

Code Optimization Many Fundamental Techniques

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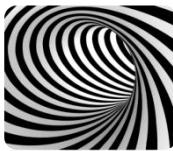
Outline



Avoid the avoidable
inefficiencies



Cache &
Memory



Loops



Unleash
the
Compiler

Pipelines

Outline



Avoid the avoidable
inefficiencies



Branches



Pipelines



Cache &
Memory



Loops



Unleash
the
Compiler



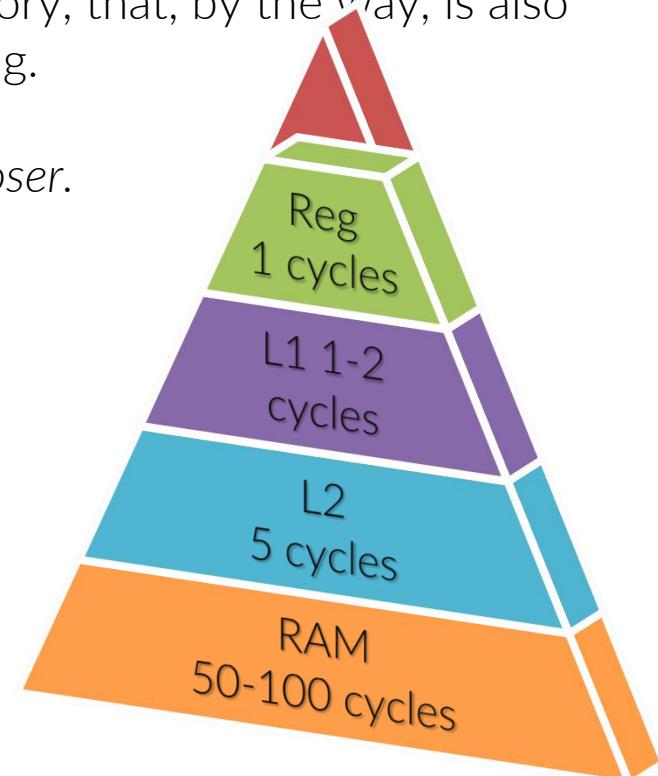
The cache memory

The solution is to equip your CPU with a *faster* memory, that, by the way, is also way more expensive and way more energy consuming.

Furthermore, to be faster it ought to be *extremely closer*. All in all, the new memory that will be called **cache**, will be much *smaller* than RAM.

The cache itself has a hierarchy:

- Level-I is inside each core.
- Level-II is also inside the core, or may be shared by more cores.
- Level-III is inside the CPU, shared by many cores.





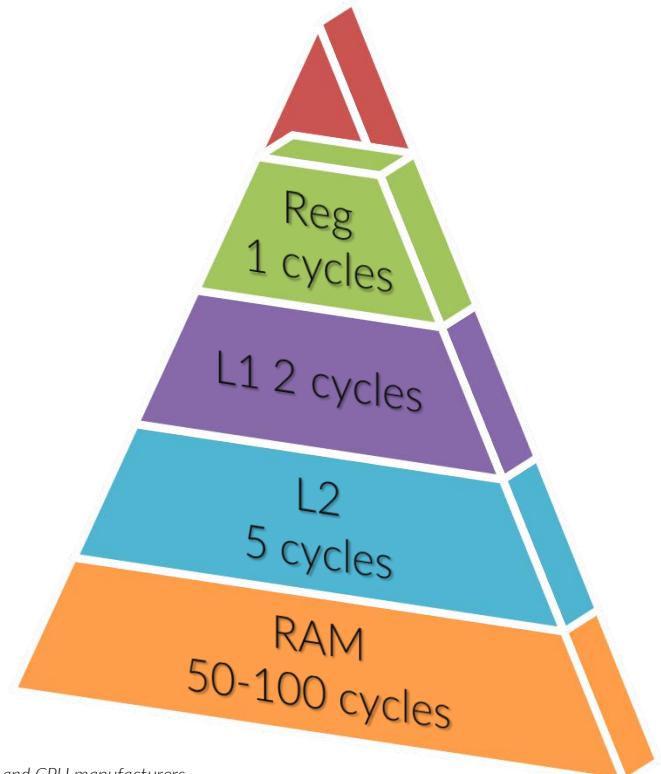
The cache memory

The cost of memory access

L1 cache + RAM

$$L_{1\text{cost}} + Miss_1 \times RAM_{\text{cost}}$$

- 100% L1 hit → 1-2 cycles
- 99% L1 hit → 2.5 - 3
- 97% L1 hit → 3.5 - 5 cycles



These figures are not "exact", they are just representative. True ones depend on the details of the system, DDRx CAS latency and other characteristics, and CPU manufacturers



L1 cache + RAM

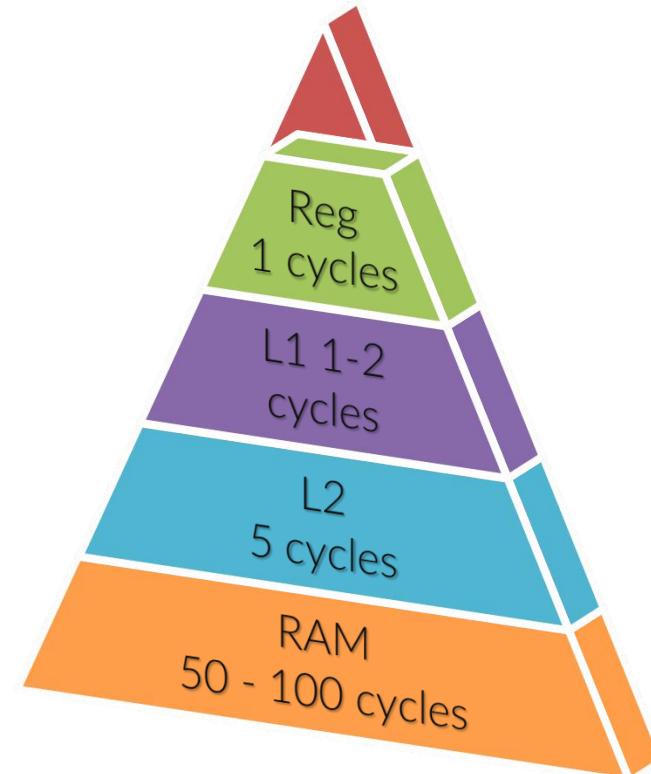
$$L_{1cost} + Miss_1 \times RAM_{cost}$$

- 100% L1 hit → 1-2 cycles
- 99% L1 hit → 2.5 - 3 cycles
- 97% L1 hit → 3.5 - 5 cycles

L1 cache + L2 cache + RAM

$$L_{1cost} + Miss_1 \times (L2_{cost} + Miss_2 \times RAM_{cost})$$

- 100% L1 hit → 1-2 cycles
- 99% L1 hit, 100% L2 hit → 1.04 - 2 cycles
- 97% L1 hit, 100% L2 hit → 1.12 - 2.1cycles
- 90% L1 hit, 97% L2 hit → 1.6 - 2.6 cycles





The principle of locality

We are quite naturally led to the “principle of locality”:

Data are defined “local” when they reside in a “small”portion of the address space that is accessed in some “short” period of time

→ local data are likely to be in the cache

Temporal locality if an address is referenced, it is likely to be referenced again soon

Spatial locality if an address is referenced, close addresses are likely to be referenced soon



Cache recap in two slides

**3C for the
foes**

▶ **Compulsory misses**

Unavoidable misses when data are read for the first time

▶ **Capacity misses**

- Not enough space to hold all data
- Too much data accessed in between successive use

▶ **Conflict misses**

Cache trashing due to data mapping to same cache lines



Cache recap in two slides

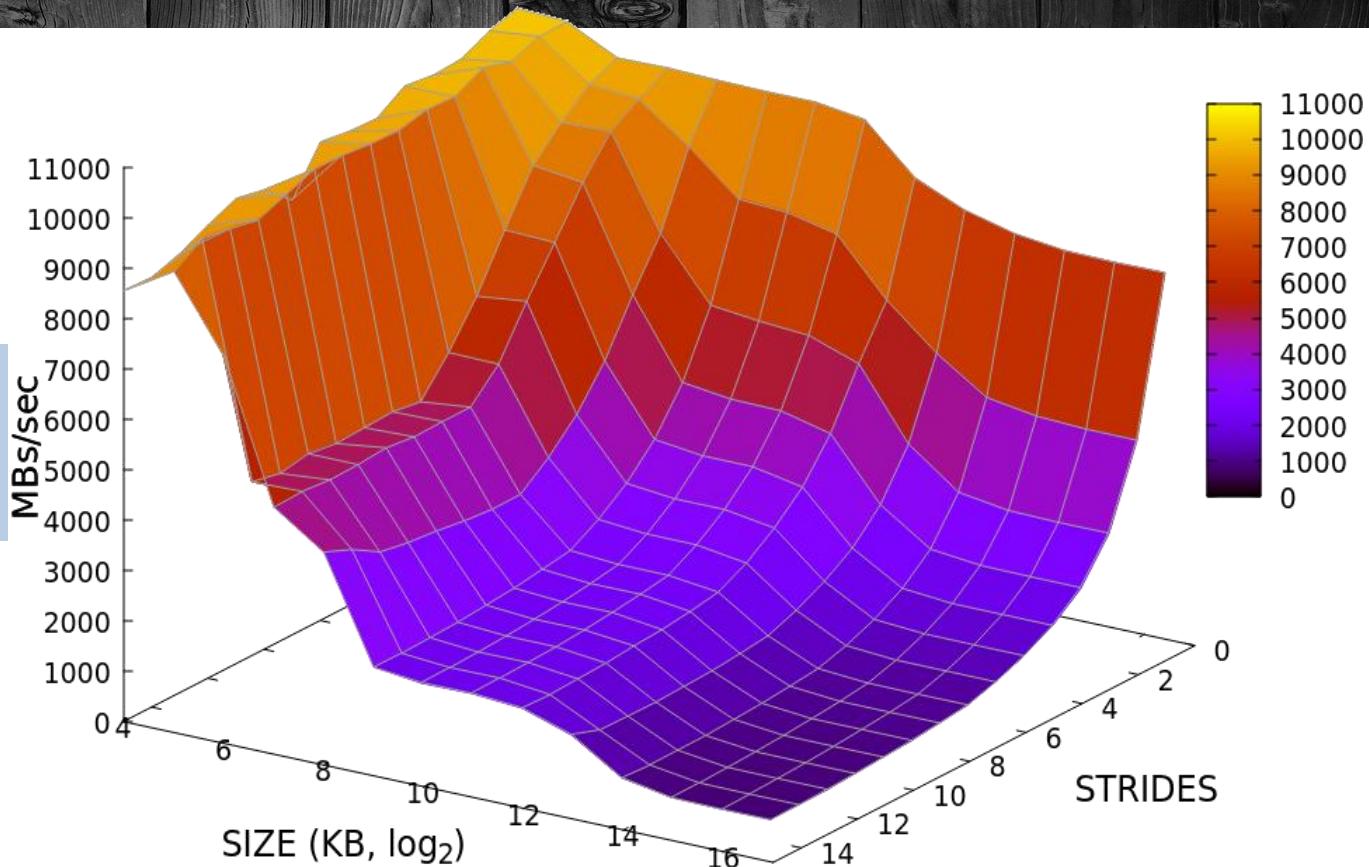
**3R for the
friends**

- ▶ **Rearrange (code & data)**
Design layout to improve temporal & spatial locality
- ▶ **Reduce (size)**
 - Smaller data size – smaller chunks accessed
 - Fewer instructions
- ▶ **Reuse (cache lines)**
Increase spatial & temporal locality – keep resident data for more operations



The memory access pattern

The result is..
the memory mountain



Just a preview;
more details in the next lecture



Question:

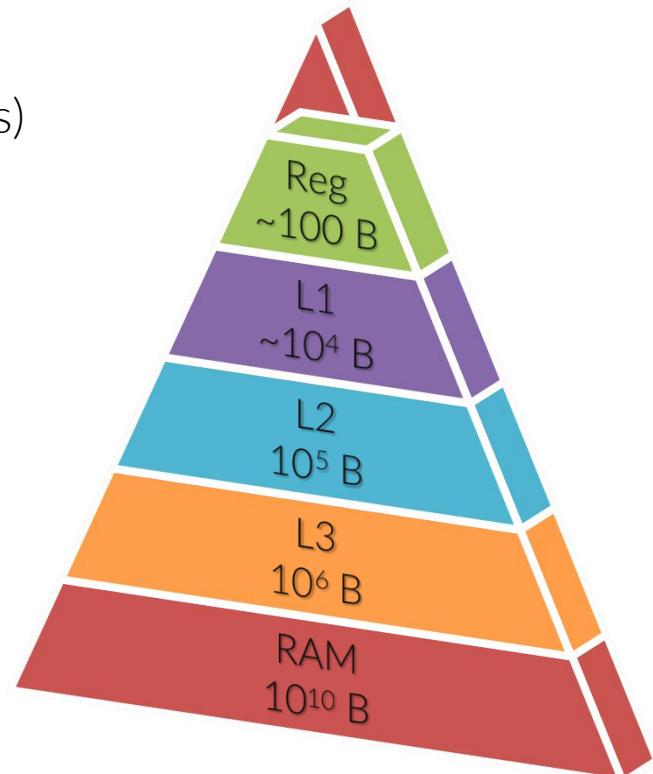
The RAM contains $\sim 10^9$ bytes, while L1 contains $\sim 10^4$ bytes (32KB for data and 32KB for instructions)

So, how do you map the RAM in to a given level of cache, for instance L1, in an effective way?

The main problems are:

- Where to map an address
- What if the location in L1 is already occupied?

...we'll see some details





Memory→Cache mapping

Let's say that both the RAM and the cache are subdivided in blocks of equal size (for instance, 64B): you do not load just a byte in your cache but an entire block (normally called *line*)

RAM	Block number	0	1	2	3	4	5	6	7	8	9	A	B	C	D	E	F
		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	
cache	cache block number	0	1	2	3	4	5	6	7								
	memory block number	•	•	•	•	•	•	•	•								
	data	■	■	■	■	■	■	■	■								
	valid bit	0	0	0	0	0	0	0	0								
	dirty bit	0	0	0	0	0	0	0	0								

Each “block” here is 64B long

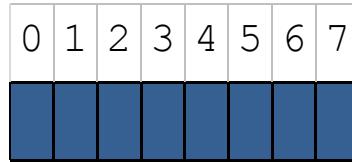


Memory→Cache mapping

Full mapping

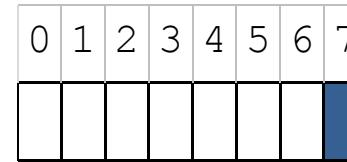
Data can be placed
in any free cache
block

cache



Direct mapping

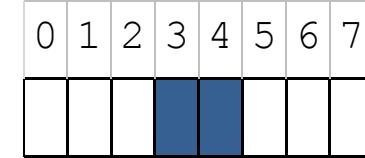
Data can be placed
only in a given block
i.e. **block_num %**
blocks_in_cache



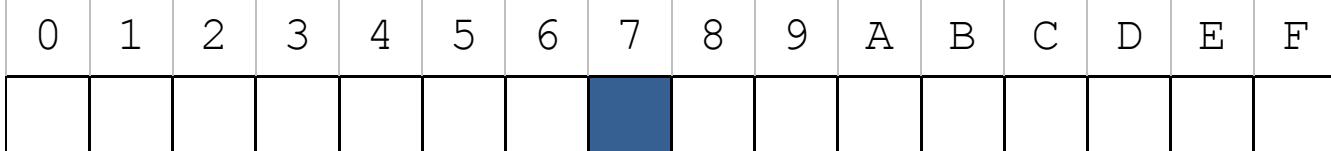
n-way associative

Data can be placed in
few cache blocks i.e.
block_num %
(blocks_in_cache / n)

n=2



RAM





Memory → Cache mapping

Full mapping

Data can be placed in any free cache block.

Pros

Very efficient in writing (minimizes conflicts).

Cons

Very inefficient in reading (all the locations could contain the addressed data).

Direct mapping

Data can be placed only in a given block

Pros

Very efficient in writing (no search for available locations).

Cons

Maximizes the cache conflicts, for only 1 location is eligible for a vast amount of addresses.

n-way associative

Data can be placed in few cache blocks i.e.
A good trade-off

Pros

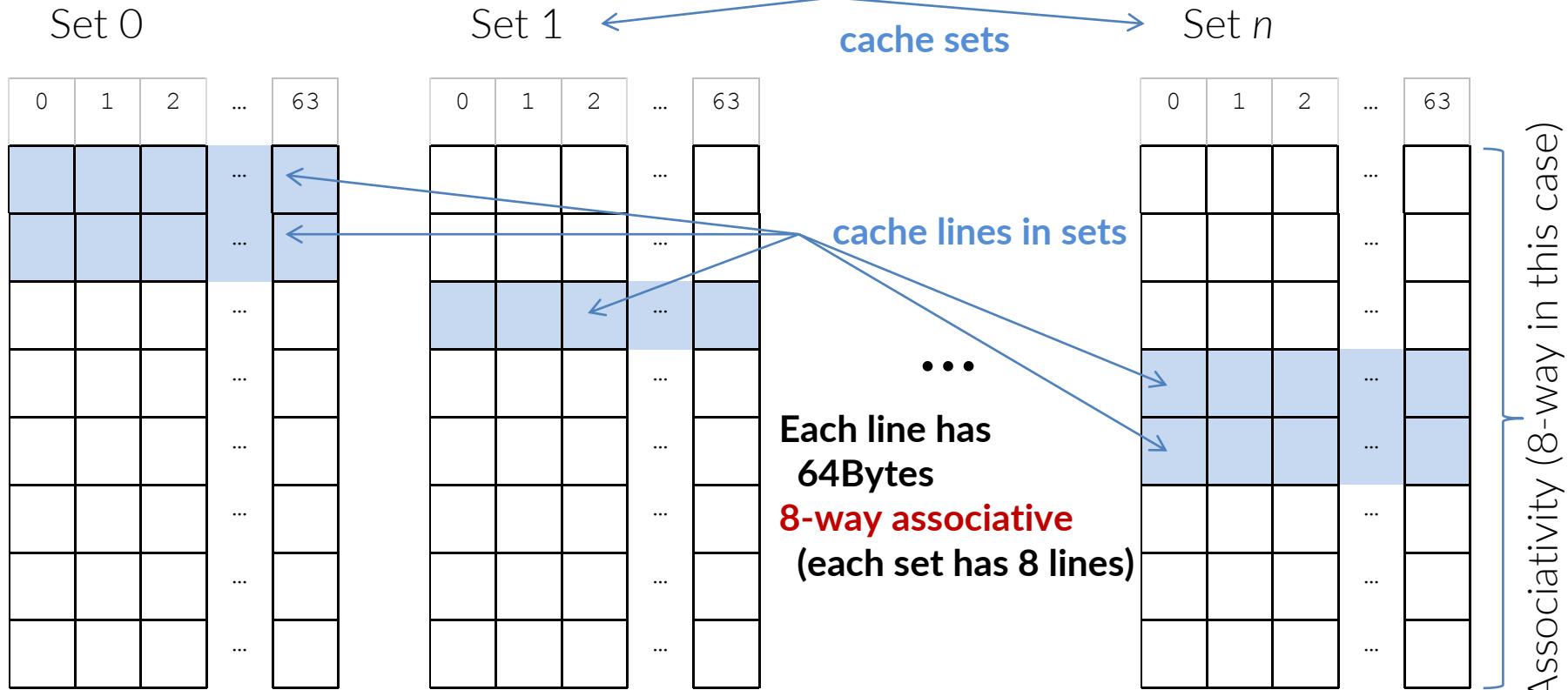
Very efficient in determining the set (only one per memory address). Smaller rate amount of cache conflicts.

Cons

More complicated logics; larger number of operations for the access.



