Tools for performance analysis

Optimization training at CINES

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How to compare two versions of a code ?

- The most simplest way is to compare the restitution time (alias the execution time) of the two versions
  - The faster one (shorter time) is the best
- This is simple but we have to remember it when we try to improve the performance of a code
- Be careful to always compare the same time
  - In scientific codes it is very common to have a pre-processing part and a solver part
  - Be sure to measure only the part in witch you are interested
  - Otherwise, there is a chance that you will not see the effect of your modification

Measuring the performance of a parallel code

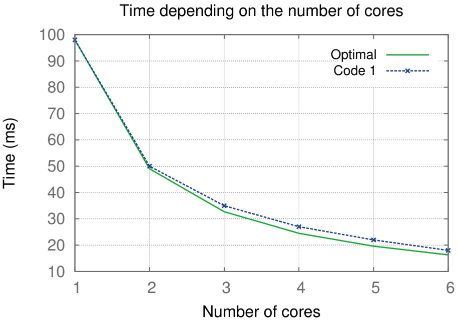
- Time is a basic tool for comparing two versions of a code
  - Consider that we have a time t_1 for the sequential version of code
  - If we put 2 cores we can hope to divide the time by 2 ($t_2 = \frac{t_1}{2}$)
  - If we put 3 cores we can hope to divide the time by 3 ($t_3 = \frac{t_1}{3}$)
- The table below shows the execution time of a code named `Code 1`
  - The real time refers to the measured restitution time of `Code 1`
  - The optimal time refers to the best theoretical time ($optiTime = \frac{seqTime}{nbCores}$)

nb. of cores	real time	opti. time
1	98 ms	98.0 ms
2	50 ms	49.0 ms
3	35 ms	32.7 ms
4	27 ms	24.5 ms
5	22 ms	19.6 ms
6	18 ms	16.3 ms

Time in function of the number of cores for `Code 1`

Time graph

- The previous table is difficult to read for an analysis
- It is easier to observe results with a graph



- This graph is not so bad but it is hard to see how far we are from the optimal time...

Introducing speed up

- An other way to compare performance is to compute the speed up
- The standard is to use the sequential time as the reference time
- The optimal speed up is always equal to the number of cores we use

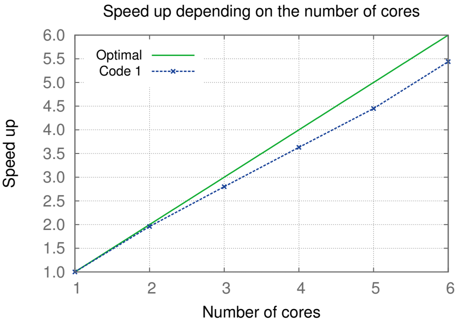
$$sp = \frac{seqTime}{parallelTime},$$

with $seqTime$ the time measured from the 1 core version of the code and $parallelTime$ the time measured from the parallel version of the code.

nb. of cores	real time	speed up
1	98 ms	1.00
2	50 ms	1.96
3	35 ms	2.80
4	27 ms	3.63
5	22 ms	4.45
6	18 ms	5.44

Time and speed up in function of the number of cores for `Code 1`

Speed up graph



- Now, with the speed up, it is much easier to see how far we are from the optimal speed up!

Amdahl's law

- Can we indefinitely put more cores and get better performances?
  - Amdahl said no!
  - Or, to be more precise, it depends on the characteristics of the code...
  - If the code is fully parallel we can indefinitely put more cores and get better performances
  - If not, there is a limitation on the maximal speed up we can reach

$$sp_{max} = \frac{1}{1 - ft_p},$$

with sp_{max} the maximal speed up reachable and ft_p the parallel fraction of time in the code ($0 \leq ft_p \leq 1$).

