"What makes a program fast" or "How CPUs are complex beasts"

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Section 1

What is this talk about

Recent articles

You might have seen a recent article/talk regarding CPUs and how they affect our code.

- C Is Not a Low-Level Language (2018) Hacker News
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This talk is an extension of that

A basic concept of CPUs

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A basic concept of CPUs

In order to understand CPUs and how they affect us we need to understand a couple of simple concepts:

- A CPU is currently a Hardware VM
- Memory is really slow compared to cache

Latency scale

System Event	Actual Latency	Scaled Latency
CPU Cycle	0.4 ns	1 s
L1 Cache access	0.9 ns	2 s
L2 Cache access	2.8 ns	7 s
L3 Cache access	28 ns	1 min
Main Memory access	$\sim\!100~\text{ns}$	4 min

Section 2

Let's explore CPU optimizations

The code to optimize

```
sum(
   object.key
   for object in list_of_objects
   if object.key < 0.5
)</pre>
```

A note about these benchmarks

In practice we will do all the benchmarks in C++ as it will allow us control over the code generated.

All of these methods are CPU dependent though and should be useful regardless of programming language used.

The object itself that we will measure

```
struct Object {
    float key;
    int filler1;
    int filler2;
    int filler3;
    int filler4;
    int filler5;
    int filler6;
    int filler7;
};
```

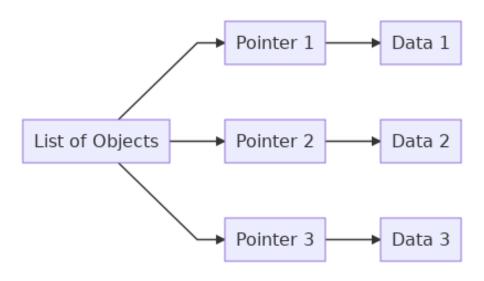
Section 3

The naive version

The code

```
static void naiveVersion(benchmark::State &state) {
    auto elements = naiveObjects(state.range(0));
    for (auto : state) {
        float total = 0;
        for (const auto &element : elements) {
            if (element->key < 0.5) {
                total += element->key;
            }
        benchmark::DoNotOptimize(total);
```

How is it structured in memory?



The measurements

Benchmark	Elements	Time	Iterations
Naive	8	7 ns	100597298
Naive	64	53 ns	12658713
Naive	512	419 ns	1702633
Naive	4096	15597 ns	44802
Naive	32768	167514 ns	4132
Naive	65536	342738 ns	2046

Section 4

Data Local version (Removing one indirection)

The code

```
static void localVersion(benchmark::State &state) {
    auto elements = localObjects(state.range(0));
    for (auto : state) {
        float total = 0;
        for (const auto &element : elements) {
            if (element.key < 0.5) {
                total += element.key;
            }
        benchmark::DoNotOptimize(total);
```

How is the memory laid out?



The results

Benchmark	Elements	Time	Iterations
Local	8	6.22 ns	98679509
Local	64	45.4 ns	12803676
Local	512	425 ns	1588957
Local	4096	14199 ns	49682
Local	32768	147016 ns	4733
Local	65536	295354 ns	2378

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- In C/C++ it's a matter of just using structs
- In Java you can't do this, it's in progress with Project Valhalla :(
- In C# they are the so-called structs too
- Usually called Value Types, so search for them in your preferred language

Section 5

Columnar version

The idea

• We are storing "rows" of objects

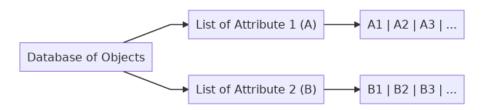
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- We are storing "rows" of objects
- What if we store one column per attribute instead?

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- We are storing "rows" of objects
- What if we store one column per attribute instead?
- We only have to iterate all the key attribute instances that are packed next to each other!

The memory layout



The code

```
static void columnar Version (benchmark:: State & state) {
    auto elements = columnarObjects(state.range(0));
    auto &column = elements.getColumn<0>();
    for (auto : state) {
        float total = 0;
        for (const auto element : column) {
            if (element < 0.5) {
                total += element:
        benchmark::DoNotOptimize(total);
```

The results

Benchmark	Elements	Time	Iterations
Columnar	8	6.34 ns	111646812
Columnar	64	48.9 ns	13275731
Columnar	512	422 ns	1573965
Columnar	4096	12675 ns	55300
Columnar	32768	139632 ns	4997
Columnar	65536	287098 ns	2449

 \dots just a 3% decrease over the previous results

Section 6

Pros and cons

Pros:

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- Allows vectorization of code if needed (will be shown)

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- Will couple database with object type

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But can we make it faster?