A typical today cache





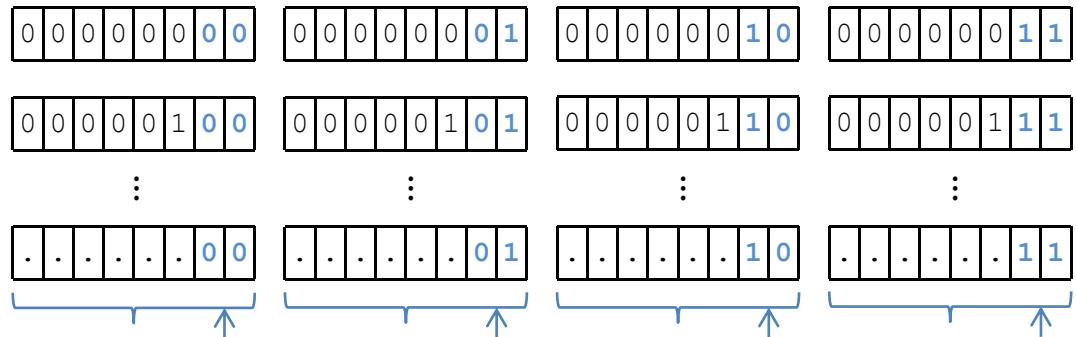
How a byte is actually mapped into a cache location ?

The “elemental” unit of the cache is a line, which normally today has 64 bytes. Then, 64 subsequent bytes in the RAM are mapped in the same line of the cache.

You can achieve that if the *position of the byte* in the target cache line is determined by the least significant bits of its address. Those bits are the fastest changing and, of course, they “cycle”.

Let's build up an example →

Let's suppose, for simplicity, that we have only 256Bytes of memory. Then 8 bits, are sufficient to address our memory:



These bytes will always be at pos 0 in a cache line

These bytes will always be at pos 1 in a cache line

These bytes will always be at pos 2 in a cache line

These bytes will always be at pos 3 in a cache line

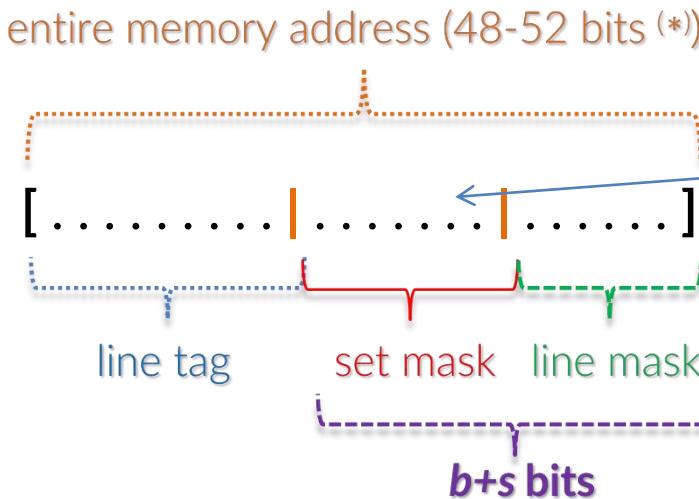
If you consider the first n bits, will have a cycle of 2^n bits; if $n=6$, the position will have a cycle of 64.

So, the least significant bits decides the position of a given address in a cache line, by group of 64.
But what line exactly ?



Memory → Cache mapping

How a byte is actually mapped into a cache location ?



(*) The space reserved for an address is 64bits; however, normally only 48 are used.
In some architectures up to 52 bits are used to address memory.

If your cache size has **c** bytes in total and it is **w**-way associative with lines of size **L** bytes with

$$L = 64B = 2^b \text{ bytes}, w = 8, c = 32KB$$

then there are $c / (L \times w) = 128 = 2^s$ sets (where $s = 7$).

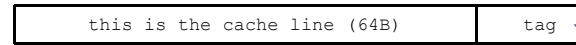
To map the memory addresses into the cache, the first $s+b$ bits are used to determine to what byte in a free line of what cache set that address will be stored.

The first **b** bits determines the position of the byte in the line, the second **s** bits determine **uniquely** the set to which that line belongs:

$$\text{set} = \text{set_mask_value \% } 2^s$$

- the set masking is like a “direct mapping”: 1-to-1 between a byte and a set
- the fact that each set has 8 possible lines is like the “fully associative” mapping, i.e. it gives you enough flexibility to cope with conflicts.

Eventually, to allow the recovering of the full address of a line stored in a cache line the final bits of the address are copied in a location, called tag, aside the line:



This is the tag of the first byte of the corresponding line in memory



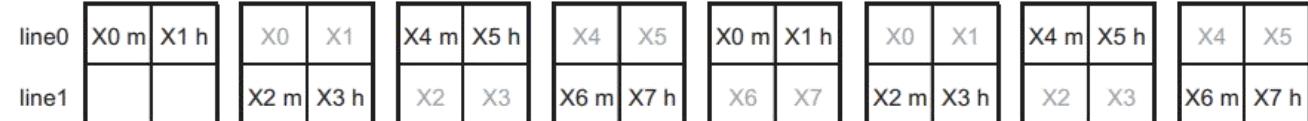
The memory access pattern

When the cache is hit and when it is not: a simple model

Consider a simple direct mapped **16 byte data cache** with **two cache lines**, each of size 8 bytes (two floats per line)

Consider the following code sequence, in which the array **X** is cache-aligned (that is, **X[0]** is always loaded into the beginning of the first cache line) and accessed twice in consecutive order:

```
float X[8];
for(int j=0; j<2; j++)
    for(int i=0; i<8; i++)
        access(X[i]);
```



The hit-miss pattern is : MH MH MH MH MH MH MH MH,
the miss-rate is 50% (the first miss is compulsory miss).



The memory access pattern

Let's consider another code sequence that access the array twice as before, but with a strided access

```
float X[8];
for(int j=0; j<2; j++)
{
    for(int i=0; i<7; i+=2)
        access(X[i]);
    for(int i=1; i<8; i+=2)
        access(X[i]);
}
```



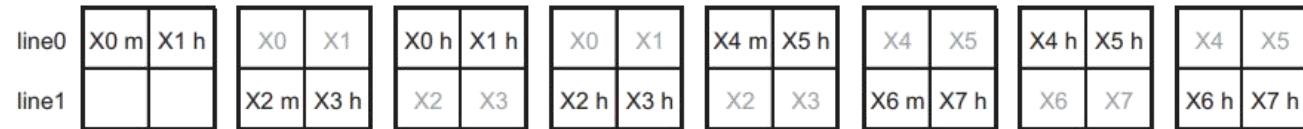
The hit-miss pattern now is : MM MM MM MM MM MM MM MM,
the miss-rate is 100%



The memory access pattern

Finally, consider a third code sequence that again access the array twice:

```
for(int k = 0; k < 2; k++)  
    for(int i = 0; i < 2; i++)  
        for(int j = 4*k; j < (k+1)*4; j ++)  
            access(X[ j ]);
```



The hit-miss pattern now is : MH MH HH HH MH MH HH HH,
the miss-rate is 25%

The main message is: memory access pattern is of primary importance



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foes**

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Unavoidable misses when data are read for the first time

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▶ **Conflict misses**

Cache trashing due to data mapping to same cache lines



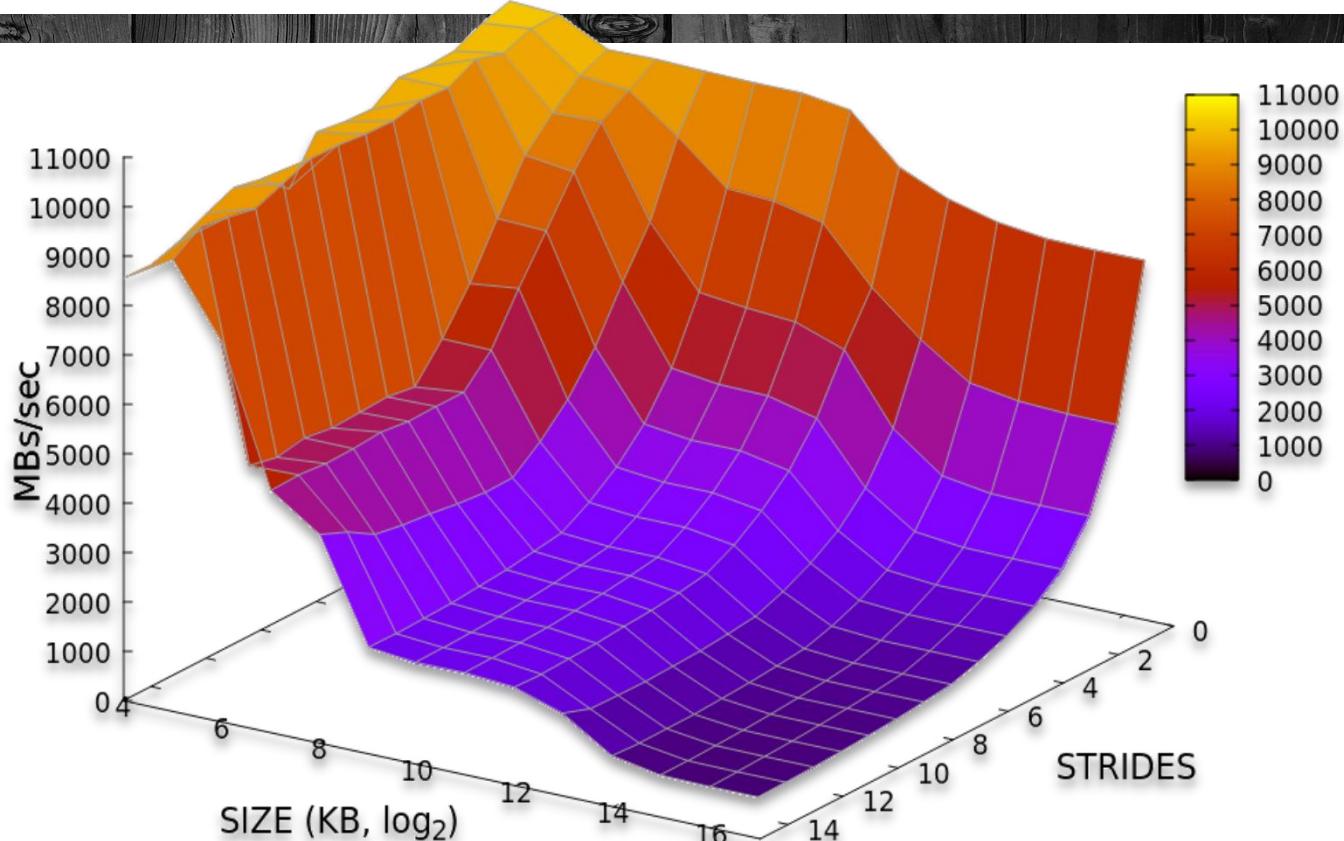
Cache recap in two slides

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The memory access pattern



The result is..
the memory mountain



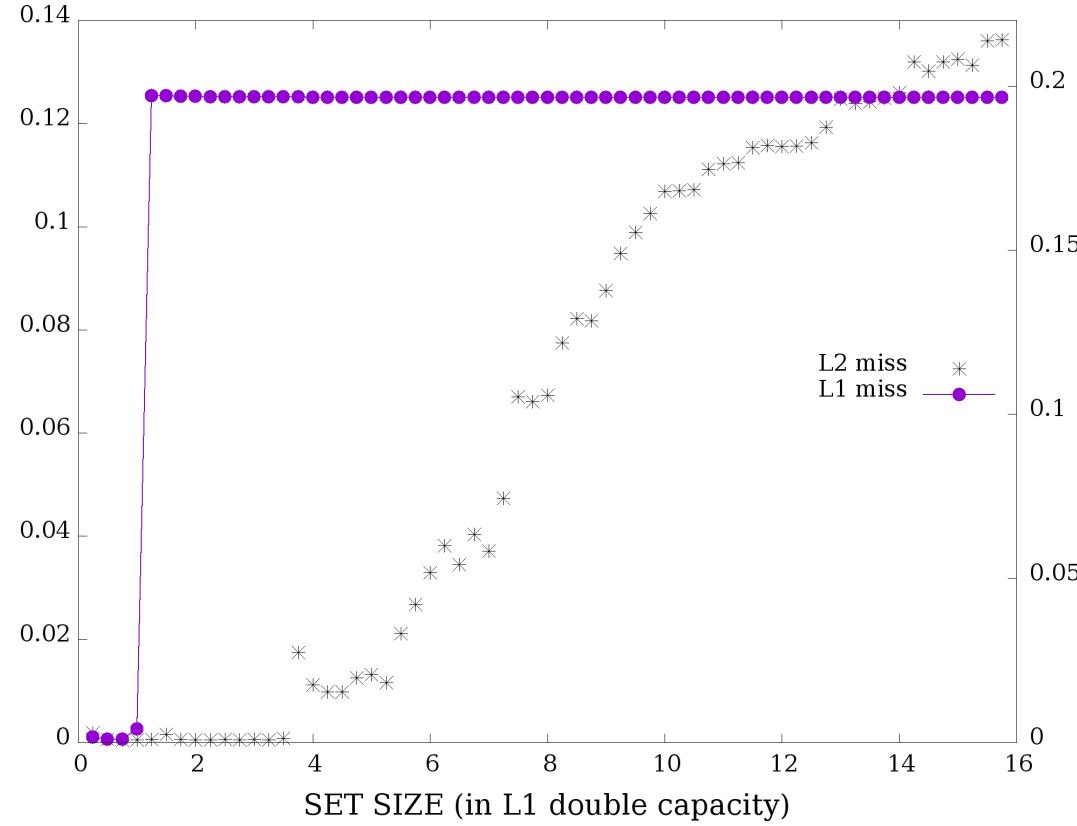
[SCO/Examples_on_cache/
memory_mountain/mountain.c](#)



The cache-miss signature

Let's find out our
cache size

```
for (j=0; j < size; j++)  
    array[j] =  
        2.3*array[j]+1.2;
```



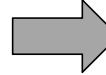


Strided access

Let's consider a quite common problem: the transpose of a matrix.

Matrix transpose

A_{00}	A_{01}	\dots	A_{0N}
A_{10}	A_{11}	\dots	A_{1N}
\dots	\dots	\dots	\dots
A_{N0}	A_{N1}	\dots	A_{NN}



B_{00}	B_{01}	\dots	B_{0N}
B_{10}	B_{11}	\dots	B_{1N}
\dots	\dots	\dots	\dots
B_{N0}	B_{N1}	\dots	B_{NN}

 $=$

A_{00}	A_{10}	\dots	A_{N0}
A_{01}	A_{11}	\dots	A_{N1}
\dots	\dots	\dots	\dots
A_{0N}	A_{1N}	\dots	A_{NN}

$$A_{ij}^T = A_{ji}$$



Strided access

The very simple, straightforward implementation is:

```
for(int row = 0; row < N; row++)  
    for(col = 0; col < N; col++)  
        A [ col*N + row ] = B [ row*N + col ];
```

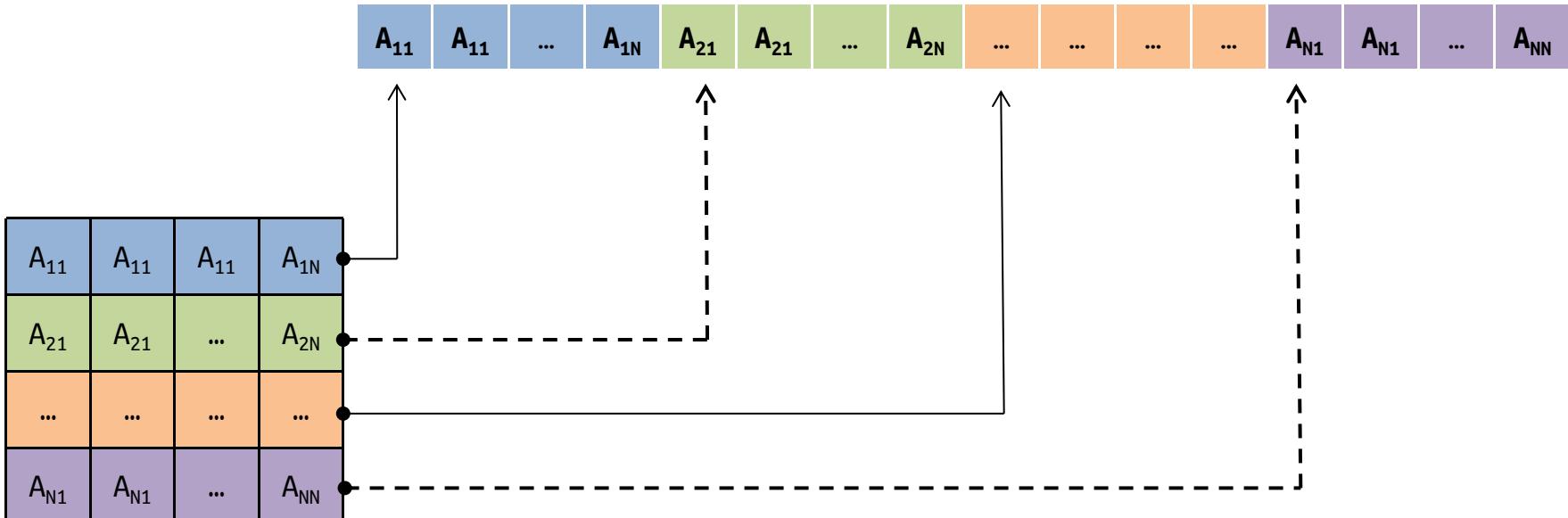
Matrix transpose



SCO/Examples_on_cache/
matrix_transpose/matrix_transpose.c

Note: how a matrix is stored in memory

Remember the obvious fact that your memory is a continuous 1-dimensional stream of bytes. A 2D matrix is stored in memory by rows:

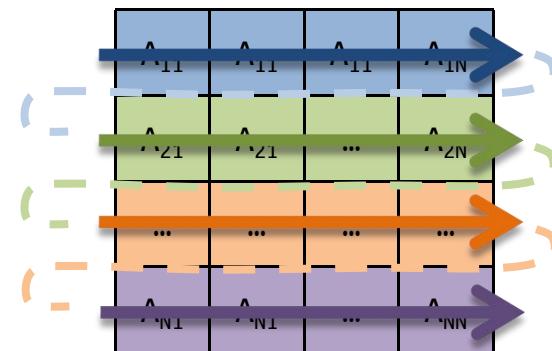


This convention is the C/C++ convention, which is labelled as **row-major order**. Note that the Fortran convention is opposite, with columns being contiguous in memory (column-major).

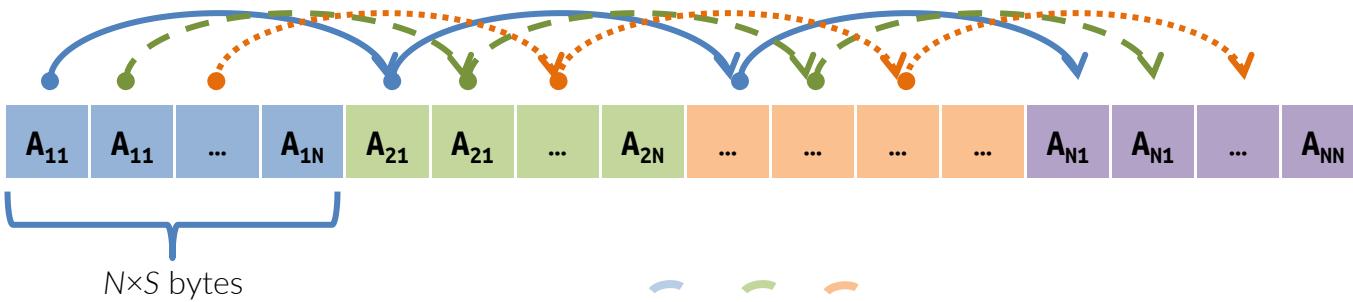
Note: how a matrix is stored in memory



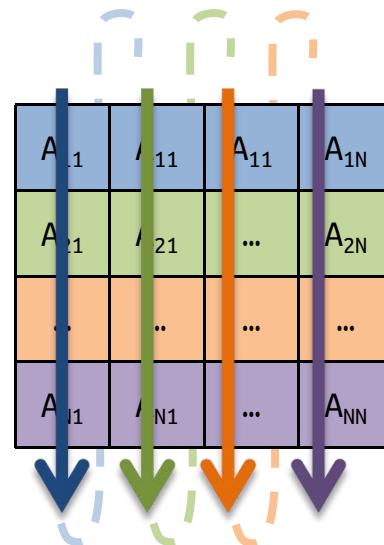
Then, traversing the matrix in the same row-major order corresponds to traverse the memory in contiguous order.