Amdahl law: example

- If we have a code composed of two parts:
  - 20% is intrinsically sequential
  - 80% is parallel
- What is the maximal reachable speed up?

$$sp_{max} = \frac{1}{1 - ft_p} = ...$$

Amdahl law: example

- If we have a code composed of two parts:
  - 20% is intrinsically sequential
  - 80% is parallel
- What is the maximal reachable speed up?

$$sp_{max} = \frac{1}{1 - ft_p} = \frac{1}{1 - 0.8} = \frac{1}{0.2} = 5.$$

- We have to try hard to limit the sequential part of the code
- It is essential to reach a good speed up
- In many cases, the sequential part remains in the pre-processing part of the code but also in IOs and communications...

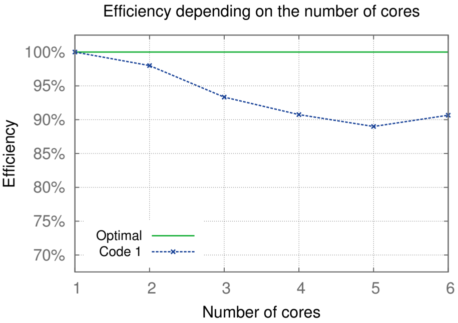
Efficiency of a code

- The efficiency is the relation between the real version of a code and the optimal version
- There are many ways to define the efficiency of a code
  - With the speed up: $eff = \frac{realSp}{optiSp}$
  - With the restitution time: $eff = \frac{optiTime}{realTime}$
  - Etc.
- The efficiency can be expressed as a percentage: $0\% < eff \leq 100\%$

nb. of cores	real time	speed up	efficiency
1	98 ms	1.00	100%
2	50 ms	1.96	98%
3	35 ms	2.80	93%
4	27 ms	3.63	91%
5	22 ms	4.45	89%
6	18 ms	5.44	91%

Time, speed up and efficiency in function of the number of cores for `Code 1`

Efficiency graph



- How far we are from the optimal code becomes very clear with the efficiency!

Scalability

- The scalability of a code is its capacity to be efficient when we increase the number of cores
- A code is scalable when it can use a lot of cores
- But, how do we measure the scalability of a code ? How do we know when a code is no more scalable ?
- In fact, there is no easy answer
- However, there are two well-known models for qualifying the scalability of a code
    - Strong scalability
    - Weak scalability

Strong scalability

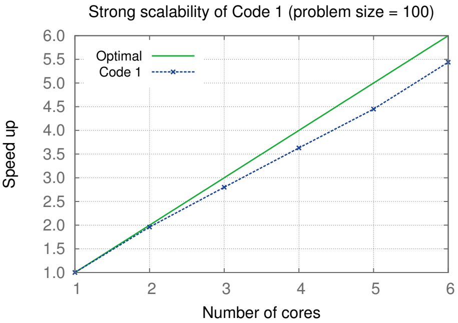
- In this model we measure the code execution time each time we add a core
- And we keep the same problem size each time: the problem size is a constant

nb. of cores	problem size	real time	speed up
1	100	98 ms	1.00
2	100	50 ms	1.96
3	100	35 ms	2.80
4	100	27 ms	3.63
5	100	22 ms	4.45
6	100	18 ms	5.44

Problem size, time and speed up in function of the number of cores for `Code 1`

Strong scalability graph

- This is the same graph presented before for the speed up: it represents an analysis of the strong scalability of `Code 1`



- We can see that the strong scalability of `Code 1` is pretty good for 6 cores: we reach a 5.4 speed up, this is not so far from the optimal speed up!