Section 7

Let's talk about the CPU pipeline

What is it

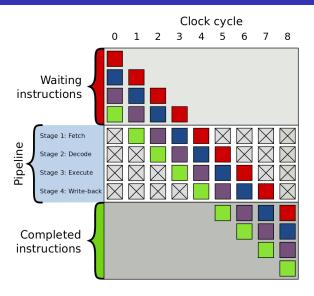


Figure 1: Pipeline

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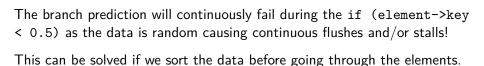
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Usually CPUs will do a combination of all of these:

- Stall the pipeline a bit by inserting a NOP in some steps and waiting until results can be used
- Predict which branch we usually take and accordingly pipeline their instructions in order to avoid stalling
 - If we fail to predict then we have to flush all the pipelined instructions and rewind back to where we should be.
 - Current Intel CPUs have upwards of 14/16 stages so a flush can be VERY expensive.

Let's go back to the naive version

```
static void naiveVersion(benchmark::State &state) {
    auto elements = makeDataElements(state.range(0));
    for (auto : state) {
        float total = 0;
        for (const auto &element : elements) {
            if (element->key < 0.5) {
                total += element->key;
            }
        benchmark::DoNotOptimize(total);
```



The results

Benchmark	Elements	Time	Iterations
Naive + Sorted	32768	49329 ns	14257
Naive + Sorted	65536	120139 ns	6129
Local + Sorted	32768	36984 ns	18995
Local + Sorted	65536	74605 ns	9569
${\sf Columnar} + {\sf Sorted}$	32768	24906 ns	27385
${\sf Columnar} + {\sf Sorted}$	65536	50529 ns	13968

The gains are pretty substantial!

We've decreased the time taken by

Type of data	Before	After	Reduction %
Naive version	342738 ns	120139 ns	~65%
Local version	295354 ns	74605 ns	~75%
Columnar version	287098 ns	50529 ns	~82%

A caveat for this particular case

Current CPUs have assembly instructions for doing conditional moves that effectively nullifies the difference between sorted and unsorted sets in our example.

These are called conditional moves and exist both for integers and floats. Oddly enough, the compilers are only using the integer ones and disregarding the assembly codes for floating point conditional moves.

This example wanted to showcase the branch prediction thus the reason for using floats and not ints.

Section 8

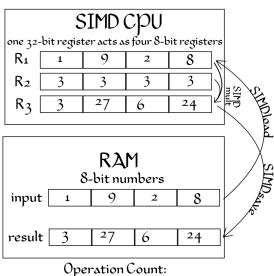
One final trick with SIMD

What is it

Single Instruction Multiple Data

Also called Vectorization

How it works



Operation Count: 1 load, 1 multiply, and 1 save

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- ullet C# has the capability by using the System.Numerics package
- \bullet C/C++ has CPU intrinsics available, but I personally use xsimd to be CPU independent

The final results

Benchmark	Elements	Time	Iterations
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Naive + Sorted	65536	120139 ns	6129
Local + Sorted	65536	74605 ns	9569
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${\sf Columnar} + {\sf Sorted} + {\sf SIMD}$	65536	16622 ns	41787

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We've achieved a:

- \sim 67% reduction of time spent compared to the sorted columnar version, or a 3x increase in throughput
- \sim 95% reduction of time spent compared to the original naive version, or a 20x increase in throughput

A final note about all of this

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- In low numbers almost none of this matters
 - Except SIMD for obvious reasons

Elements	Time	Iterations
512	422 ns	1699728
512	430 ns	1666707
512	454 ns	1495578
512	445 ns	1596756
512	554 ns	1265820
512	400 ns	1874843
512	133 ns	5061195
	512 512 512 512 512 512 512	512 430 ns 512 454 ns 512 445 ns 512 554 ns 512 400 ns

Conclusion

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- Only do this if you absolutely need the performance.
- Most of the time don't even bother being smart about code, memory layout, or CPU specifics until you reach a certain size