Note: how a matrix is stored in memory



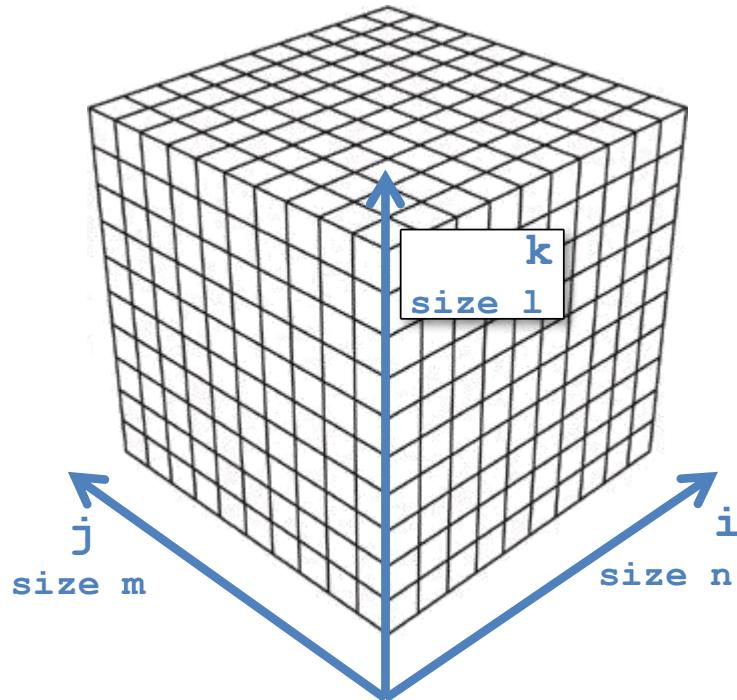
Whereas, traversing the matrix in the opposite column-major order amounts to jump in memory by N positions, i.e. $N \times S$ bytes, where S is the size of each element.



Note: how a matrix is stored in memory

How a 3D matrix, indexed as $[i][j][k]$, is stored in memory ?

```
double M[n][m][l]
```

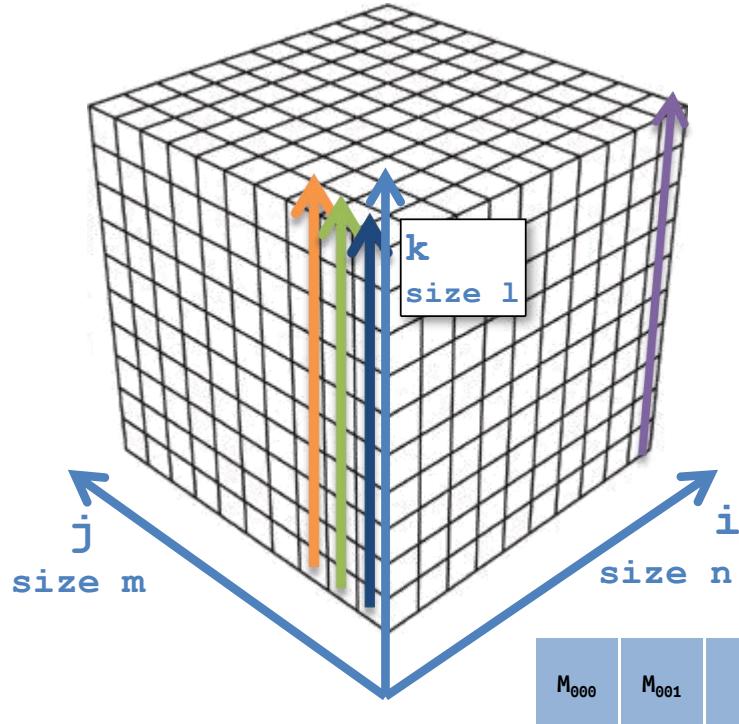


The innermost index is the one that varies at the fastest pace, and traces the memory contiguity.
Hence $M[i][j][k]$ is contiguous to $M[i][j][k+1]$.

Note: how a matrix is stored in memory

How a 3D matrix, indexed as $[i][j][k]$, is stored in memory ?

double $M[n][m][l]$



The innermost index is the one that varies at the fastest pace, and traces the memory contiguity.
Hence $M[i][j][k]$ is contiguous to $M[i][j][k+1]$.

In the choice that we made here, the 3D matrix is then stored along the z direction, which is our k index.
Then by slices along the y direction, which is our j index.
And finally along the x direction, which is our i index, the slowest in changing.

The, to directly reference the entry $[i][j][k]$ in M one should use

$$M + i * (m * l) + j * l + k$$



Strided access

The very simple, straightforward implementation is:

```
for(int row = 0; row < N; row++)  
    for(col = 0; col < N; col++)  
        A [ col*N + row ] = B [ row*N + col ];
```

Matrix transpose

NOTE: strided access to either **A** or **B** is unavoidable.

However: is it better to have it either on *read* or on *write* ?



Dealing with writes

When you modify the content of a variable, that change amounts to overwrites a memory location. When the variable is loaded in to the cache memory, what is loaded is a *copy* of the variable, that maintains its original location in the main memory.

So, if we modify its value, shall we modify it in the cache only or in the main memory too?

there are 2 possible policies:

1) **write-through**

memory and cache are kept consistent, so the value is immediately written back in memory

2) **write-back**

the new value is stored only in the cache, and it is propagated to lower levels when the cache row is replaced.



Strided access

The very simple, straightforward implementation is:

```
for(int row = 0; row < N; row++)  
    for(col = 0; col < N; col++)  
        A [ col*N + row ] = B [ row*N + col ];
```

Matrix transpose

NOTE: strided access to either **A** or **B** is unavoidable.

However: is it better to have it either on *read* or on *write* ?



Strided access

Naïve version:

```
for(int row = 0; row < N; row++)  
    for(col = 0; col < N; col++)  
        A [ col*N + row ] = B [ row*N + col ];
```

Matrix transpose

NOTE: strided access to either **A** or **B** is unavoidable.

However: is it better to have it either on *read* or on *write* ?

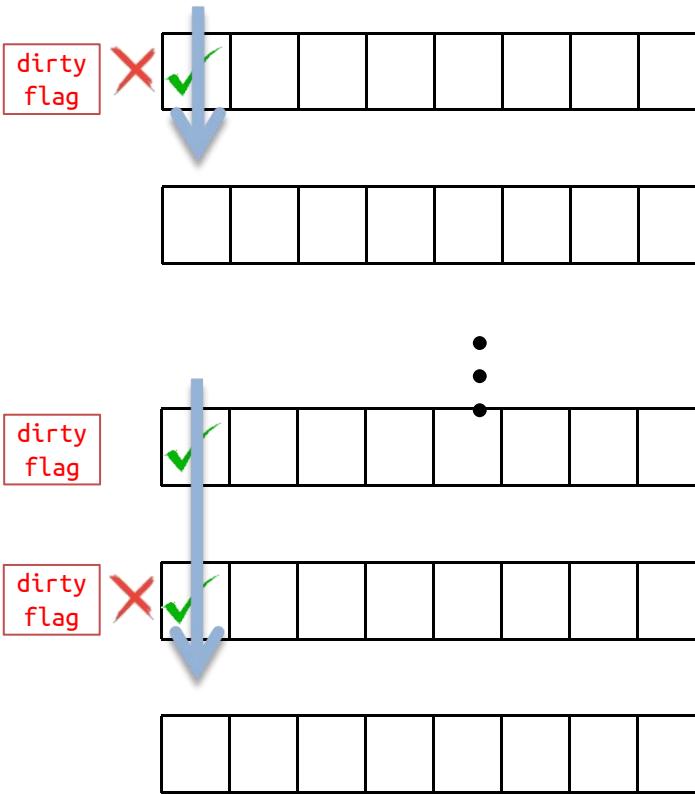
Due to write-allocate transactions in the cache, **strided writes are more expensive than strided loads.**



SCO/Examples_on_cache/
matrix_transpose/matrix_transpose_swapped.c



Strided access

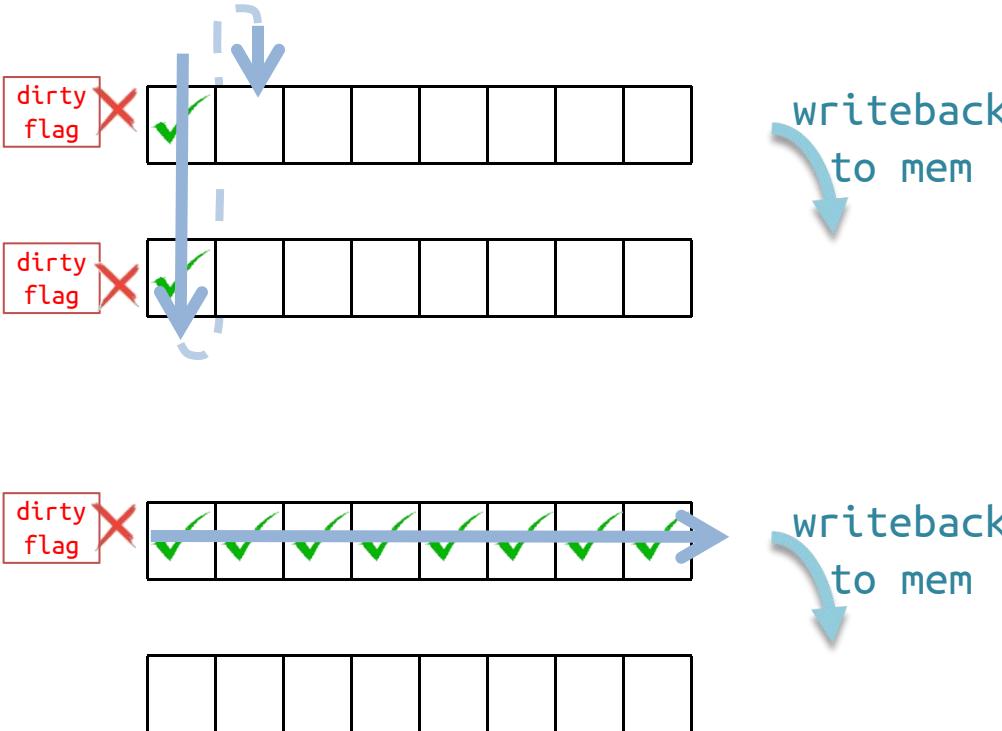


As we [have seen](#), as you traverse in column-major order, you are traversing also the memory in the same way; since we are considering a non-trivial case in which the matrix does not fit in the cache, this means that accessing the subsequent elements of a column you are accessing different lines in a cache.

When the content of the corresponding entry of the transposed matrix is written, the entire cache line is flagged as “dirty”. To enforce the memory-cache coherency, the line must then be flushed back in memory if it is replaced.



Strided access



Then, when you are back again on the first line, which is flagged dirty, and you continue the col-major on the next column. At this point, before you can access that location, the line is written back in memory and refreshed

If you wrote in row-major, instead, you would write an entire line of cache that is afterwards entirely written back into memory. This greatly reduces the cache-memory transactions.



Strided access

Let C be the cache size and L_C the cache line size, we should expect 3 different regimes:

1. $2 \times N^2 < C$

both matrices can fit in the cache, traversal order and locality does not impact on performance (bandwidth ~ maximum)

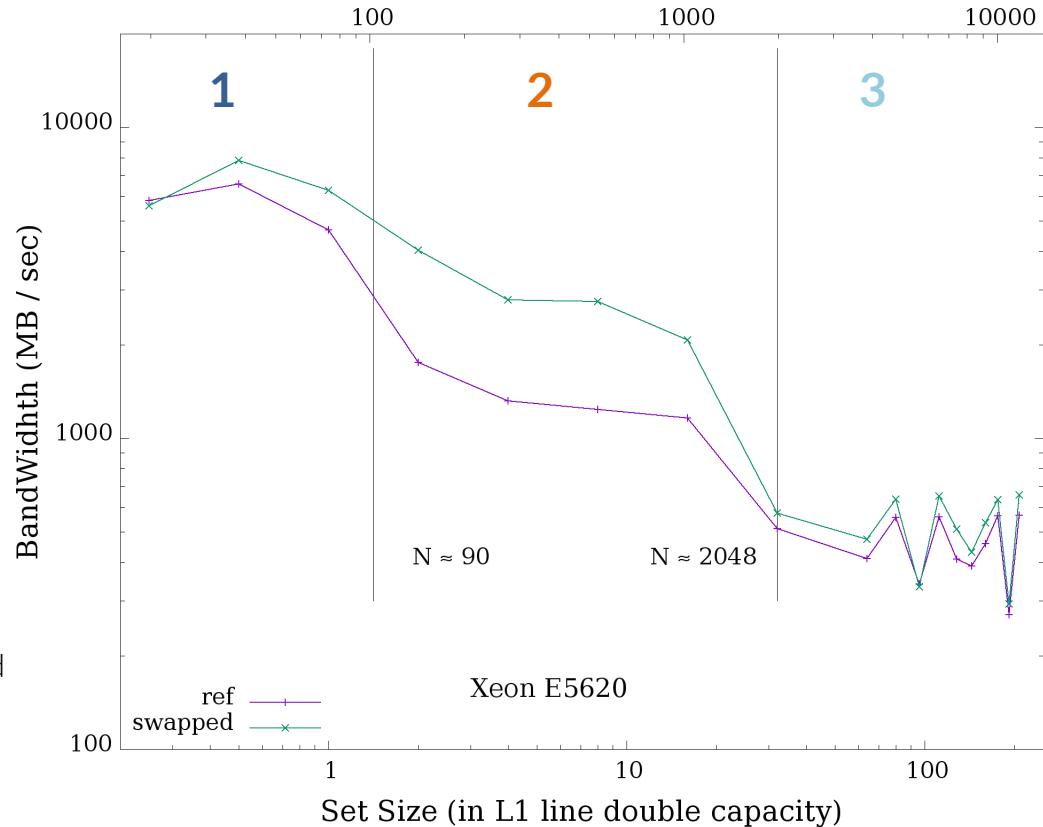
2. $N \times L_C < C$

strided write is alleviated by fraction of column fitting in the cache

3. $N > C \times L_C$

Each access to A determines a cache miss and a *write-allocate*.

A sharp drop in performance is expected since basically only one entry per line will be used.





Strided access

Let C be the cache size and L_C the cache line size, we should expect 3 different regimes:

1. $2 \times N^2 < C$

both matrices can fit in the cache.

Inner cycle flipped:

$$\mathbf{A} [\text{row} * N + \text{col}] =$$

$$\mathbf{B} [\text{col} * N + \text{row}]$$

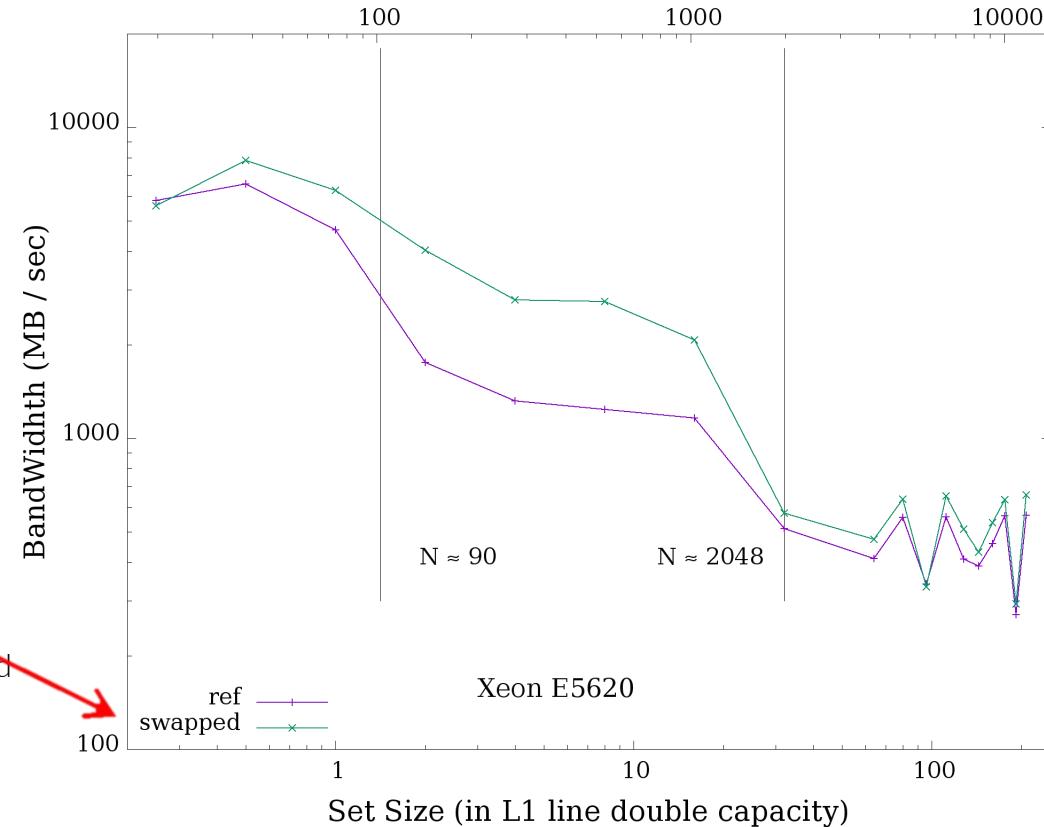
3. $N > C \times L_C$

Each access to A determines a cache miss and a write-allocate.

A sharp drop in performance is expected since basically only one entry per line will be used.

Due to time constraints, we can't go in deeper details.

Ask if interested, though.





Cache-associativity conflicts

Let C be the cache size and L_C the cache line size, we should expect 3 different regimes:

1. $2 \times N^2 < C$

both matrices can fit in the cache,
traversal order and locality does not
impact on performance (bandwidth \sim maximum)

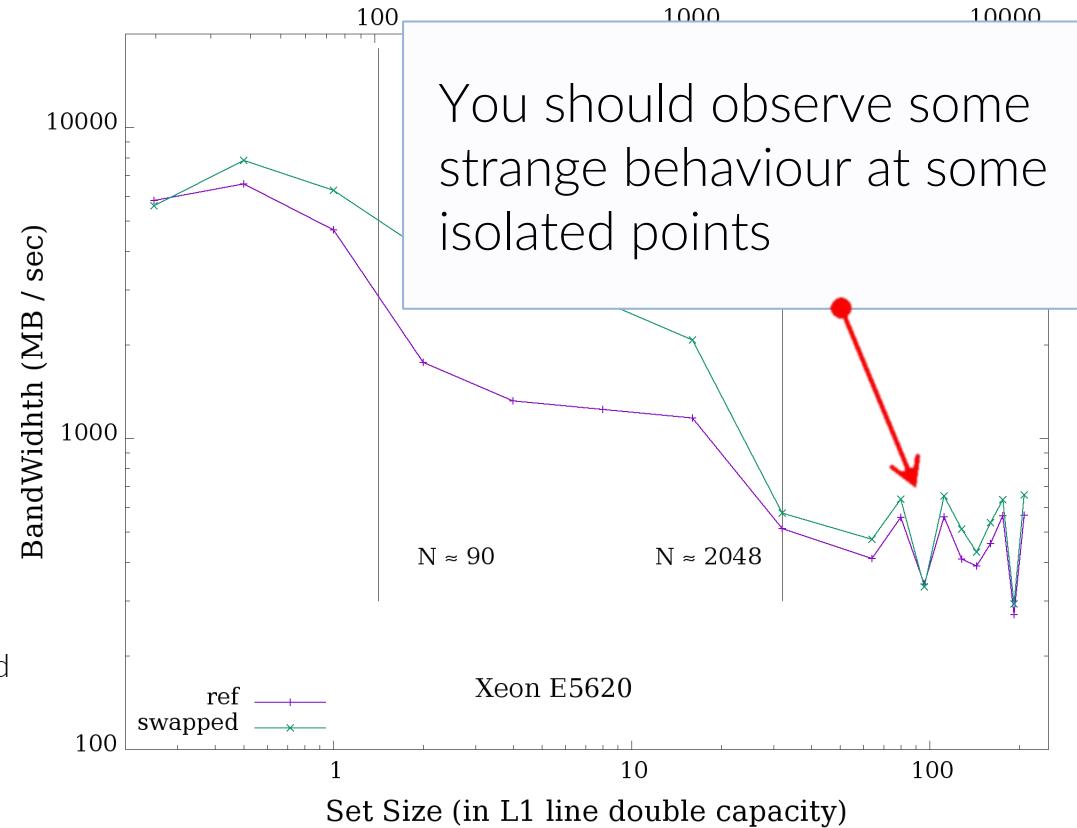
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Each access to A determines a cache
miss and a *write-allocate*.