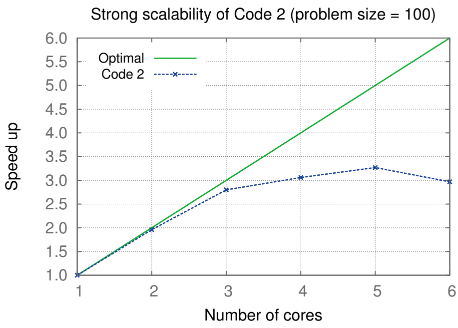
Strong scalability of `Code 2`

- Now we introduce `Code 2`
- Measurements of this code are presented below

nb. of cores	problem size	real time	speed up
1	100	98 ms	1.00
2	100	50 ms	1.96
3	100	35 ms	2.80
4	100	32 ms	3.06
5	100	30 ms	3.27
6	100	33 ms	2.97

Problem size, time and speed up in function of the number of cores for `Code 2`

Strong scalability of `Code 2` (graph)



- We can see that `Code 2` has a bad strong scalability
- But this is not a sufficient reason to put it in the trash!
- What about its weak scalability?

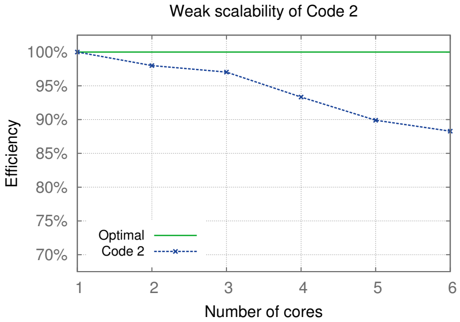
Weak scalability

- In this model we measure the execution time depending on the number of cores
- And we change the problem size in proportion to the number of cores!
- We cannot compute the speed up because we do not compare same problem sizes
- But we can compute an efficiency: $eff = \frac{optiTime}{parallelTime} = \frac{seqTime}{parallelTime}$

nb. of cores	problem size	real time	efficiency
1	100	98 ms	100%
2	200	100 ms	98%
3	300	101 ms	97%
4	400	105 ms	93%
5	500	109 ms	90%
6	600	111 ms	88%

Problem size, time and speed up in function of the number of cores for `Code 2`

Weak scalability graph



- The weak scalability of `Code 2` is pretty good ($\approx$ 90% of efficiency with 6 cores)
- So, why the strong scalability was so bad ?
  - Perhaps because the problem size was to small...
  - Remember Amdahl's law, perhaps the parallel fraction of time was not big enough with a problem size of 100

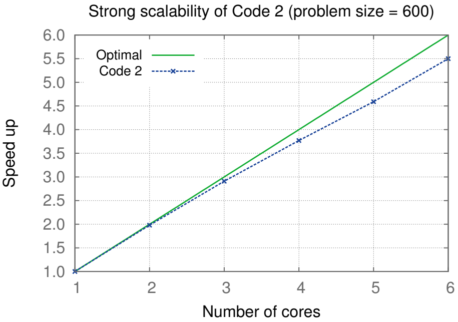
Strong scalability of `Code 2`

- Let's redo the strong scalability test for `Code 2`
- But with a bigger problem size (600)!

nb. of cores	problem size	real time	speed up
1	600	611 ms	1.00
2	600	308 ms	1.98
3	600	210 ms	2.91
4	600	162 ms	3.77
5	600	133 ms	4.59
6	600	111 ms	5.50

Problem size, time and speed up in function of the number of cores for `Code 2`

Strong scalability of `Code 2` (graph)



- With a bigger problem size the strong scalability is much better!
- Strong scalability results are much more dependent on the problem size than for weak scalability
- But it is not always possible to perform a complete weak scalability test
- This is why the two models are complementary to estimate the scalability of a code

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Floating-point operations

- In the previous section, we saw how to compare different versions of a code (tools for a comparative analysis)
- But we did not speak about concepts to analyse the performance of the code itself
- The number of floating-point operations is an important characteristic of an algorithm
  - Well-spread in the High Performance Computing world

```
float sum(float *values, int n)
{
  float sum = 0.f;

  // total flops = n * 1
  for(int i = 0; i < n; i++)
    sum = sum + values[i]; // 1 flop because of 1 addition

  return sum;
}
```

