b)



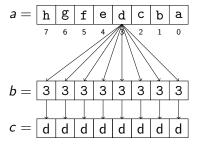
## Example of shuffle — reverse

Operation is c = shuffle(a, b)



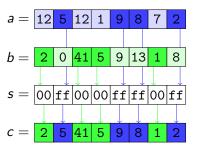
# Example of shuffle — broadcast

Operation is c = shuffle(a, b)



# Example of blend

Operation is c = s ? a : b



As a raw bit operations c = (s and a) or (not s and b)

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- $\min(240 + 100, 255) = \min(340, 255) = 255$

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- Saturated arithmetic is as fast as wrap-around one

Saturated addition example — increase image brightness

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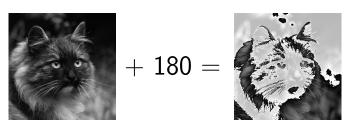
Wrap-around arithmetic





# Saturated addition example — increase image brightness

Wrap-around arithmetic



Saturated arithmetic



#### SIMD instructions in real life

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1 void vector_add(float* a, float* a, float* c, size_t N) {
2     for (size_t i=0; i < N; i++)
3         c[i] = a[i] + b[i];
4 }</pre>
```

#### SIMD instructions in real life

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How about adding two vectors of arbitrary size? (c = a + b)
   void vector_add(float* a, float* a, float* c, size_t N) {
       for (size_t i=0; i < N; i++)
           c[i] = a[i] + b[i];
   Function vector_add can rewritten (vectorized) as:
   void vector_add(float* a, float* b, float* c, size_t N) {
       for (size_t i=0; i < N; i += 8) {
           auto Va = vector\_load(a + i);
           auto Vb = vector\_load(b + i);
           auto Vc = vector_add(Va, Vb);
           vector_store(c + i, Vc);
7
8
       for (size_t i = (N / 8) * 8; i < N; i++)
           c[i] = a[i] + b[i];
10
11
```

#### Is it really better?

```
1  void vector_add(float* a, float* b, float* c, size_t N) {
2     for (size_t i=0; i < N; i += 8) {
3         auto Va = vector_load(a + i);
4         auto Vb = vector_load(b + i);
5         auto Vc = vector_add(Va, Vb);
6         vector_store(c + i, Vc);
7     }
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9     for (size_t i=(N / 8) * 8; i < N; i++)
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Now it is more complicated, as there are two loops

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- ▶ We need to know how these magic vector\_foo functions work to reason about the code
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- ▶ What if we wanted to port it for another CPU, which is capable to process 16, 32 or 64 numbers?

#### More complex code pays off in peformance boost

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- SIMD requires designed data structures to use full power
- ... typical example: instead of a single array of records use separate array for each record's field

# More realistic example — signal mixing

Following vector code mixes two signals (image, sound) using linear interpolation

$$c = a \cdot p + b \cdot (1 - p), p \in [0, 1]$$

```
void vector_lerp(float* a, float* b, float* c, size_t N, float p) {
       auto Vp = vector\_broadcast(p); // Vp = [p, ..., p]
       auto Vq = vector\_broadcast(1 - p); // Vq = [1-p,...,1-p]
       for (size_t i=0; i < N; i += 8) {
           auto Va = vector_load(a + i);
6
           auto Vb = vector\_load(b + i);
           auto Vt0 = vector_mul(Va, Vp); // a * p
8
           auto Vt1 = vector_mul(Vb, Vq); // b * (1 - p)
9
           auto Vc = vector_add(Vt0, Vt1);
10
           vector_store(c + i, Vc);
11
12
       for (size_t i = (N / 8) * 8; i < N; i++)
13
           c[i] = (a[i] * p) + (b[i] * (1 - p));
14
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- Compilers can autovectorize loops they do similar transformation as we did to vector\_add
- Autovectorization is not as smart as human, but is decent

### Signal mixing in practise

This is actual C++ code for signal mixing which uses Intel intrinsics functions for AVX2 extension (full list on Intrinsics Guide)

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#include <immintrin.h>
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    void vector_lerp(float* a, float* b, float* c, size_t N, float p) {
        _{m256} Vp = _{mm256_{set1_{ps(p)}}}
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         for (size_t i=0; i < N; i += 8)
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    It compiles! gcc -mavx2 -c vector-lerp-avx2.cpp
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- ► More and more software libraries use SIMD instructions, we can benefit from it without changing our code