A sharp drop in performance is expected
since basically only one entry per line
will be used.





| Enhancing the locality

- 1) by how you go through the data
- 2) by how you organize the data



Getting through the data to enhance locality

Scanline
order
row-major

Block order
+ scan sub-
order

That will be
an exercise

(a) 0 1 2 3 4 5 6 7
8 9 10 11 12 13 14 15
16 17 18 19 20 21 22 23
24 25 26 27 28 29 30 31
32 33 34 35 36 37 38 39
40 41 42 43 44 45 46 47
48 49 50 51 52 53 54 55
56 57 58 59 60 61 62 63

(b) 0 8 16 24 32 40 48 56
1 9 17 25 33 41 49 57
2 10 18 26 34 42 50 58
3 11 19 27 35 43 51 59
4 12 20 28 36 44 52 60
5 13 21 29 37 45 53 61
6 14 22 30 38 46 54 62
7 15 23 31 39 47 55 63

(c) 0 1 2 3 16 17 18 19
4 5 6 7 20 21 22 23
8 9 10 11 24 25 26 27
12 13 14 15 28 29 30 31
32 33 34 35 48 49 50 51
36 37 38 39 52 53 54 55
40 41 42 43 56 57 58 59
44 45 46 47 60 61 62 63

Scanline order
col-major

What if you could generate the same by-blocks pattern “naturally”, without hard-coding it into the code, which brings a fine-tuning of a parameter (the value of the block size) on a given platform?

The performance may be not as optimal as with a fine-tuning but the average performance on all platforms may result to be very good.



Getting through the data to enhance locality

Scanline
order
row-major

Block order
+ scan sub-
order

That will be
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(a)

0	1	2	3	4	5	6	7
8	9	10	11	12	13	14	15
16	17	18	19	20	21	22	23
24	25	26	27	28	29	30	31
32	33	34	35	36	37	38	39
40	41	42	43	44	45	46	47
48	49	50	51	52	53	54	55
56	57	58	59	60	61	62	63

(b)

0	8	16	24	32	40	48	56
1	9	17	25	33	41	49	57
2	10	18	26	34	42	50	58
3	11	19	27	35	43	51	59
4	12	20	28	36	44	52	60
5	13	21	29	37	45	53	61
6	14	22	30	38	46	54	62
7	15	23	31	39	47	55	63

(c)

0	1	2	3	16	17	18	19
4	5	6	7	20	21	22	23
8	9	10	11	24	25	26	27
12	13	14	15	28	29	30	31
32	33	34	35	48	49	50	51
36	37	38	39	52	53	54	55
40	41	42	43	56	57	58	59
44	45	46	47	60	61	62	63

(d)

0	1	4	5	16	17	20	21
2	3	6	7	18	19	22	23
8	9	12	13	24	25	28	29
10	11	14	15	26	27	30	31
32	33	36	37	48	49	52	53
34	35	38	39	50	51	54	55
40	41	44	45	56	57	60	61
42	43	46	47	58	59	62	63

Scanline order
col-major

Z- order or
Bit-interleaved
or
Morton order



Organizing data to enhance locality

When the memory bandwidth is “limited” – which may be the case for highly parallel + multicore systems with a strong NUMA hierarchy, **data locality optimization** can play a strong role.

Re-organizing data in “space” (whichever is their n -dimensional space) so that the access pattern is optimal for a given algorithm is related to such locality optimization.



Hot & cold fields

Reorder the fields in structures so that what is used together stays together

Linked-list node

```
struct my_node {  
    double   key;  
    char     my_data[300];  
    my_node *next_node; }
```

Linked-list traversal

```
void myfunc(my_node *p, double key, <...>)  
{  
    while( p != NULL ) {  
        if( p->key == key ) {  
            do_something( <...> );  
            break;  
        }  
        p = p → next_node;  
    }  
}
```



Hot & cold fields

Reorder the fields in structures so that what is used together stays together

Since we are looking for a unique node in the list, the one that has the `key` we are looking for, all but one nodes are discarded in our search.

Then, the usual execution pattern is

```
while( p != NULL ) {
    if( p->key == key ) {}
    p = p → next_node; }
```

Or, in other words, the `key` and `next_node` fields are temporary local, in that they are accessed one after the other.

Linked-list traversal

```
void myfunc(my_node *p, double key, <...>)
{
    while( p != NULL ) {
        if( p->key == key ) {
            do_something( <...> );
            break;
        }
        p = p → next_node;
    }
}
```



Hot & cold fields

Reorder the fields in structures so that what is used together stays together

However, there are 300 bytes in between `key` and `next_node`, which is not an optimal way of organizing the data because for sure they are not spatially local neither in memory nor in cache, while they are temporally local.

```
struct my_node
{
    double   key;
    char     my_data[300];
    my_node *next_node;
}
```



Hot & cold fields

Reorder the fields in structures so that what is used together stays together

```
struct my_node
{
    double   key;
    char     my_data[300];
    my_node *next_node;
}
```



```
struct my_node
{
    double   key;
    my_node *next_node;
    char     my_data[300];
}
```

A first move is simply to swap the position of `my_data` and `next_node`.

That is a simple example, to clarify what it means to optimize the data layout for cache locality



Hot & cold fields

Reorder the fields in structures so that what is used together stays together

Still, the data bunch **my_data** is the real breaker.

A most significant move, is to separate the *metadata* **key** and **next_node** from the *data* **my_data** that are accessed only once the search in the linked list is successful.

During the traversal of the linked list, **key** and **next_node** fields are the *hot* fields, while the **my_data** is a *cold* field.

A good strategy in general, is to keep the hot fields (i.e. data temporally close) spatially close together as much as possible.

```
struct my_node
{
    double   key;
    my_node *next_node;
    char     my_data[300];
}
```



Hot & cold fields

Split the fields so that to keep consecutive the fields that are used sequentially

```
struct my_node
{
    double   key;
    char     my_data[300];
    my_node *next_node;
}
```



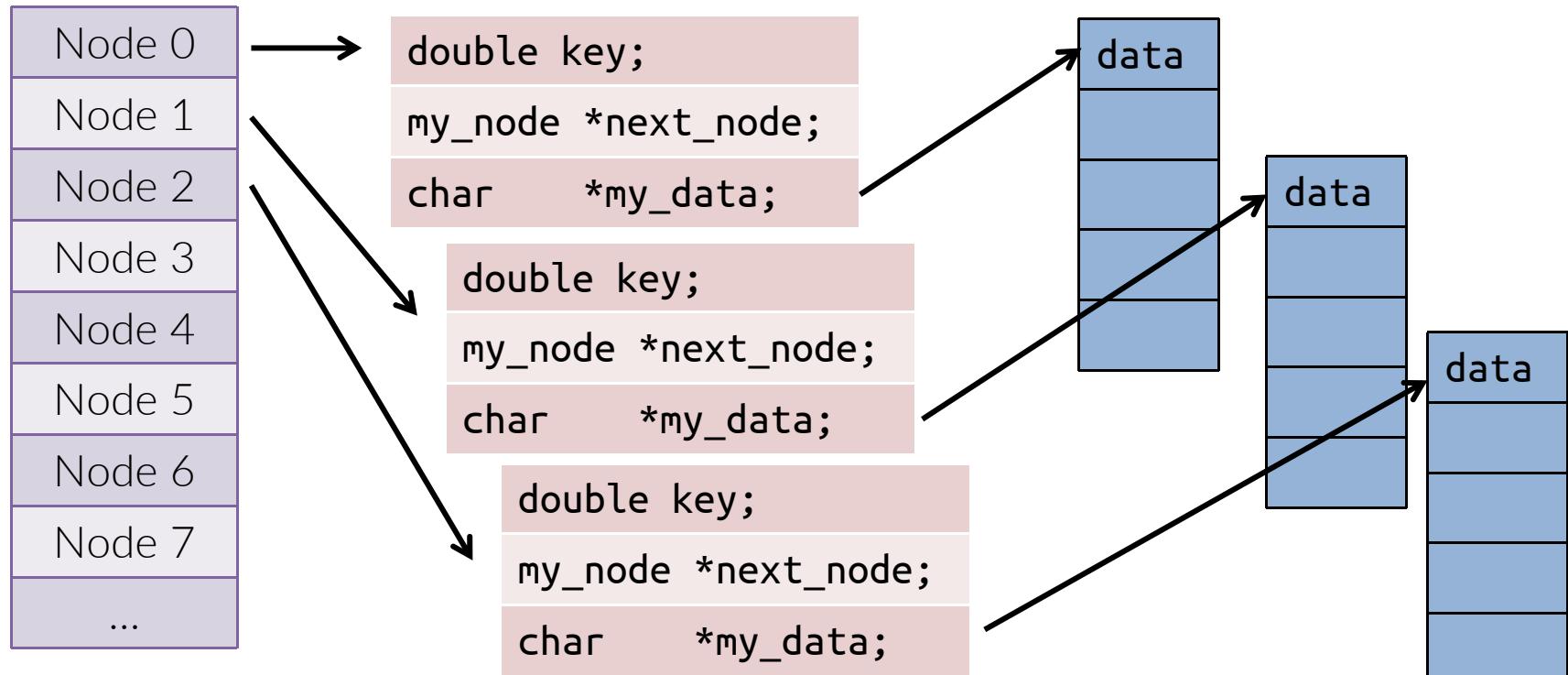
```
struct my_node
{
    double   key;
    my_node *next_node;
    void     *my_data;
}

struct my_data
{
    char data[300];
}
```



Hot & cold fields

Those are called *hot* and *cold* fields



Outline



Avoid the avoidable
inefficiencies



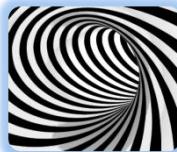
Branches



Pipelines



Cache &
Memory

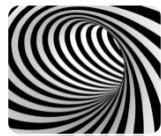


Unleash
the
Compiler



Loops



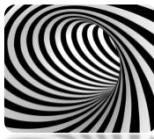


Loop classification

$$A_I = \frac{f(n)}{n}$$

Arithmetic Intensity: the **ratio** between the **number of performed operations** and the **amount of the data**.

1. $O(N) / O(N)$
scanning arrays, 1D vector ops, ..
optimization potential limited
2. $O(N^2) / O(N^2)$
matrix \times vect, matr. transp, matr. add, ...
some more opportunities for opt.
3. $O(N^3) / O(N^2)$
matrix \times matr, ...
significant optimization potential



Cache access in loops: $O(N)/O(N)$

Example

1-level loops: Scalar products, vector additions, sparse matrix-vector multiplication

Inevitably memory-bound for very large N ; in general, improvements come from *avoiding unnecessary operations and/or repeated memory accesses, and increasing data reuse*

[check the possibility for loops fusion]

$O(N) / O(N)$

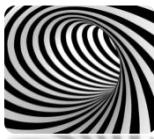
```
for(int j=0; j<2; j++)  
    A[i] = B[i] × C[i]
```

```
for(int j=0; j<2; j++)  
    Q[i] = B[i] + D[i]
```

```
for(int j=0; j<2; j++)  
{  
    A[i] = B[i] × C[i]  
    Q[i] = B[i] + D[i]  
}
```

Loop fusion: in the version on the right, B is recalled from memory only once.



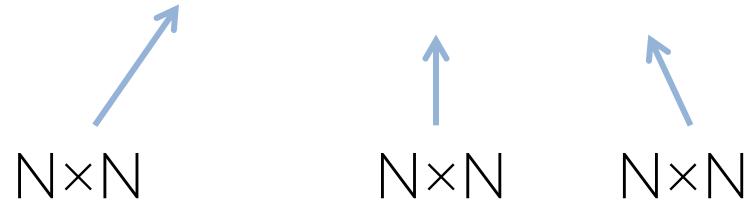


Example

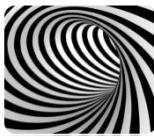
2-levels loops: dense matrix-vector mul, matrix transpos., matrix add, ...

Improvements comes again from increasing *data reuse*, exploiting *locality* and avoiding unnecessary operations and memory accesses.

```
for(int i=0; i < N; i++)  
    for(int j=0; j<N; j++)  
        C[i] += A[i][j] * B[j];
```



→ $3 \times N^2$ memory accesses



Step 1: Avoid unnecessary loads /stores

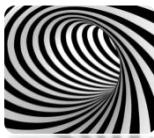
```
for(int i=0; i < N; i++)  
    for(int j=0; j<N; j++)  
        C[i] += A[i][j] * B[j];
```



```
for(int i=0; i < N; i++) {  
    c_temp = C[i];  
    for(int j=0; j < N; j++)  
        c_temp += A[i][j] * B[j];  
    C[i] = c_temp; }
```

Now it is clear for the compiler that **C[i]** needs to be loaded and stored only 1 time

→ $2 \times N^2 + N$ memory accesses



Step 2:

Unroll outer loop and fuse in the inner loop; there is potential for vectorisation.

```
for(int i=0; i < N; i++)  
    for(int j=0; j<N; j++)  
        C[i] += A[i][j] * B[j];
```



$$\rightarrow N^2 \times (1+1/m) + N$$

```
for(int i=0; i < N; i += m){  
    for(j = 0; j < N; j++){  
        b_temp = B[j];  
        C[i] += A[i][j] * b_temp;  
        C[i+1] += A[i+1][j] * b_temp;  
        ...  
        C[i+m] += A[i+m][j] * b_temp; }  
}
```

$N \times N/m$



Cache access in loops: $O(N^2)/O(N^2)$

Sometimes no magic wand can cure the fact that you have to access N^2 memory locations.

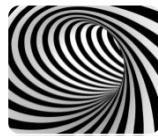
For instance: in matrix transpose you have to access all the source matrix and all the destination matrix once.

Unroll & Jam strategy can bring benefits as long as the cache can hold N lines.

An L_C -way unrolling is too much aggressive and may easily result in register pressure.

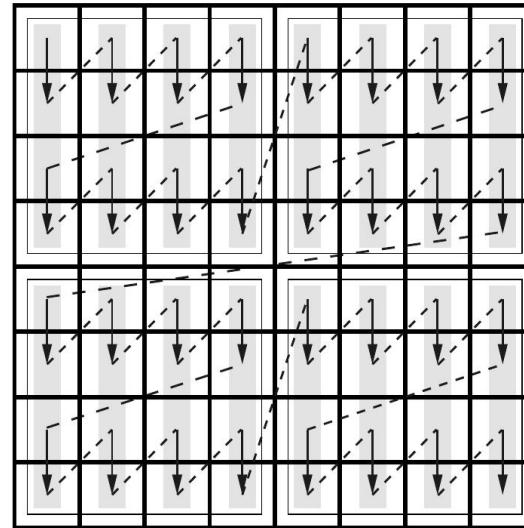
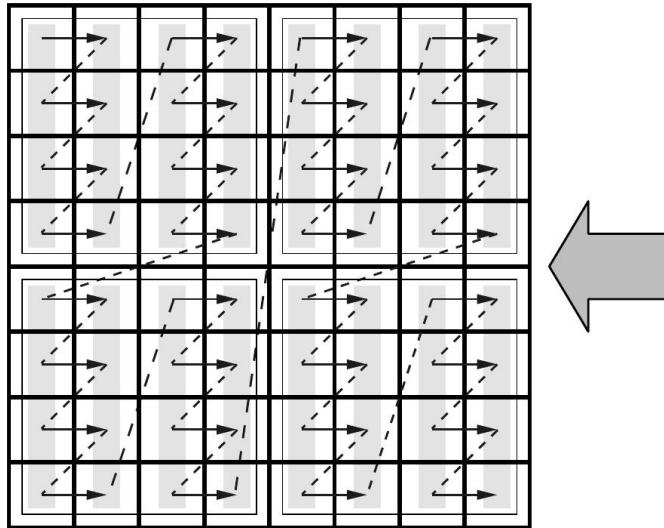
Loop tailing (or blocking) is a good strategy that does not save memory loads but increase dramatically the cache hit ratio.

We have mentioned it in the past, we'll see it in more detail at the end of this lecture.



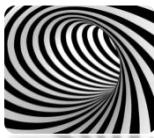
Loops

Cache access in loops: $O(N^2)/O(N^2)$



Step 3:
Fully exploit locality of referenced data; cut TLB misses by accessing 2D arrays by blocks

Image taken from: introduction to HPC for scientists and engineers

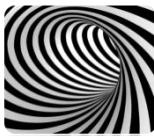


Cache access in loops: $O(N^3)/O(N^2)$

These algorithms (ex: matrix-matrix multiplication or dense matrix diagonalization) are very good candidates for optimizations that lead flop/s performance very close to the theoretical peak (in fact, MMM is at the core of `linpack`).

Tailing, unroll&jam + vectorization of operations, reorganization of ops to exploit CPU's pipelines and out-of-order capability, are all used by extremely **specialized libraries**.

→ **It is a brilliant idea to link those library instead of developing your own algorithm, unless some very special needs must be met.**



matrix-matrix multiplication is a very common task in HPC.

Although there are highly optimized library that performs the job, it is a very classical and useful case study to understand the loop tiling and the cache-oblivious algorithms.

Let's start from the definition of the problem.