Counting flops in a basic `sum` kernel

Floating-point operations per second

- Number of floating-point operations alone is not very interesting
- But with this information we can compute the number of floating-point operations per second (flop/s)!
  - Flop/s is very useful because we can directly compare this value with the peak performance of a CPU
  - With flop/s we can know if we are making a good use of the CPU
  - Today CPUs are very fast and we will use Gflop/s as a standard (1 Gflop/s = 10^9 flop/s)

Peak performance of a processor

- The peak performance is the maximal computational capacity of a processor
- This value can be calculated from the maximum number of floating-point operations per clock cycle, the frequency and the number of cores:

$$peakPerf = nOps \times freq \times nCores,$$

with $nOps$ the number of floating-point operations that can be achieved per clock cycle, $freq$ the processor's frequency and $nCores$ the number of cores in the processor.

Peak performance of a processor: example

CPU name	Core i7-2630QM
Architecture	Sandy Bridge
Vect. inst.	AVX-256 bit (4 double, 8 simple)
Frequency	2 GHz
Nb. cores	4

Specifications from `http://ark.intel.com/products/52219`

The peak performance in simple precision:

$$peakPerf_{sp} = nOps \times freq \times nCores = (2 \times 8) \times 2 \times 4 = 128\ Gflop/s$$

The peak performance in double precision:

$$peakPerf_{dp} = nOps \times freq \times nCores = (2 \times 4) \times 2 \times 4 = 64\ Gflop/s$$

- $nOps = 2 \times vectorSize$ because with the Sandy Bridge architecture we can compute 2 vector instructions in one a cycle (`add` and `mul`)

Arithmetic intensity

- Previously we have seen how to compute the Gflop/s of our code and how to compute the peak performance of a processor
- Sometime the measured Gflop/s are far away from the peak performance
  - It could be because we did not optimize well our code
  - Or simply because it is not possible to reach the peak performance
  - In many cases both previous statements are true!
- So, with the arithmetic intensity we consider more than just computational things: we add the memory accesses/operations

$$AI = \frac{flops}{memops}$$

Arithmetic intensity: example

```c
float sum(float *values, int n)
{
  float sum = 0.f; // we did not count sum as a memop
                   // because it is probably a register

  // total flops = n * 1  ||  total memops = n * 1
  for(int i = 0; i < n; i++)
    sum = sum + values[i]; // 1 flop because of 1 addition
                           // 1 memop because of 1 access
                           // in an wide array (values)

  return sum;
}
```

Counting flops and memops in a basic `sum` kernel

- The arithmetic intensity of `sum` function is: $AI_{\mathtt{sum}} = \frac{n \times 1}{n \times 1} = 1$
- The higher the arith. intensity is, the more the code is limited by the CPU
- The lower the arith. intensity is, the more the code is limited by the RAM

Operational intensity

- Compare to the arithmetic intensity, the operational intensity is slightly different because it also depends on the size of data

$$OI = \frac{flops}{memops \times sizeOfData} = \frac{AI}{sizeOfData}$$

$sizeOfData$ depends on the type of data we use in our code, `int` and `float` are 4 bytes, `double` is 8 bytes.

- In the previous code (`sum`) we worked with `float` so the operational intensity is: $OI_{\texttt{sum}} = \frac{n \times 1}{(n \times 1) \times 4} = \frac{1}{4}$
- Like the arithmetic intensity:
  - The higher the ope. intensity is, the more the code is limited by the CPU
  - The lower the ope. intensity is, the more the code is limited by the RAM

Operational intensity

```c
// AI = 1  ||  OI = 1/4
float sum1(float *values, int n)
{
  float sum = 0.f;
  for(int i = 0; i < n; i++)
    sum = sum + values[i];
  return sum;
}
```

A basic `sum1` kernel in simple precision

```c
// AI = 1  ||  OI = 1/8
// this code is more limited by RAM than sum1 code
double sum2(double *values, int n)
{
  double sum = 0.0;
  for(int i = 0; i < n; i++)
    sum = sum + values[i];
  return sum;
}
```