Given 2 matrices, A and B, having respectively (m, n) and (n, p) rows and columns respectively, their product is defined as the matrix C(m, p)

$$C_{i,j} = \sum_{k=0}^n A_{i,k} \times B_{k,j}$$



Loops

| $O(N^3)/O(N^2)$ example

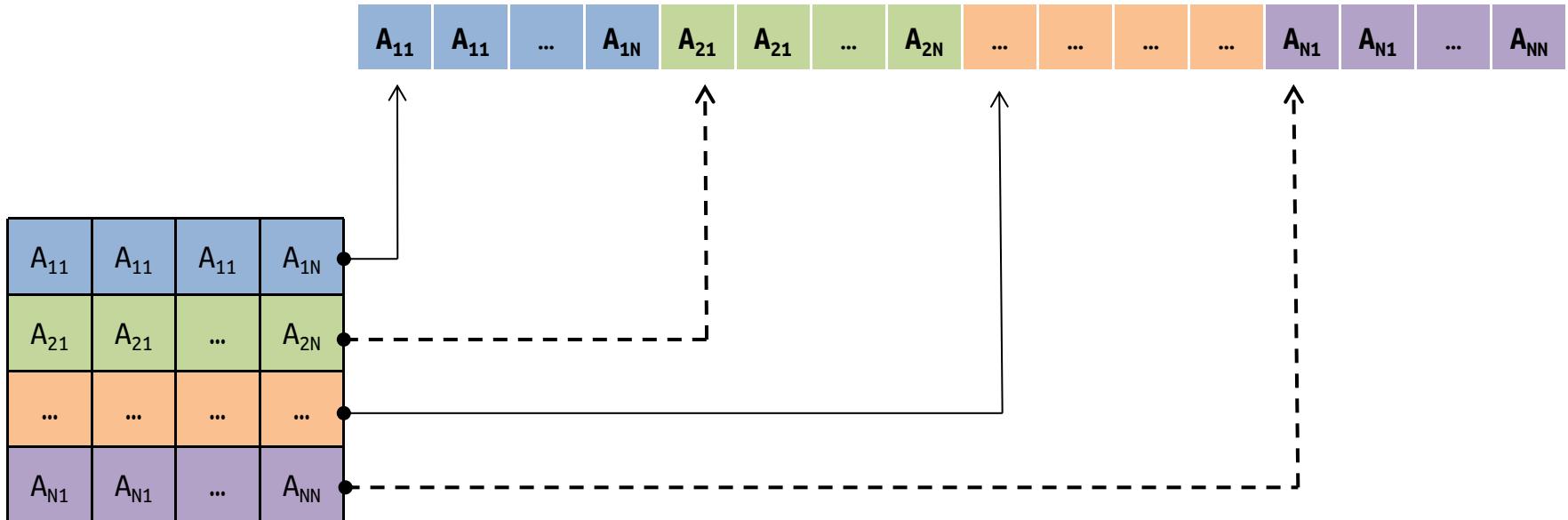
$$C_{i,j} = \sum_{k=0}^n A_{i,k} \times B_{k,j}$$

A possible obvious straightforward implementation of this algorithm is as follows:

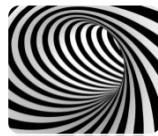
```
for ( int i = 0; i < m; i++ )           // traverse the A's (and C's) rows
    for ( int k = 0; k < p; k++ )         // traverse the B's rows ( Ac = Br )
        for ( int j = 0; j < n; j++ )
            C[i][k] += A[i][j] * B[j][k];
```

Remind: how a matrix is stored in memory

Remember the obvious fact that your memory is a continuous 1-dimensional stream of bytes.



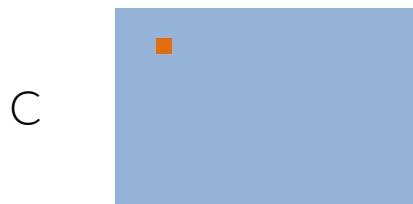
This convention is the C/C++ convention, which is labelled as *row-major order*. Note that the Fortran convention is opposite, with columns being contiguous in memory (*column-major*).



Loops

$O(N^3)/O(N^2)$ example

Matrix representation



=



\times

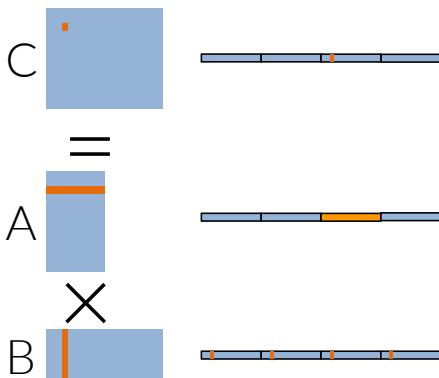


Memory representation





$O(N^3)/O(N^2)$ example



The naïve implementation has an obvious issue with data locality for large enough matrixes.

For each C's element, possibly all accesses to B result in a cache miss.
Then, we may have mnp/L cache misses (if L is the line capacity of the cache in terms of the data type used) only to traverse B.

The total number of expected misses is:

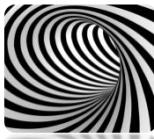
$$\begin{aligned} & mp/L + \\ & mnp/L + \\ & mnp \end{aligned}$$

C is traversed once
A is scanned entirely p times
B is accessed randomly

In fact, the naïve implementation is never used for any large matrix multiplication: since $2mnp$ flop are required, it amounts to have nearly a cache miss per each flop.

How can we fix this problem ?

Transposing the matrix B before entering the loop should alleviate the problem; although the transposition requires some additional work, for large enough matrices there is still a performance gain.



A different strategy may consist in swapping the two inner loops:

```
for ( int i = 0; i < m; i++ )           // traverse the A's (and C's) rows
    for ( int k = 0; k < p; k++ )         // traverse the B's rows ( Ac = Br )
        for ( int j = 0; j < n; j++ )
            C[i][k] += A[i][j] * B[j][k];
```

```
for ( int i = 0; i < m; i++ )
    for ( int j = 0; j < n; j++ )
        for ( int k = 0; k < p; k++ )
            C[i][k] += A[i][j] * B[j][k];
```



SCO/examples_on_pipelines/
matrix_multiplication

Now we are still having lots of cache misses due to the fact that we are re-loading $C[i][k]$ many times (Ac times).

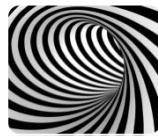
Now we expect to have

mnp/L + running over C
 mnp/L + running over A
 mnp/L running over B

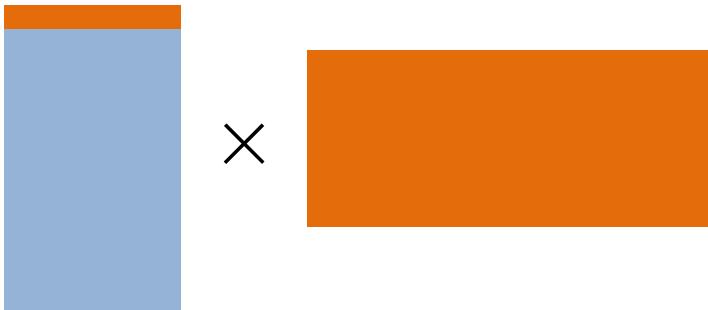
cache misses. Then, with respect to the previous nesting scheme we expect to have

$$\sim mnp(L - 2)$$

less cache misses.



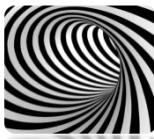
We can do even better by optimizing both the memory accesses and the data contiguity by *tailing* the loops:



To compute a single line in C we need to access the corresponding line in A p times. In the hypothesis that A,B and C can not fit in memory, each time the cache will have been flushed and the A's line will not be there anymore.

This amounts to have n/L compulsory misses per each column if B, i.e. np/L cache misses for each C's line, as we have already calculated.

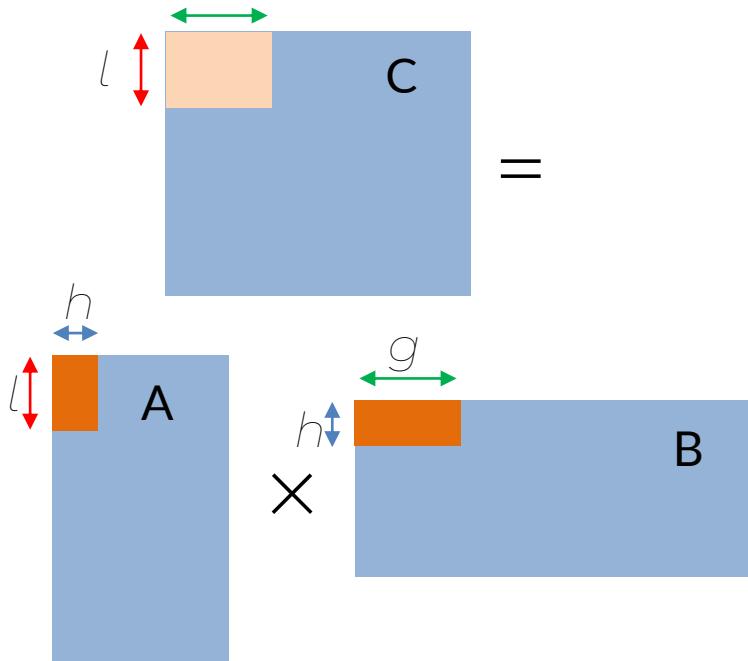
The same holds for the B' s columns and so on...



Loops

$O(N^3)/O(N^2)$ example

We can do even better by optimizing both the memory accesses and the data contiguity by *tailing* the loops:



If, instead, we keep in the cache a segment of the A's line, re-using it against the columns of B – or, better, against a columns section tall as the line segment is large (blue arrows in the figure) – we could greatly reduce the amount of cache misses per C's element.

Traversing A and B by *blocks* as in the figure allows to accumulate partial results in the corresponding C's area while decreasing the number of cache misses by a factor

$$L / (l \times h \times g)$$

where L is the cache capacity and are the block factors. With standard value, this figure becomes of the order of 0.001.



Traversing matrices by blocks

A common technique in matrix-matrix multiplication $A \times B = C$, or in matrix inversion is to process the matrices by blocks instead of traversing entire rows/columns.

Obviously, if the block size is chosen wisely, that enhances the possibility that all the 3 blocks (from A, B and C) are hosted in L1

0	1	2	3	16	17	18	19
4	5	6	7	20	21	22	23
8	9	10	11	24	25	26	27
12	13	14	15	28	29	30	31
32	33	34	35	48	49	50	51
36	37	38	39	52	53	54	55
40	41	42	43	56	57	58	59
44	45	46	47	60	61	62	63

```
void mblock (int n, int bsize,
             double *A, double *B, double *C)
{
    for (int ii = 0; ii < bsize; ++ii)
        for (int jj = 0; jj < bsize; ++jj) {
            int jjn = jj*n;
            double cij = C[jjn + ii]; /* cij = C[i][j] */

            for( int kk = 0; kk < bsize; kk++ )
                cij += A[ii+kk*n] * B[kk+jjn]; /* cij += A[i][k]*B[k][j] */

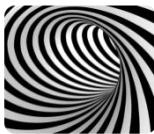
            C[ii+jjn] = cij; } /* C[i][j] = cij */

}

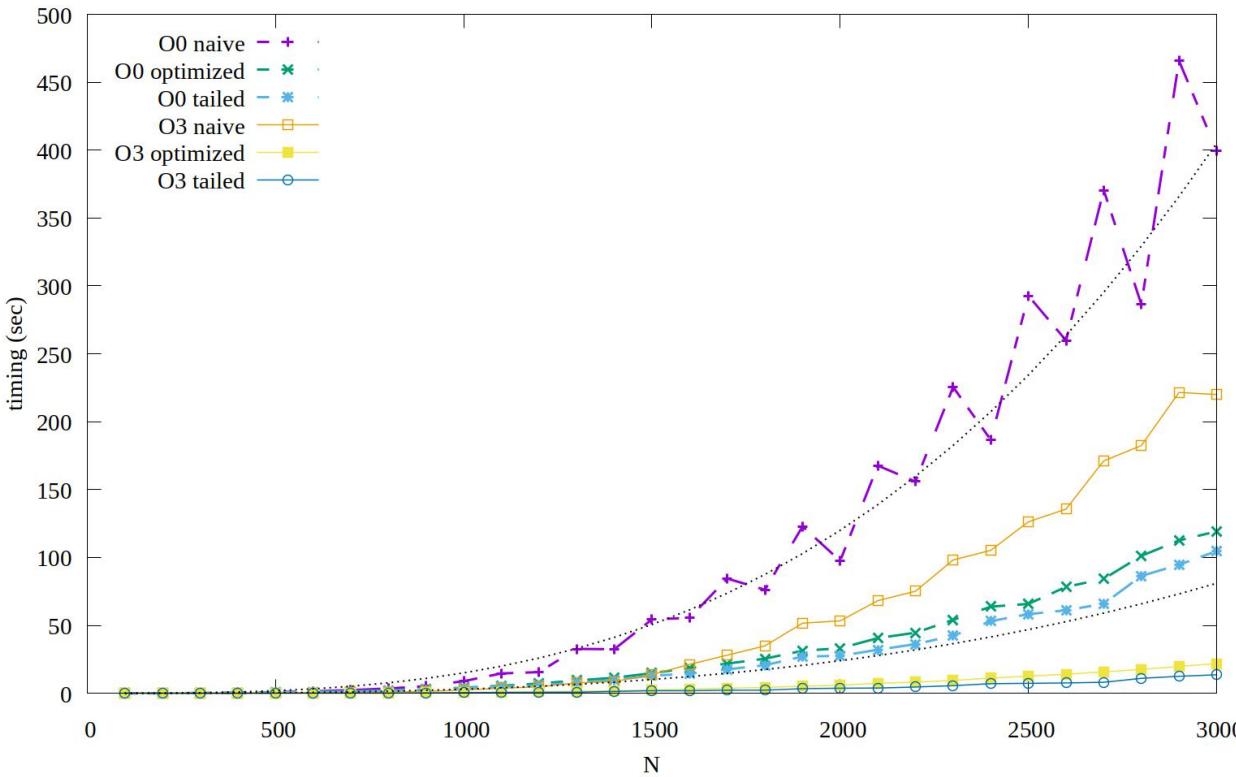
void dgemm (int n, int bsize, double* A, double* B, double* C)
/* C_ij = SUM A_ik * B_kj */
{
    for ( int j = 0; j < n; j += bsize )
        for ( int i = 0; i < n; i += bsize )
            for ( int k = 0; k < n; k += bsize ) {
                double *AA = A + k*n + i;
                double *BB = B + j*n + k;
                double *CC = C + i*n + j;
                mblock(n, bsize, AA, BB, CC); }

}
```

note: this snippet does not take into account the case $n \% bsize != 0$



Matrix multiplication results



Run time of different implementation with and without compiler's optimization

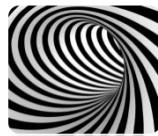
the results are for the case of 2 square matrix of dimension N

Naïve: the schoolbook's implementation

Optimized: inner loops swapped

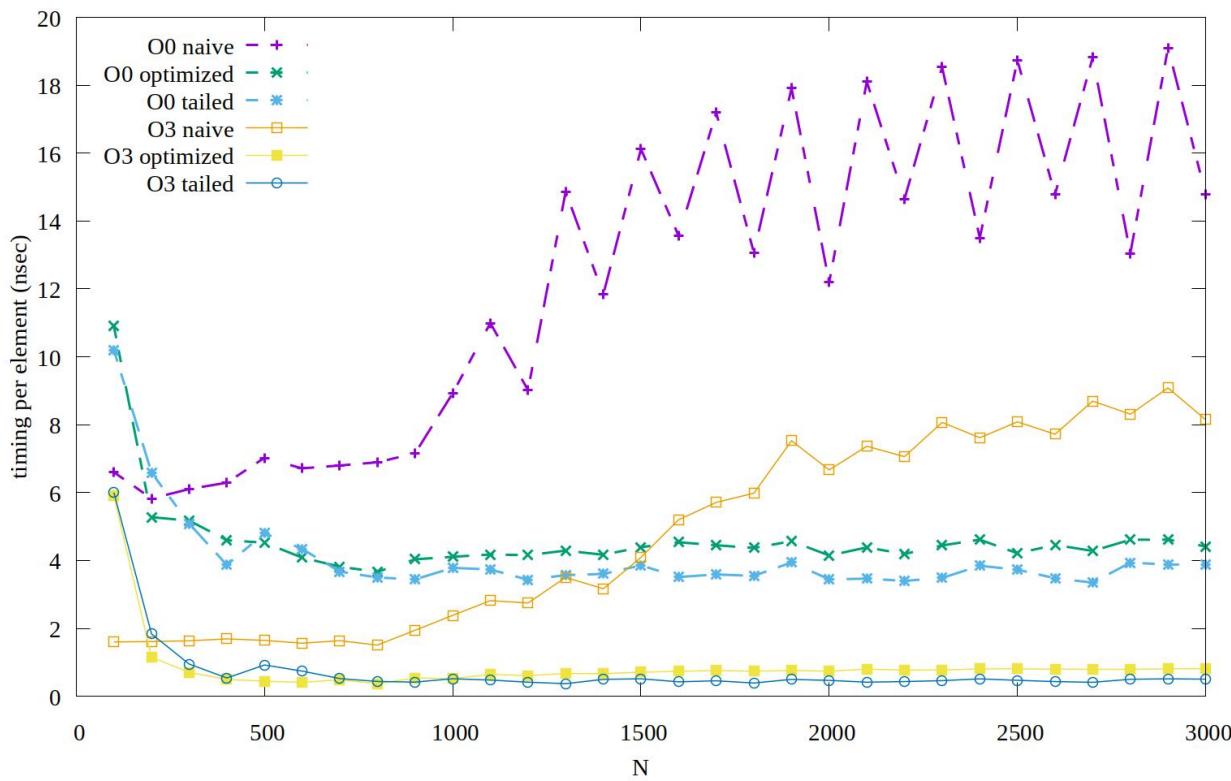
Tailed: M-M by blocks

In this plot and in the following ones dashed lines are for -O0 and solid line for -O3 -march=native (only gcc has been used)

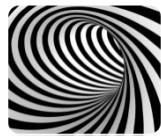


Loops

Matrix multiplication results

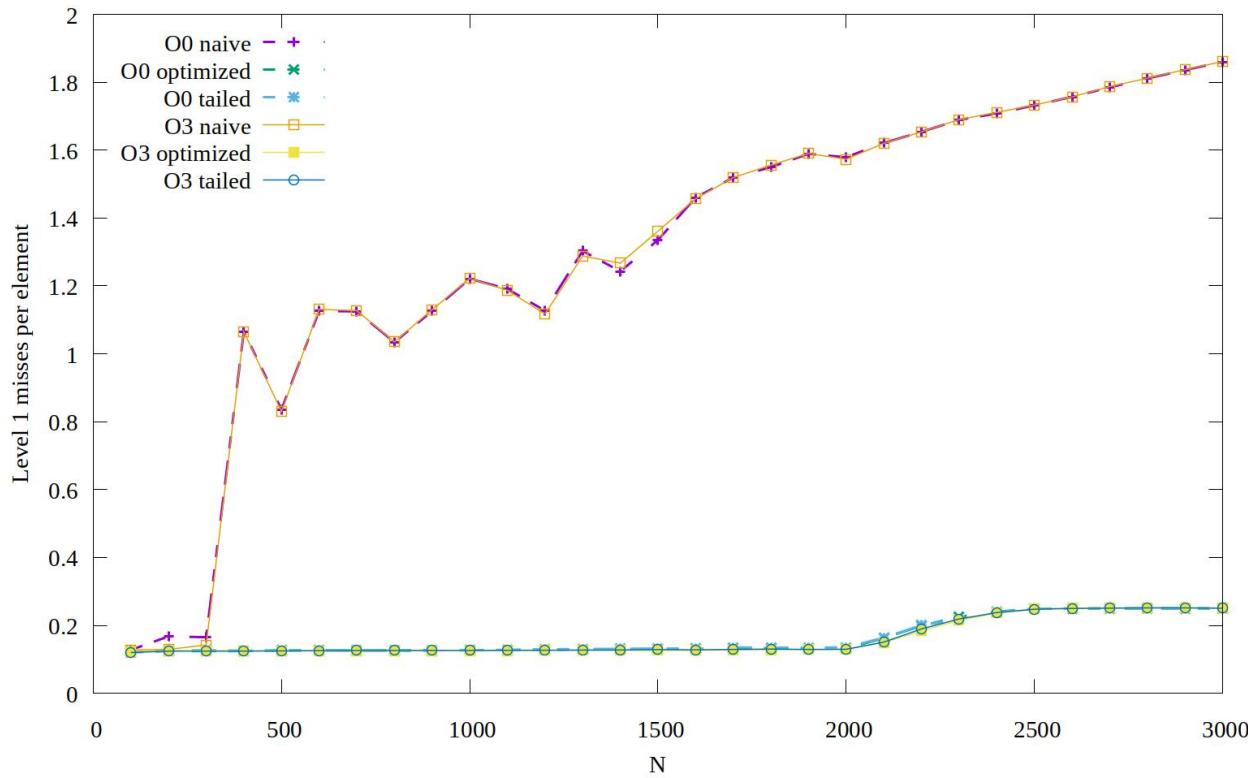


Time per element
accessed (N^3)

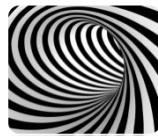


Loops

Matrix multiplication results

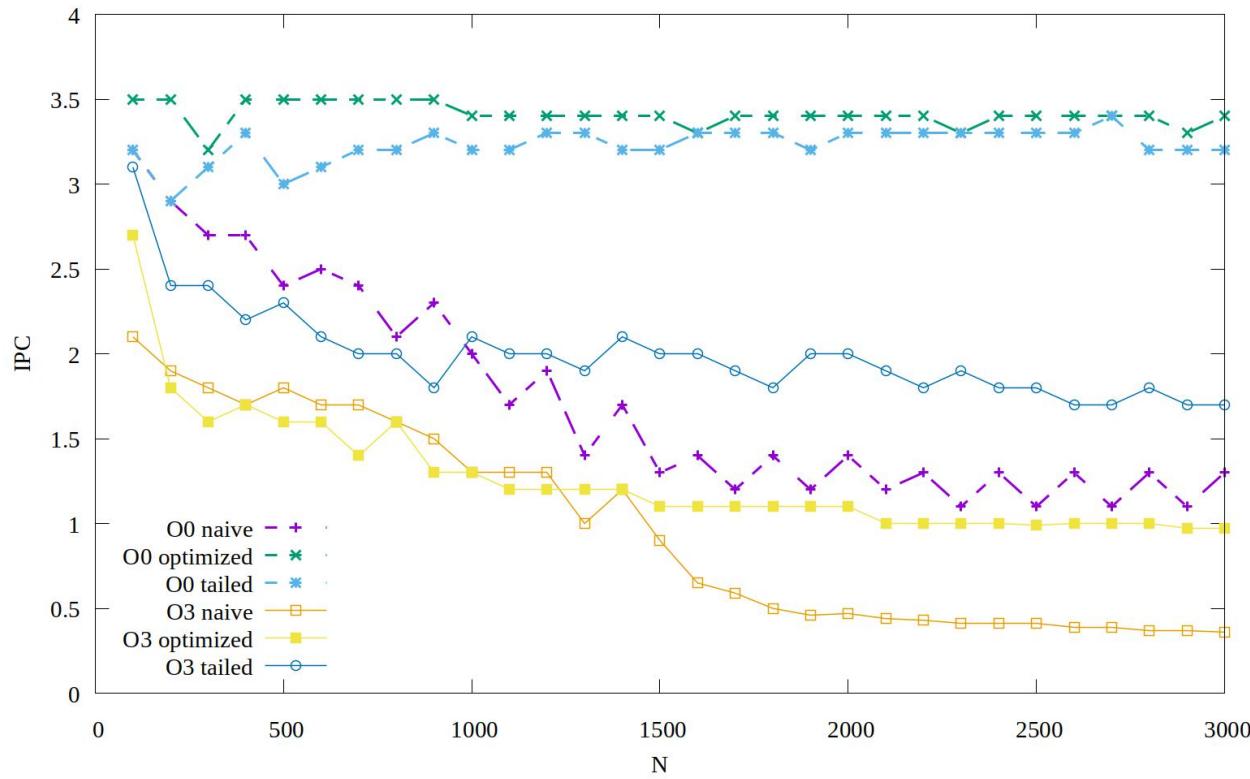


**Level 1 Data cache
misses per element**



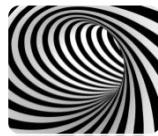
Loops

Matrix multiplication results



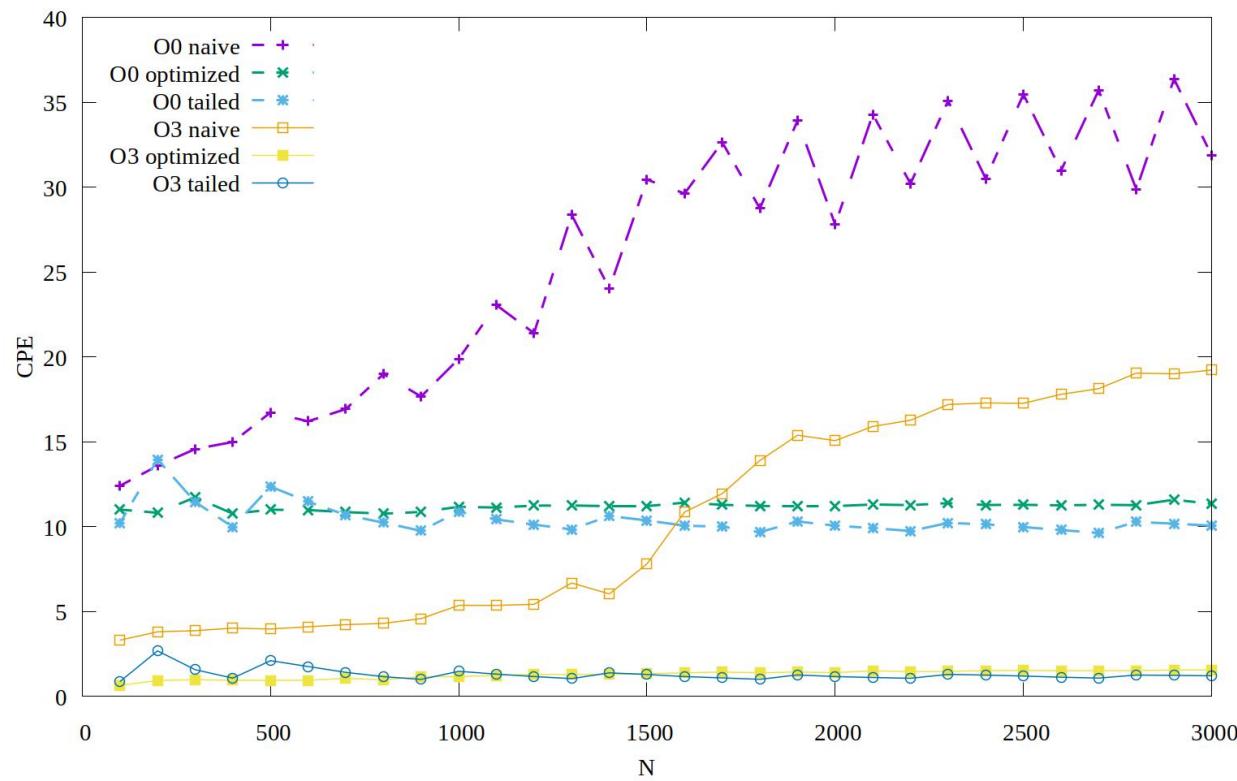
Instructions per cycle

(the larger the better)

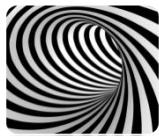


Loops

Matrix multiplication results



Cycles per element
(the smaller the better)



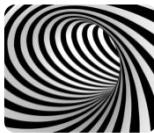
Loop unrolling

Loop unrolling is a fundamental code transformation which usually helps significantly in improving your code performance:

- It reduces the loop overhead (counter update, branching)
- It exposes *critical data path* and dependencies
- It helps in exploiting ILP, especially in case of memory aliasing

We have already seen this technique in the examples from past lecture, although we did not really focus on it.

Now, let's understand it with some more detail.



Loop unrolling



Let's examine this simple *reduction*:

```
for ( int i=0; j<N; i++ )  
    S += A[i];
```

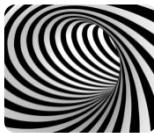
-00

```
.L3:  
# reduction.c:41:    acc = acc OP array[ii];  
    mov    rax, QWORD PTR -24[rbp] # ii  
    lea    rdx, 0[0+rax*8]  
    mov    rax, QWORD PTR -48[rbp] # array  
    add    rax, rdx  
    movsd  xmm0, QWORD PTR [rax]  
    movsd  QWORD PTR -56[rbp], xmm0  
    fld    QWORD PTR -56[rbp]  
# reduction.c:41:    acc = acc OP array[ii];  
    fld    TBYTE PTR -16[rbp]      # acc  
    faddp st(1), st  
    fstp   TBYTE PTR -16[rbp]      # acc  
# reduction.c:40:    for ( uLint ii = 1; ii < N; ii++ )  
    add    QWORD PTR -24[rbp], 1    # ii,  
.L2:  
# reduction.c:40:    for ( uLint ii = 1; ii < N; ii++ )  
    mov    rax, QWORD PTR -24[rbp] # ii  
    cmp    rax, QWORD PTR -40[rbp] # N  
    jb    .L3
```

-03 -march=native

```
.L3:  
# reduction.c:41:    acc = acc OP array[ii];  
    fadd   QWORD PTR [rax] # array  
    add    rax, 8          #  
# reduction.c:40:    for ( uLint ii = 1; ii < N; ii++ )  
    cmp    rdx, rax        # N  
    jne    .L3  
  
    ret
```

With optimization turned on the compiler manages much better the loop overhead, but does not optimize the FP ops in any way.



Loop unrolling

If we compile exactly *the same code* but using `int` as data type instead of `double`, we obtain a quite different result:

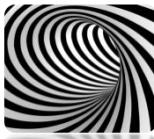
-00

```
.L3:  
# reduction.c:43:    acc = acc OP array[ii];  
    movq  -8(%rbp), %rax # ii  
    leaq  0(%rax,4), %rdx  
    movq  -32(%rbp), %rax # array  
    addq  %rdx, %rax  
    movl  (%rax), %eax  
    movl  %eax, %eax  
# reduction.c:43:    acc = acc OP array[ii];  
    addq  %rax, -16(%rbp)  
# reduction.c:42:    for ( uLint ii = 1; ii < N; ii++ )  
    addq  $1, -8(%rbp)    #, ii  
.L2:  
# reduction.c:42:    for ( uLint ii = 1; ii < N; ii++ )  
    movq  -8(%rbp), %rax # ii  
    cmpq  -24(%rbp), %rax # N  
    jb   .L3
```

-03 -march=native

```
.L4:  
# reduction.c:43:    acc = acc OP array[ii];  
    vmovdqu 4(%rax), %ymm0  
    addq    $32, %rax  
    vpmovzxdq %xmm0, %ymm1  
    vextracti128 $0x1, %ymm0, %xmm0  
    vpmovzxdq %xmm0, %ymm0  
# reduction.c:43:    acc = acc OP array[ii];  
    vpaddq  %ymm0, %ymm1, %ymm0  
    vpaddq  %ymm0, %ymm2, %ymm2  
    cmpq    %rdx, %rax  
    jne     .L4
```

Now the compiler opts for the complete vectorization of the loop, with a very strong impact on performances !!



Loop unrolling

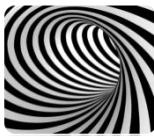


Why does the compiler choose to optimize the loop when the data are of type **int** and it does not when the data are of type **double** ?

It is due to the fact that, as we have seen the compiler is NOT free to restructure the code that deals with floating-point numbers.

Since the math with floating point is not associative, changing the exact order of the operations in your code may – from what the compiler may judge at compile time – change the correctness of the calculations at run time.

For instance, in the example that we have considered, changing the order of the operations obviously impacts on the result. From the point of view of the compiler, you may have chosen a given workflow exactly because you know that it is the most correct with respect to the data it will apply to!



Loop unrolling

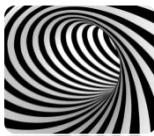
Then, we are left with the responsibility of optimizing this simple code. Since we are traversing it continuously in natural memory order, the cache is not an issue.

Our aim is to re-structure the code so that the compiler could exploit the CPU's ILP (*Instruction-Level Parallelism*).

```
for ( int i=0; j<N; i++ )  
    S += A[i];
```



SCO/examples_on_pipelines
reduction



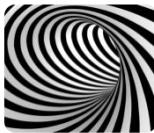
Step 1: unrolling $2 \times I$

Our first attempt is to **reduce the loop overhead** and **expose some parallelism** among the data by explicitly processing 2 elements per iteration.

```
for ( int i=0; i<N; i++ )  
    S = S OP A[i];
```



```
for ( int i=0; i<N-2; i+=2 )  
    S = (S OP A[i]) OP A[i+1] ;
```



Step 1: unrolling $2^{\times} I$



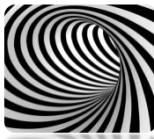
Note: when unrolling, you always have to **care about the final iterations** that would be left behind. A common way to do it for an unrolling factor U (usually U ranges in [2..16] of a loop with N iterations is:

```
int N_ = (N/U)*U;      // by construction  
this is the largest multiple of U  
                           // smaller than N  
for ( int i = 0; i < N_; i += U )  
    iteration_ops;  
  
for ( int i = N_; i < N; i++ )  
    iteration_ops;
```

```
for ( int i=0; i<N; i++ )  
    S = S OP A[i];
```



```
for ( int i=0; i < N-2; i+=2 )  
    S = (S OP A[i]) OP A[i+1] ;
```



Step 1: unrolling 2×1



NOTE:

The unrolling is expressed in general as $n \times m$ (in this slide $n=2$, $m= 2$; in the previous slides, $n=2$, $m=1$).

n refers to the number of iterations that are unrolled

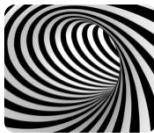
m refers to the number of accumulators that are being used

So, both the case presented in this slide and the one discussed in the previous slide unroll 2 iterations (in other words: the iteration counter is increased by 2!). However, this case uses 2 accumulators, and so it is 2×2 , while the previous one uses only one and then it is 2×1 .

```
for ( int i=0; i<N; i++ )  
    S = S OP A[i];
```



```
for ( int i=0; i < N-2; i+=2 )  
    S = (S OP A[i]) OP A[i+1] ;
```



Step 1: unrolling $2^{\times} I$

The compiler generates (*)
the following assembly code:

```
.L17:  
    vmovupd ymm1, YMMWORD PTR [rax]  
    add     rax, 32  
    vaddsd xmm0, xmm0, xmm1  
    vunpckhpd xmm2, xmm1, xmm1  
    vextractf128 xmm1, ymm1, 0x1  
    vaddsd xmm0, xmm0, xmm2  
    vaddsd xmm0, xmm0, xmm1  
    vunpckhpd xmm1, xmm1, xmm1  
    vaddsd xmm0, xmm0, xmm1  
.LVL18:  
    cmp     rax, rcx  
    jne     .L17
```

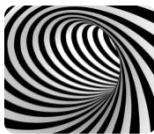
load 32B (4 double) starting from i th element.
ymm1 has 256bits.

rax contains the address to the i th element of the array, *[rax]* means “the address pointed by *rax*”

registers' reshuffle to move each double at the begin, in order to use **vaddsd**

all these instructions sum with,
and store in, **xmm0**

(*) in the following we will always comment the code generated with **-O3 -march=native**



Loops

Step 1: unrolling $2^{\times} I$



In a (hopefully) simpler view,
the scheme of what happens
is the following



.L17:

```

vmovupd ymm1, YMMWORD PTR [rax]
add    rax, 32
vaddsd xmm0, xmm0, xmm1
vunpckhpd xmm2, xmm1, xmm1
vextractf128 xmm1, ymm1, 0x1
vaddsd xmm0, xmm0, xmm2
vaddsd xmm0, xmm0, xmm1
vunpckhpd xmm1, xmm1, xmm1
vaddsd xmm0, xmm0, xmm1

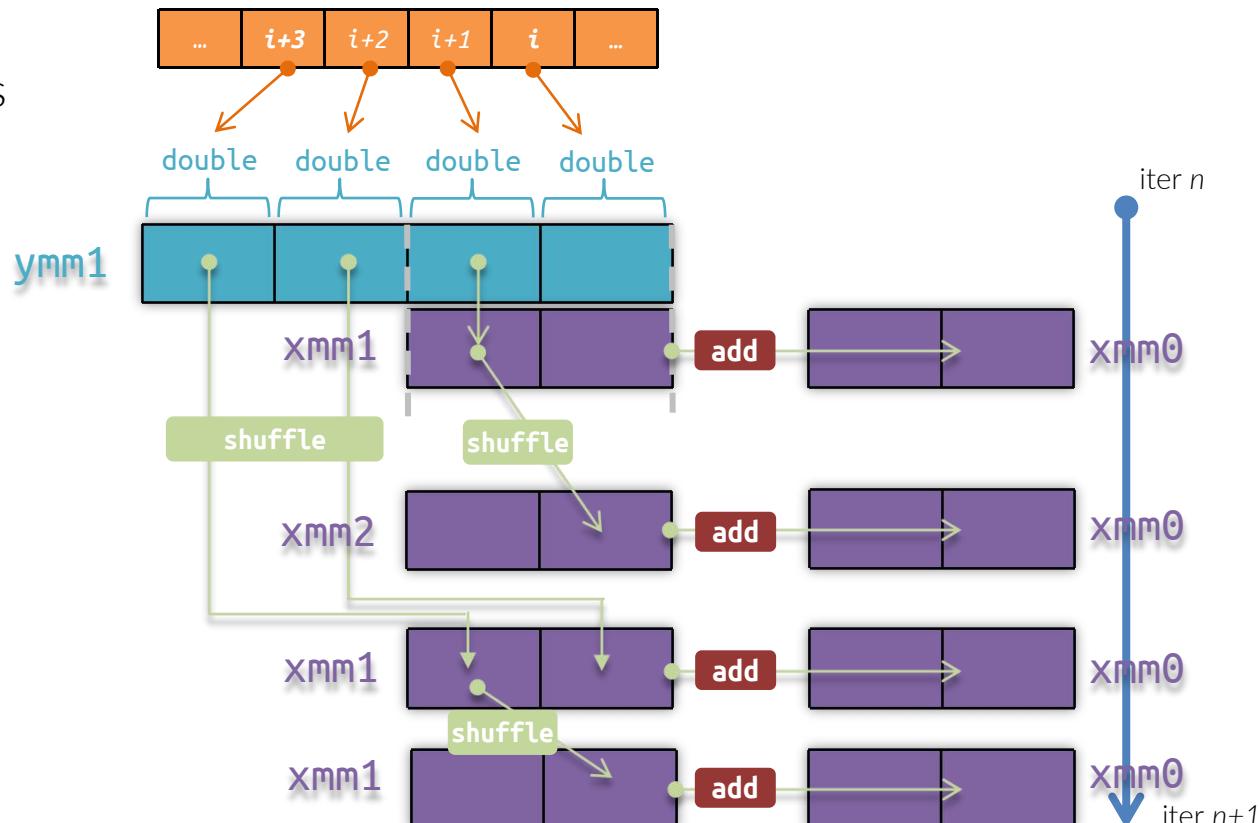
```

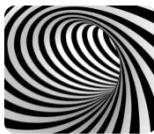
.LVL18:

```

cmp    rax, rcx
jne    .L17

```





Step 1: unrolling $2 \times I$



Then, we have the following abstraction:
 (arrows indicate a dependency)

.L17:

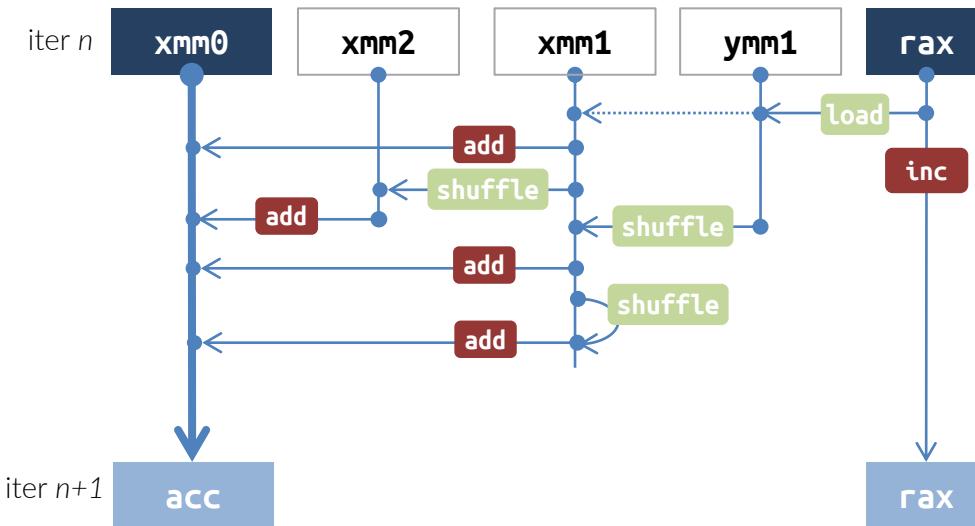
```

vmovupd ymm1, YMMWORD PTR [rax]
add     rax, 32
vaddsd xmm0, xmm0, xmm1
vunpckhpd xmm2, xmm1, xmm1
vextractf128 xmm1, ymm1, 0x1
vaddsd xmm0, xmm0, xmm2
vaddsd xmm0, xmm0, xmm1
vunpckhpd xmm1, xmm1, xmm1
vaddsd xmm0, xmm0, xmm1
  
```

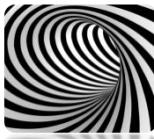
.LVL18:

```

cmp    rax, rcx
jne    .L17
  
```



`xmm0` carries a loop dependency because its value is to be used in the next iteration (that is true for `rax` too, but its latency is smaller than that of FP operations)
 It forms a **critical path** that limits the efficiency.