A basic `sum2` kernel in double precision

The Roofline model

- The Roofline is a model witch has be made in order to limit the maximal reachable performance
- This model takes into consideration two things
  - Memory bandwidth
  - Peak performance of the processors
- Depending on the operational intensity, the code is limited by memory bandwidth or by peak performance
- Be careful, this model is relevant when the size of data is bigger than the CPU cache sizes!

$$Attainable\ Gflop/s = min \begin{cases} Peak\ floating\ point\ performance, \\ Peak\ memory\ bandwidth \times OI. \end{cases}$$

Memory bandwidth measure

- We know how to calculate the CPU peak performance and the operational intensity of a code but have not spoken about the memory bandwidth
- The memory bandwidth is the number of bytes (8 bits) that memory can bring to the processor in one second (B/s or GB/s)
- How to know what is memory bandwidth?
  - We could theoretically calculate this value
  - But we prefer to measure the bandwidth with a micro benchmark: STREAM
- STREAM is a little code specially made in order to compute the memory bandwidth of a computer
  - It gives good and precise results
  - This is better than the theoretical memory bandwidth because there is always a difference between the theory and the reality...

The Roofline model: example

Here is an example (same as before) of a the specifications of a processor with the measured memory bandwidth:

CPU name	Core i7-2630QM
Architecture	Sandy Bridge
Vect. inst.	AVX-256 bit (4 double, 8 simple)
Frequency	2 GHz
Nb. cores	4
Peak perf sp	128 GFlop/s
Peak perf dp	64 GFlop/s
Mem. bandwidth	17.6 GB/s

Specifications from `http://ark.intel.com/products/52219`

The Roofline model: example

We only keep the needed specifications for the Roofline model:

CPU name	Core i7-2630QM
Peak perf sp	128 GFlop/s
Peak perf dp	64 GFlop/s
Mem. bandwidth	17.6 GB/s

We will take the previous `sum1` and `sum2` codes as an example for the Roofline model.

The Roofline model: example

```c
// AI = 1  ||  OI = 1/4
float sum1(float *values, int n)
{
  float sum = 0.f;
  for(int i = 0; i < n; i++)
    sum = sum + values[i];
  return sum;
}
```

A basic `sum1` kernel in simple precision

```c
// AI = 1  ||  OI = 1/8
// this code is more limited by RAM than sum1 code
double sum2(double *values, int n)
{
  double sum = 0.0;
  for(int i = 0; i < n; i++)
    sum = sum + values[i];
  return sum;
}
```

A basic `sum2` kernel in double precision

The Roofline model: example

Peak perf sp	128 GFlop/s
Peak perf dp	64 GFlop/s
Mem. bandwidth	17.6 GB/s

We will take the previous `sum1` and `sum2` codes as an example for the Roofline model:

- The `sum1` operational intensity is $\frac{1}{4}$
- The `sum2` operational intensity is $\frac{1}{8}$

Let's see what is the attainable performance with the Roofline model:

$$Attainable\ Gflop/s = min \begin{cases} Peak\ floating\ point\ performance, \\ Peak\ memory\ bandwidth \times OI. \end{cases}$$

$$\Rightarrow$$

$$Attainable\ Gflop/s_{\mathtt{sum1}} = min \begin{cases} 128\ Gflop/s, \\ 17.6 \times \frac{1}{4}\ Gflop/s. \end{cases} = 4.4\ Gflop/s$$

The Roofline model: example

Peak perf sp	128 GFlop/s
Peak perf dp	64 GFlop/s
Mem. bandwidth	17.6 GB/s

We will take the previous `sum1` and `sum2` codes as an example for the Roofline model:

- The `sum1` operational intensity is $\frac{1}{4}$
- The `sum2` operational intensity is $\frac{1}{8}$

Let's see what is the attainable performance with the Roofline model:

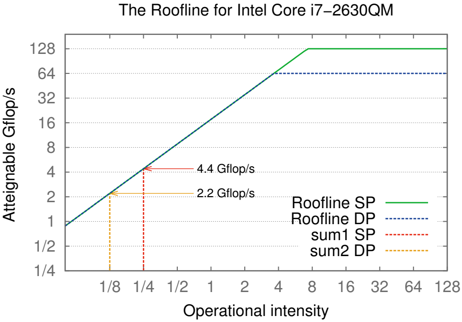
$$Attainable\ Gflop/s = min \begin{cases} Peak\ floating\ point\ performance, \\ Peak\ memory\ bandwidth \times OI. \end{cases}$$

$$\Rightarrow$$

$$Attainable\ Gflop/s_{\mathtt{sum2}} = min \begin{cases} 64\ Gflop/s, \\ 17.6 \times \frac{1}{8}\ Gflop/s. \end{cases} = 2.2\ Gflop/s$$

The Roofline model: example on a graph

- The graph below represents the Roofline for the previous processor
- There are two different Rooflines
  - One for the simple precision floating-point computations
  - One for the double precision floating-point computations



- Here, it is clear that the `sum1` and `sum2` codes are limited by the memory bandwidth

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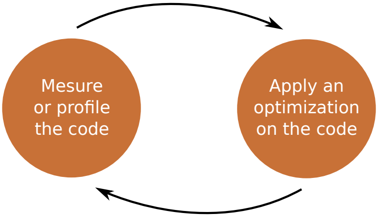
The optimization process

- Optimize a code is an iterative process
  - Firstly we have to measure or to profile the code
  - And secondly we can try optimizations (taking the profiling into consideration)



Iterative optimization process

Determine the code bottleneck

- In the profiling part we have to determine the code bottlenecks
  - Memory bound
  - Compute bound
- We can use the previous the Roofline model to do that
  - This is a very good way to understand the code limitations and the code itself!
- But sometimes the code is too big and we cannot apply the Roofline model everywhere (too much time consuming)
  - We can use a profiler in order to detect hotspots in the code
  - When we know hotspot zones we can apply the Roofline model on them!

Some profilers

- There are a lot of profilers
  - gprof
  - Tau
  - Vtune
  - Vampir
  - Scalasca
  - Valgrind
  - Paraver
  - PAPI
  - Etc.
- The most important feature of a profiler is to easily see which part of the code is time consuming
  - It is that part of the code we will try to optimize
- Of course we can do much more than that with a profiler but this is not in the range of this lesson

gprof example

```
Flat profile:

Each sample counts as 0.01 seconds.
  %   cumulative   self
 time   seconds   seconds      calls   name                          remarks
 14.94      1.01     1.01              __intel_new_memcpy            very typical syndrome in C++ codes
  6.81      1.47     0.46      13216   pass2_                        most time consuming code routine
  5.84      1.87     0.40  189251072   Complexe::Complexe(...)       related to __intel_new_memcpy
  5.77      2.26     0.39   64927232   Complexe::operator=(...)      related to __intel_new_memcpy
  5.62      2.64     0.38  189251072   _ZN8ComplexeC9Edd             probably an external call
  3.70      2.89     0.25      92160   factblu_                      second most time consuming routine
  3.55      3.13     0.24  124392960   Zvecteur::operator()(...)
  3.55      3.37     0.24  142265344   operator*(...)
  3.11      3.58     0.21              __intel_new_memset
  2.96      3.78     0.20      23040   Zvitesse::CoeffCheb(...)
  2.81      3.97     0.19   58766848   Spectral3D::operator()(...)
  2.66      4.15     0.18       4224   fft2dlib_
  2.37      4.31     0.16     184320   resblu_
  2.37      4.47     0.16         60   Vecteur3D::operator*=(...)
  2.22      4.62     0.15              operator<<(...)
  ...
```

gprof flat profiling of a code