Step 2: unrolling $2 \times i +$ reshuffle

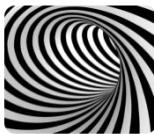


Let's explore what happens if we apport a semantic change to our code, just using the fact that our OP is associative.

```
for ( int i=0; i<N-2; i+=2 )  
    S = (S OP A[i]) OP A[i+1] ;
```



```
for ( int i=0; i<N-2; i+=2 )  
    S = S OP (A[i] OP A[i+1]) ;
```



Loops

Step 2: unrolling $2^{\times} i +$ reshuffle



```
for ( int i=0; i<N-2; i+=2 )
S = S OP (A[i] OP A[i+1]) ;
```



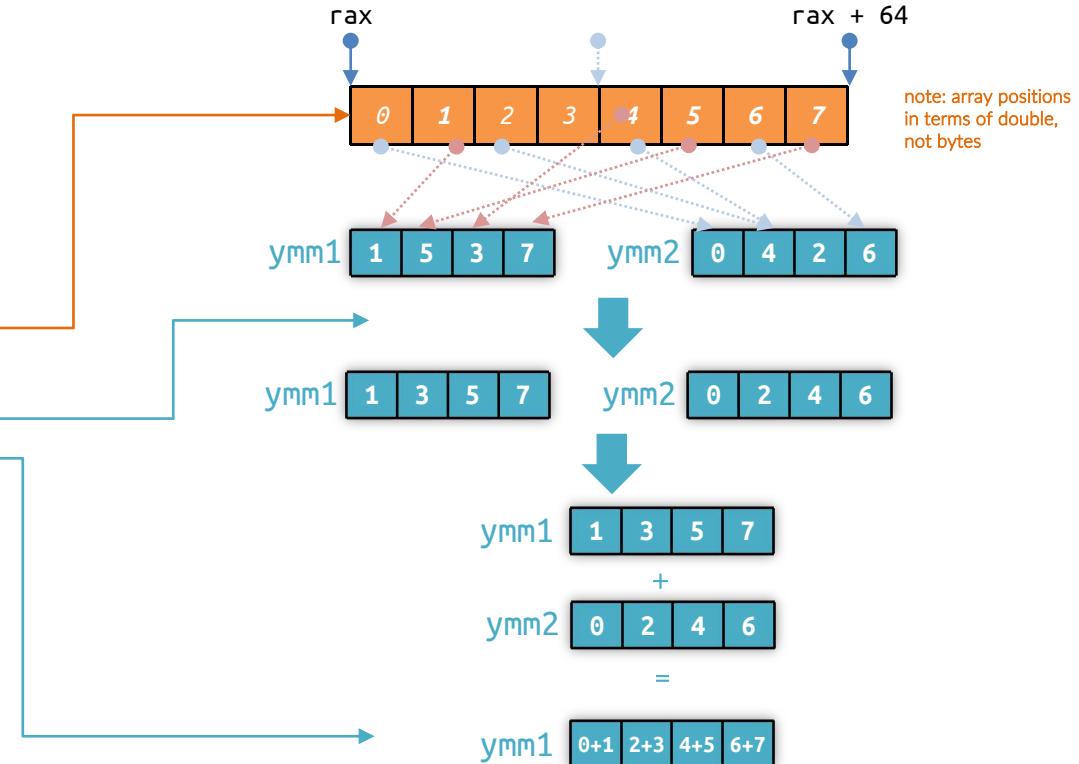
.L33:

```

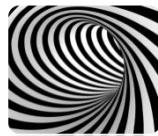
vmovupd ymm4, YMMWORD PTR [rax]
add    rax, 64
vunpcklpd  ymm1, ymm4, YMMWORD PTR -32[rax]
vunpckhpd  ymm2, ymm4, YMMWORD PTR -32[rax]
vpermpd ymm1, ymm1, 216
vpermpd ymm2, ymm2, 216
vaddpd ymm1, ymm1, ymm2
vaddsd xmm0, xmm0, xmm1
vunpckhpd  xmm3, xmm1, xmm1
vextractf128 xmm1, ymm1, 0x1
vaddsd xmm0, xmm0, xmm3
vaddsd xmm0, xmm0, xmm1
vunpckhpd  xmm1, xmm1, xmm1
vaddsd xmm0, xmm0, xmm1

```

8 doubles are processed per iteration; thanks to the re-association of operations, the compiler can reshuffle operations in a more efficient way



4 summation of subsequent elements in the array!



Step 2: unrolling $2^{\times} i + \text{reshuffle}$

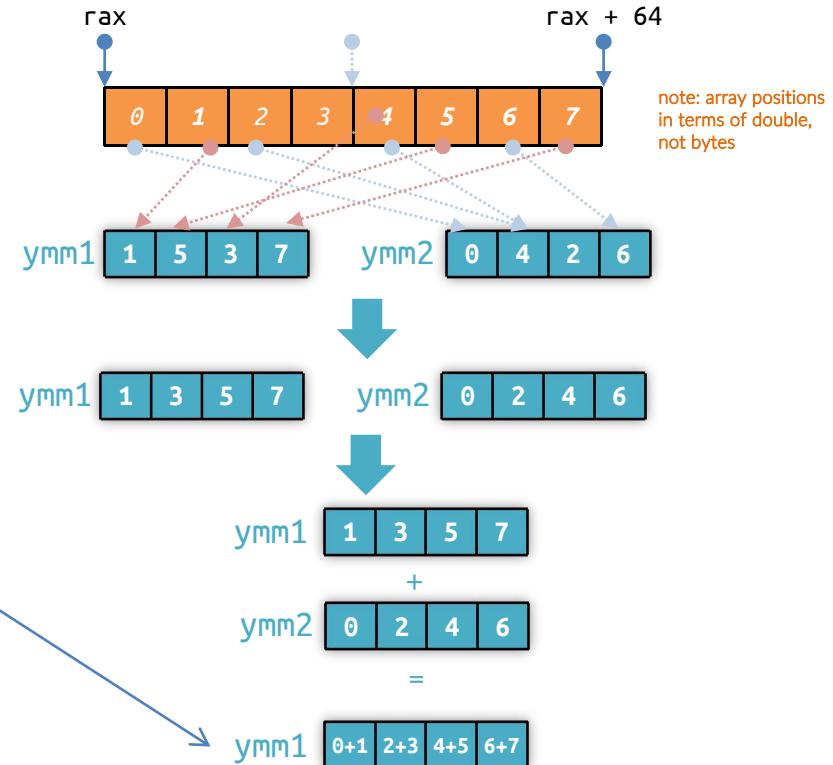


To be clearer: just because we re-associated the math expression in the loop,
from $S = (S \text{ OP } A[i]) \text{ OP } A[i+1]$;
to $S = S \text{ OP } (A[i] \text{ OP } A[i+1])$;

the compiler is entitled to exploit the fact that *in the semantics that now we are giving*, the operation order will be

$\text{Sum} = ((([0]+[1]) + ([2]+[3])) + ([4]+[5])) + ([6]+[7])\dots$

And the result is what we have just discussed, more efficient than what we obtained with the previous



4 summation of subsequent elements in the array!



Let's inquire more (still accounting for the fact that in floating point the OP is *not* associative) the difference among

```
1 for ( int i = 0; i < N; i++ )      [A]
2     S = S OP a[i];
3
4 for ( int i = 0; i < N; i+=2 )      [B]
5     S = S OP (a[i] OP a[i+1]);
```

If we define OP to be ‘+’ and S_i to be the i_{th} partial result, i.e. the value of S after the first $i - 1$ iterations, the cases [A] and [B] expand to (square brackets cluster what happens in each single iteration)

$$[A] \rightarrow [[[0 + a_0] + a_1] + a_2] + a_3] + \dots \$$$

$$S_0 = a_0$$

$$S_1 = S_0 + a_1$$

$$S_2 = S_1 + a_2$$

...

$$S_i = S_{i-1} + A_i$$

$$[B] \rightarrow [[0 + (a_1 + a_2)] + (a_3 + a_4)] + (a_5 + a_6)] + \dots$$

$$S_0 = 0 + (a_0 + a_1)$$

$$S_1 = S_0 + (a_2 + a_3)$$

$$S_3 = S_2 + (a_4 + a_5)$$

...

$$S_i = S_{i-1} + (a_i + a_{i+1})$$



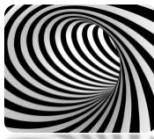
It is evident that for [A] the basic “*element*” of each iteration is the single array entry a_i , whereas in [B] the basic element is the sum $a_i + a_{i+1}$. Hence, while in the first case there is nothing we can do but subsequently calculate the S_i , in the second case we can *separately* calculate as many $[a_i + a_{i+1}]$ elements as possible and *then* sum them up subsequently. Actually, in the second case (because of how we specified the operations!) each a_i, a_{i+1} pair *must* be summed up *before* being summed to S_i .

Q : And how many $[a_i + a_{i+1}]$ elements can we separately calculate in a cycle?

A : In this case, since we are using only 1 accumulator, most probably the choice of the compiler will depend on how wide a vector register is. In fact, since

1. there is the computation of only 1 S_i per iteration, with a subsequent summation
2. it is most effective to exploit a single vector load

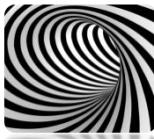
the most effective choice is the one made by the compiler, i.e. to use a 2 vector registers to load 8 a 's entries and to reshuffle them in order to obtain 4 $[a_i + a_{i+1}]$ elements in just one $+$ operation, and to sum them up subsequently. If the vector register was 512bits instead of 256bits, it would have loaded 16 entries in order to obtain 8 $[a_i + a_{i+1}]$ elements and so on.



Step 3: unrolling 2×2

As we have seen, what is the blocking element is the critical path of the accumulator, because we are using a unique place to store the summation. A logical step is to separate partial results in multiple accumulators.

```
for ( int i=0; i<N; i++ )  
    S = S OP A[i];  
  
    ↓  
  
for ( int i=0; i<N-2; i+=2 )  
{  
    s0 = s0 OP A[i];  
    s1 = s1 OP A[i+1];  
}  
return s0 = s0 OP s1;
```



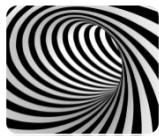
Step 2: unrolling 2×2

```
for ( int i=0; i<N-2; i+=2 ) {  
    s0 = s0 OP A[i];  
    s1 = s1 OP A[i+1]; }
```



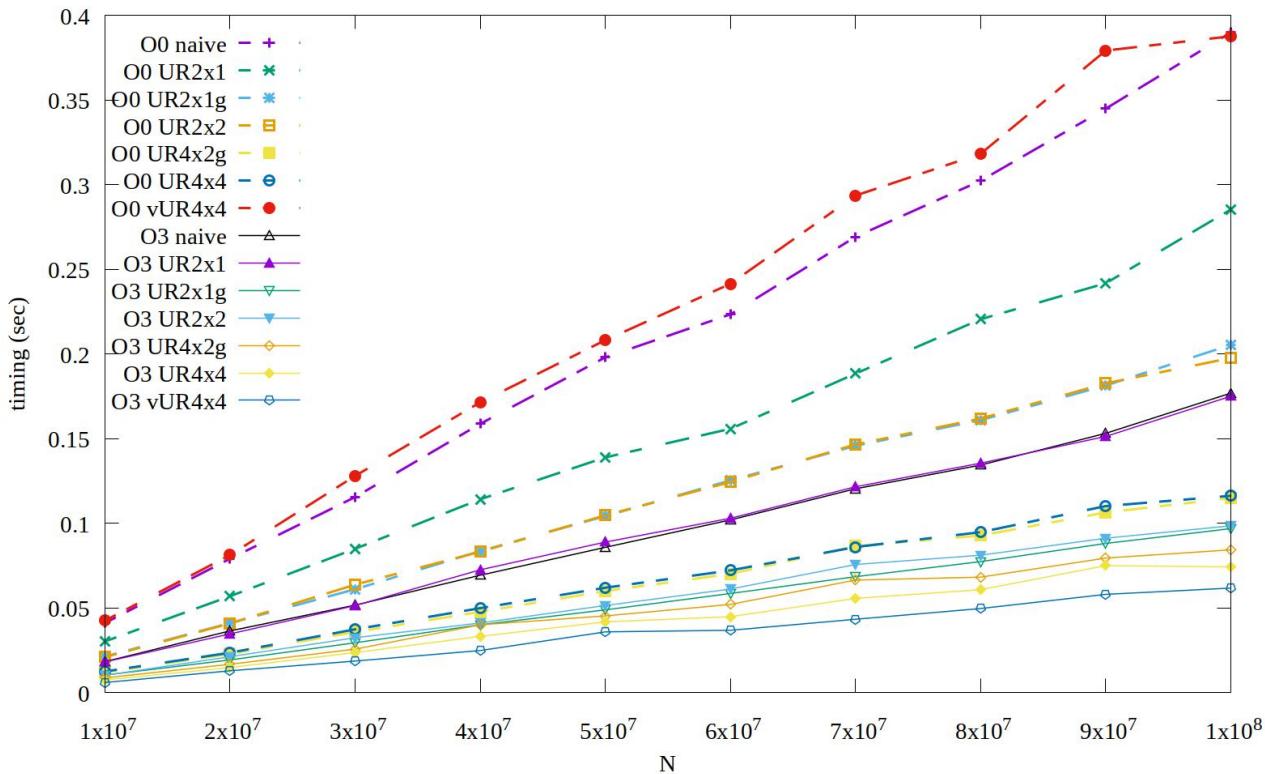
```
.L49:  
    vmovupd    ymm4, YMMWORD PTR [rax]  
    vmovupd    ymm3, YMMWORD PTR 32[rax]  
    vmovapd    xmm2, xmm4  
    vaddsd    xmm1, xmm1, xmm4  
    vunpckhpd  xmm2, xmm2, xmm2  
    vaddsd    xmm0, xmm0, xmm2  
    vextractf128  xmm4, ymm4, 0x1  
    vaddsd    xmm1, xmm1, xmm4  
    vunpckhpd  xmm4, xmm4, xmm4  
    vaddsd    xmm0, xmm0, xmm4  
    vmovapd    xmm6, xmm3  
    vaddsd    xmm5, xmm1, xmm3  
    vunpckhpd  xmm6, xmm6, xmm6  
    vaddsd    xmm0, xmm0, xmm6  
    vextractf128  xmm3, ymm3, 0x1  
    vaddsd    xmm1, xmm5, xmm3  
    add       rax, 64  
    vunpckhpd  xmm3, xmm3, xmm3  
    vaddsd    xmm0, xmm0, xmm3  
  
    cmp       rax, rcx  
    jne       .L49
```

As before (2x1g) the compiler feels free to load 8 doubles per iteration, and then reshuffling them appropriately in order to respect the semantics of our coding, it sums them up using **xmm0** and **xmm1** as separate accumulators.



Loops

Reduction: results (timing)



Run time of different implementation with and without compiler's optimization

UR NxM: unrolled N times using M accumulators.

vUR4x4: UR4x4 with explicit vectorization.

In this plot and in the following ones dashed lines are for -O0 and solid line for -O3 -march=native (only gcc has been used)

Outline



Avoid the avoidable
inefficiencies



Cache &
Memory



Loops



Branches

Unleash
the
Compiler

Pipelines



Branches

Don't loose control

Whenever either (i) the sequence of operations that must be executed or (ii) the sequence of data to be processed depends on some condition, i.e. on the outcome of a test performed on some data or result, we have a *conditional execution*.

Modern architecture offer 2 distinct low-level instructions to implement a conditional execution upon a test:

- modifying the control flow → **data-dependent execution-flow**
- modifying the data flow → **data-dependent data-flow**



Branches

Low-level control

Let's see the conditional execution flow as first.

At machine level, the way to alter the execution flow is through a **jump instruction**, that causes the control to be passed to a different code section.

The jump instruction can be *conditional*, when its execution depends on the outcome of some operation (a test), or *unconditional* if it is not.

A function call is a jump instruction of particular type, in which we are not interested here.



jmp is the only *unconditional* instruction; it accepts either a *direct* destination (specified by a label) or an *indirect* destination (specified through an address in a register or in memory).

je, jne and the others, are *conditional* instructions: i.e. their execution depends on a condition.

These instructions access the values stored in the bits of the flag register, a special register where the CPU inscribes some characteristics outcomes of the last arithmetic or logical operation

CF	CARRY FLAG; a carry out of the msb has been generated, signaling an overflow in unsigned op
ZF	ZERO FLAG; the most recent op resulted in a zero
SF	SIGN FLAG; the most recent operation ended in a negative result
DF	OVERFLOW FLAG; a two's-complement overflow, either negative or positive.

This table shows some of the low-level jump instructions routinely available on modern CPUs.

jmp	<i>Label</i> * <i>Operand</i>	direct jump indirect jump
je	<i>Label</i>	jump if equal / zero
jne	<i>Label</i>	jump if not equal / zero
js	<i>Label</i>	jump if negative
jns	<i>Label</i>	jump if not negative
jg	<i>Label</i>	jump if greater
jge	<i>Label</i>	jump if greater or equal
jl	<i>Label</i>	jump if less
...



Branches

Low-level example: for loop

Let's inspect how simple for cycle translates in assembler:

```
for ( int i = 0; i < 10; i++ )  
    array[i] = 0;
```

The address to be referenced is increased (equivalent to increase the counter *i*)

Direct memory access at *i*-th element of array

.L2:

mov
add
cmp
jne

DWORD PTR [rax], 0
rax, 4
rax, rbp
.L2

The comparison operator; it amounts to *rax-rbp* and sets the flag *zf* (note: *rbp* contains the termination value)

ax contains the address of array

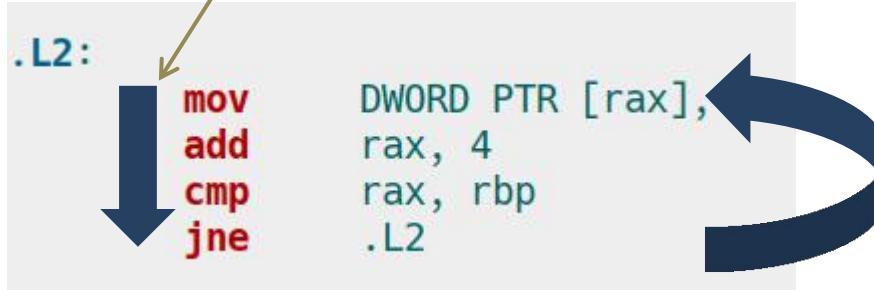
jump if not equal, i.e. jumps to .L2 if the *zf* flag is not set



Branches

Low-level example: for loop

This is the linear flow of execution in the cycle body



Until `rax <= rbp` (i.e. $i < 10$) there is a backward jump and the body is executed again.

When the jump is *not* executed and the control flow continues afterwards.



Branches

```
if ( a < b )
    c = a+b;
else
    c = a-b;
```

Low-level example: if statement

```
        mov    eax, DWORD PTR -8[rbp]
        cmp    eax, DWORD PTR -4[rbp]
        jge    .L2
        mov    edx, DWORD PTR -8[rbp]
        mov    eax, DWORD PTR -4[rbp]
        add    eax, edx
        mov    DWORD PTR -12[rbp], eax
        jmp    .L3

.L2:
        mov    eax, DWORD PTR -8[rbp]
        sub    eax, DWORD PTR -4[rbp]
        mov    DWORD PTR -12[rbp], eax

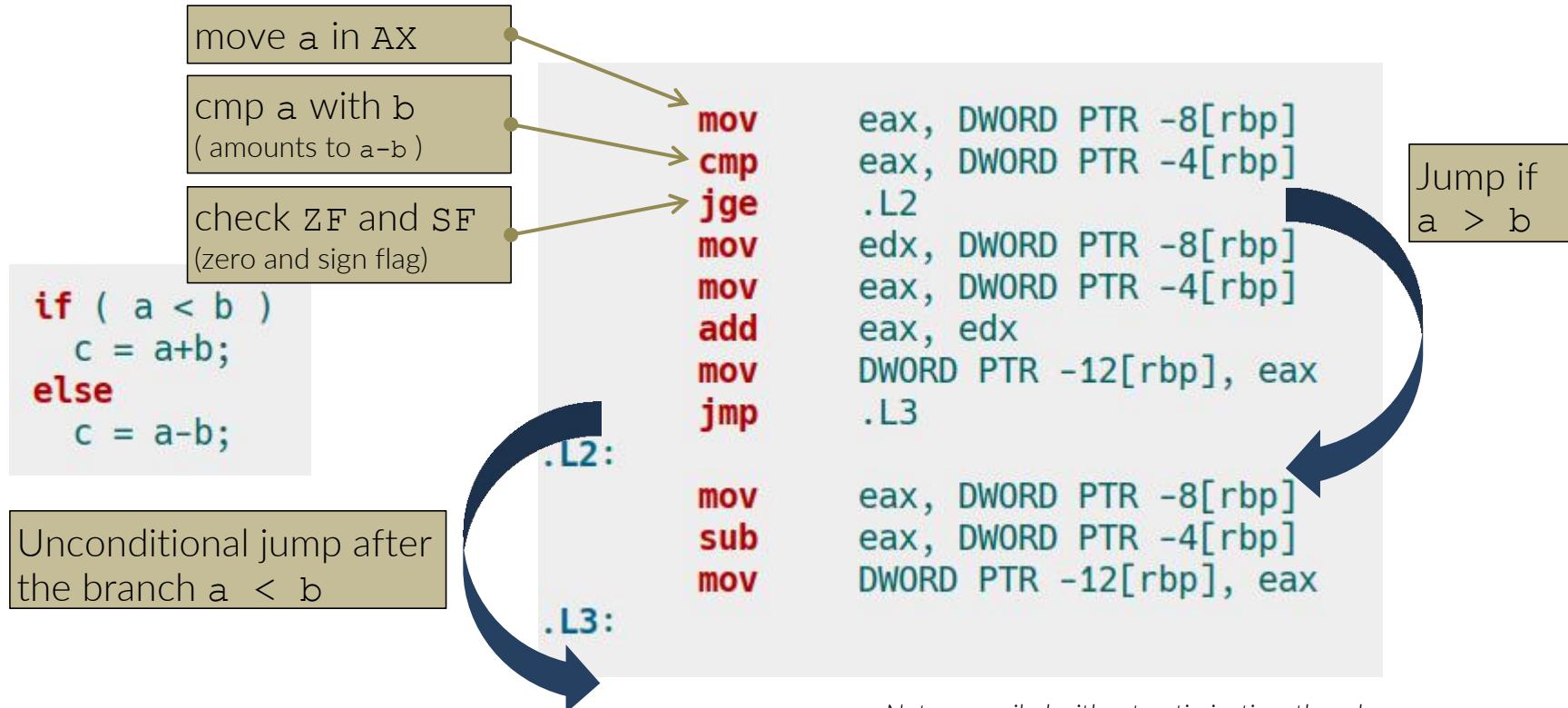
.L3:
```

Note: compiled without optimization, though



Branches

Low-level example: if statement



Note: compiled without optimization, though



Low-level example: if statement

Note:

The true branch is the closest to the test condition, while the false branch is reached upon a jump.

→ when coding, if possible pay attention to what is most likely to be true, to preserve the **code locality**.

(it is possible to suggest to compiler which branch will most probably be true)

```
c = a+b;  
else  
    c = a-b;
```

```
mov    eax, DWORD PTR -8[rbp]  
cmp    eax, DWORD PTR -4[rbp]  
.L2:  
      .L2:  
      mov    edx, DWORD PTR -8[rbp]  
      mov    eax, DWORD PTR -4[rbp]  
      add    eax, edx  
      mov    DWORD PTR -12[rbp], eax  
      jmp    .L3  
.L3:  
      mov    eax, DWORD PTR -8[rbp]  
      sub    eax, DWORD PTR -4[rbp]  
      mov    DWORD PTR -12[rbp], eax
```

Note: compiled without optimization, though



We have seen some details about the conditional transfer of the control flow through the simple jump mechanism. However, that could be quite inefficient in modern CPUs (we'll see more details on that when dealing with the pipelines).

A different mechanism is to **conditionally change the data flow**, which is the second mechanism for conditional execution that we mentioned.



The conditional transfer of data flow yields a very high performance but is possible only on a small subset of cases;

basically those are when simple values are involved.

A typical example is, for instance, the absolute value of a result, or something alike where a single-valued outcome is expected.

```
if ( a < b )
    c = a+b;
else
    c = a-b;
```

Here `c` holds the result of a very simple arithmetic operation between `a` and `b`.



Branches

Conditional data flow

```
if ( a < b )
    c = a+b;
else
    c = a-b;
```

*Compiled with
gcc -O3 -march=native*

note:
ebx = a
eax = b

mov	edx, ebx
lea	ecx, [rbx+rax]
sub	edx, eax
cmp	eax, ebx
cmove	edx, ecx

A **much** shorter and efficient code!



Branches

Conditional data flow

	eax	ebx	ecx	edx
<code>eax = b, ebx = a</code>	b	a	-	-
mov edx, ebx	b	a	-	a
lea ecx, [rbx+rax]	b	a	a+b	a
sub edx, eax	b	a	a+b	a-b
cmp eax, ebx	<i>compares a and b; sets ZF and CF (zero and carry flag)</i>			
cmove edx, ecx	move ecx's value to edx if the condition (greater than) is satisfied			

The strategy is as follows:

- (i) reg ecx contains a+b while reg edx contains a-b
- (ii) the conditional move checks the result of cmp a, b (i.e. the value of a-b)
- (iii) the content of edx is changed into ecx's just in case.

No jump instructions have been issued.



Branches

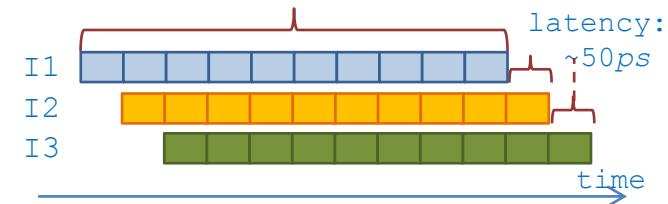
The perils of conditional branches

As we have seen in the lecture about modern architecture, **modern processors achieve great performance thanks to the pipelines and out-of-order execution**, i.e. by decomposing complex instructions in simpler steps and mixing the execution of those sub-steps for different instructions (up to tens of instructions at the same time may be “on-the-fly” in modern CPUs).

That, however, **requires the pipelines to be always full**; if not so, the toll of great penalties in terms of wasted cpu cycles is to be payed.

To achieve this goal, it is in turn mandatory for the scheduler to be able to **predict** in advance what will be the sequence of instructions to be executed.

How can that be in a world full of possibilities and branches ?



We'll see more about pipelines in forthcoming lectures



The perils of conditional branches

In order to predict what the execution flow will be, modern cpus feature a **branch predictor**, that is an internal unit of highly sophisticated logic that guesses whether a jump instruction will succeed or not.

Best branch predictors are as good as 95% of accuracy; nonetheless, the branch mis-prediction, or branch miss, determines a huge performance loss.
Typical figures for penalty are 10-30 cycles!

That is because the longer the pipeline, the further in the future you have to scrutinize the flow, the more difficult it is and the larger will be the mis-prediction penalty.

Example

Let's say we have 140 instructions in flight, and 1 every 7 is a branching instructions. What is the probability that the pipelines shall **not** be flushed with 95% correct branch predictor? And with a 90% one?

answer: ~36% and ~12%



The perils of conditional branches

In order to predict what the execution flow will be, modern CPUs feature a **branch predictor**, that is an internal mechanism that tries to guess if a jump instruction will succeed or not.

Best branch predictors are able to correctly predict the branch direction after prediction, or branch miss, due to the cost of the prediction penalty are 10-30 cycles!

That is because the longer the execution flow, the more difficult it is to predict.

Example

Let's say we have 140 instructions. What is the probability that the pipelines shall be full at least once?

That is why the 2nd strategy we have seen, the **conditional change of data flow** is preferable whenever possible and the compiler will try to use it as much as possible:

it generates no jump instructions and the execution flow is linear and perfectly predictable.

However, as we said, it applies only on a limited sub-set of cases.



Branches

Revise your code

ex. 1: about the fact that design and simplicity are the best move

Consider the following code snippet

```
// generate random numbers
for (cc = 0; cc < SIZE; cc++)
    data[cc] = rand() % TOP;

// take action depending on their value
for (ii = 0; ii < SIZE; ii++)
{
    if (data[ii] > PIVOT)
        sum += data[ii];
}
```



Branches

Revise your code

Consider the following code snippet^(*)

```
// generate random numbers
for (cc = 0; cc < SIZE; cc++)
    data[cc] = rand() % TOP;

qsort(data, SIZE, sizeof(int), compare);

// take action depending on their value
for (ii = 0; ii < SIZE; ii++)
{
    if (data[ii] > PIVOT)
        sum += data[ii];
}
```

^(*)of course, you are adding an overhead due to the sorting routine, so the total running time may be even larger. Moreover, you should have all the values available so that does not work for real-time streamings. However, the point here is to focus on how – in general – it is better to avoid conditionals inside loop, with any possible trick or change in workflow



You can do even better, without adding operations:

```
// generate random numbers
for (cc = 0; cc < SIZE; cc++)
    data[cc] = rand() % TOP;

// take action depending on their value
for (ii = 0; ii < SIZE; ii++)
{
    sum += ( data[ii]>PIVOT ) * data[ii];
    //sum += ( data[ii]>PIVOT ? data[ii] : 0);
}
```



Branches

Revise your code

-00

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred
sum is 983597794767, elapsed seconds: 5.40445
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.wow
sum is 983597794767, elapsed seconds: 2.23186
(in total: 2.44473 seconds)
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.smart
sum is 983597794767, elapsed seconds: 2.8878
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ■
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.03
sum is 983597794767, elapsed seconds: 0.660148
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.wow.03
sum is 983597794767, elapsed seconds: 0.650005
(in total: 0.795181 seconds)
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.smart.03
sum is 983597794767, elapsed seconds: 0.679286
```

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ■
```



Branches

Revise your code

-03

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.03
sum is 983597794767, elapsed seconds: 0.660148
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.wow.03
sum is 983597794767, elapsed seconds: 0.650005
(in total: 0.795181 seconds)
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.smart.03
sum is 983597794767, elapsed seconds: 0.679286
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% █
```

-03

-**marc=native**

```
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.03n
sum is 983597794767, elapsed seconds: 0.217864
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.wow.03n
sum is 983597794767, elapsed seconds: 0.215645
(in total: 0.355377 seconds)
luca@GGG:~/code/HPC_LECTURES/branch_prediction/branch_prediction_2% ./branchpred.smart.03n
sum is 983597794767, elapsed seconds: 0.224288
```



Branches

Revise your code

ex 2: code restructuring for sorting two arrays

You have 2 arrays, A and B, and you want to swap their elements so that

$$A[i] \geq B[i]$$

for all i .

A straightforward implementation would be:

```
for (i = 0; i < SIZE; i++)
{
    if ( A[i] < B[i] )
    {
        t = B[i];
        B[i] = A[i];
        A[i] = t;
    }
}
```



However, that implementation suffers exactly of the same problem we have just discussed.

An alternative way to write the same code, but in a more effective style is:

```
for (i = 0; i < SIZE; i++)
{
    int min = A[i] > B[i] ? B[i] : A[i];
    int max = A[i] >= B[i] ? A[i] : B[i];

    A[i] = max;
    B[i] = min;
}
```



Revise your code

```
for (uint ii = 0; ii < SIZE; ii++)  
{  
    if ( B[ii] > A[ii] )  
    {  
        int t = A[ii];  
        A[ii] = B[ii];  
        B[ii] = t;  
    }  
}
```

standard

```
for (uint ii = 0; ii < SIZE; ii++)  
{  
    int max = (A[ii]>B[ii])? A[ii]:B[ii];  
    int min = (A[ii]>B[ii])? B[ii]:A[ii];  
    A[ii] = max;  
    B[ii] = min;  
}
```

smart

```
for (uint ii = 0; ii < SIZE; ii++)  
{  
    int register t = -(A[ii]<B[ii]);  
    int register x = A[ii]^B[ii];  
    A[ii] = A[ii]^(x & t);  
    B[ii] = B[ii]^(x & t);  
}
```

smart2

```
for (uint ii = 0; ii < SIZE; ii++)  
{  
    int d = A[ii]-B[ii];  
    d &= (d >> 31);  
    A[ii] = A[ii] - d;  
    B[ii] = B[ii] + d;  
}
```

smart3

predictable data has a regular pattern easily spotted by the CPU's branch predictor

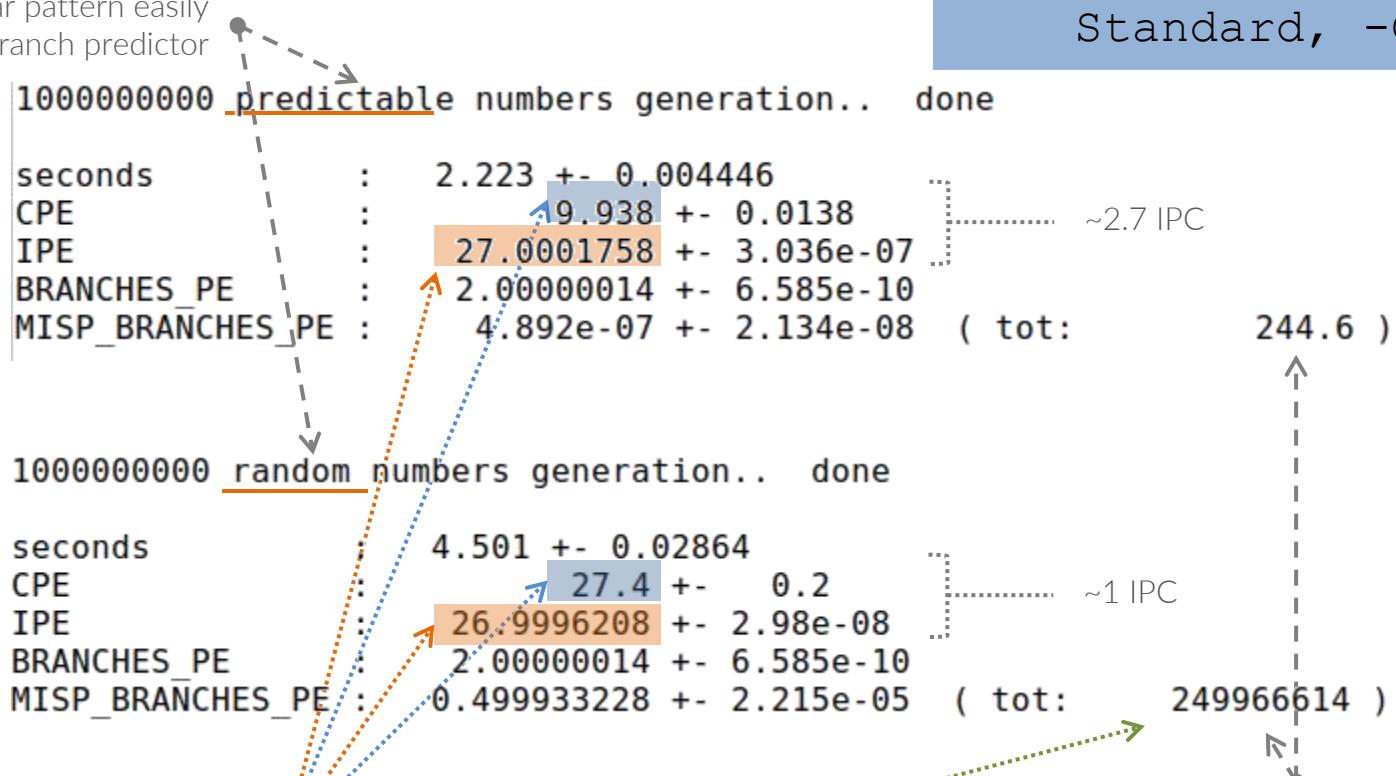
Standard, -00

loop run-time
cycles per element
Instructions per element

conditional branches
pert element
mis-predicted cond.
branches per el.

same number of IPE but almost
3 times as many CPE when
data pattern is not predictable

in fact, there is 1 mis-predicted
branch every 2
(arrays are 500,000,000 long)



total # of mis-predicted
conditional branches



Branches

Revise your code

```
seconds : 1.824 +- 0.05734
CPE      : 11.12 +- 0.341
IPE      : 34.0000018 +- 4.344e-08
BRANCHES_PE : 1.00000014 +- 3.293e-10
MISP_BRANCHES_PE : 9.94e-07 +- 3.207e-08 ( tot:
```

~3 IPC

smart, -00

predictable

number of IPE is larger than for standard case, but the CPE is stable !

```
seconds : 1.857 +- 0.001762
CPE      : 11.32 +- 0.00192
IPE      : 34.0000018 +- 2.581e-08
BRANCHES_PE : 1.00000014 +- 3.293e-10
MISP_BRANCHES_PE : 9.512e-07 +- 4.987e-08 ( tot:
```

~3 IPC

497)

mis-predicted branches are very few and comparable in both cases

green dot

random

green arrow



Branches

Revise your code

```
seconds          : 1.628 +- 0.01015
CPE             : 9.993 +- 0.0464
IPE             : 32.0000017 +- 2.356e-08
BRANCHES_PE     : 1.00000014 +- 3.293e-10
MISP_BRANCHES_PE: 3.728e-07 +- 8.898e-08 ( tot:
```

number of IPE is larger than for standard case, but the CPE is stable !

```
seconds          : 1.688 +- 0.03554
CPE             : 10.36 +- 0.211
IPE             : 32.0000017 +- 2.98e-08
BRANCHES_PE     : 1.00000014 +- 3.293e-10
MISP_BRANCHES_PE: 3.1e-07 +- 5.183e-08 ( tot:
```

~3 IPC

smart2, -00

predictable

186.4)

mis-predicted branches are very few and comparable in both cases

↓

random

155)



Branches

Change the point of view

ex. 3: about the fact that design and simplicity are the best choice

Just changing point of view sometimes may help:

```
for ( j = 0; j < N; j++ )
    for ( i = 0; i < M; i++ )
    {
        if ( i > j )
            matrix[j][i] = 1.0;
        else if ( i < j )
            matrix[j][i] = -1.0;
        else
            matrix[j][i] = 0.0;
    }
```



Branches

Change the point of view

Can easily be re-written with no conditional evaluations at all:

```
for ( int j = 0; j < N; j++ )
{
    int i;
    for ( i = 0; i < j; i++ )
        matrix[j][i] = -1.0;

    matrix[j][i] = 0.0;

    for ( i = j+1; i < M; i++ )
        matrix[j][i] = 1.0;
}
```

that's all, have fun

"So long
and thanks
for all the fish"