Workpackage 5:
High Performance Mathematical Computing

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First OpenDreamKit Project review

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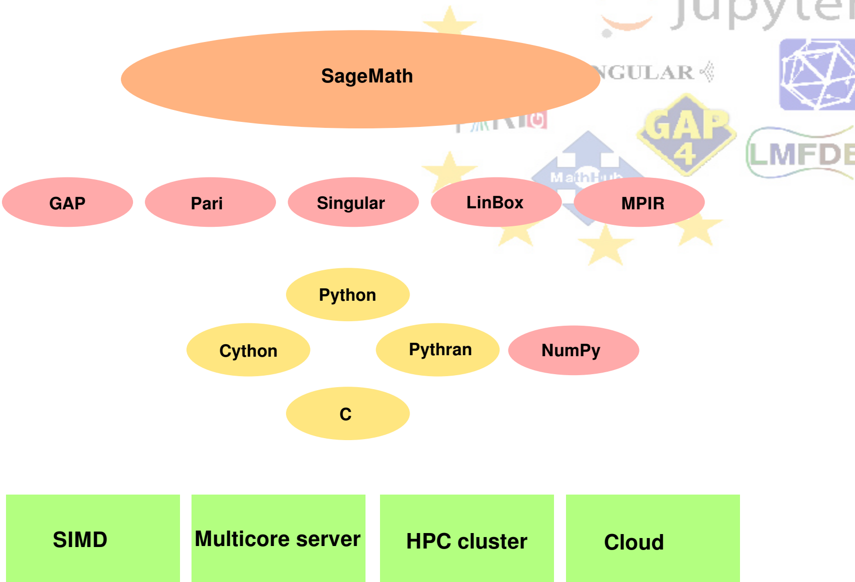
Delivering High Performance to Math VRE users



Introduction

Goal:

- Offer High Performance Computing to VRE's users
- Improve/Develop parallel computing features of dedicated software kernels
- Expose them through the software stack

Task 5.4: Singular

Singular: a library for commutative algebra.

- Already has a generic parallelization framework
- Focus on optimizing a few kernel routines for fine grain parallelism

D5.6: Quadratic sieving for integer factorization

D5.7: Parallelization of matrix fast Fourier Transform

D5.6: Quadratic Sieving for integer factorization

Quadratic Sieving for integer factorization

Problem: Factor an integer n into prime factors

Role: Crucial in algebraic number theory, arithmetic geometry, crypto.

Earlier status: no HPC implementation for large instances:

- only fast code for up to 17 digits,
- only partial sequential implementation for large numbers

D5.6: Quadratic Sieving for integer factorization

Achievements

- Completed and debugged implementation of large prime variant
- Parallelised sieving component of implementation using OpenMP
- Experimented with a parallel implementation of Block Wiedemann

Results

- Now modern, robust, parallel code for numbers in 17–90 digit range
- Block Wiedemann: **SIMD** vs **thread level** parallelism

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- Now modern, robust, parallel code for numbers in 17–90 digit range
- Block Wiedemann: **SIMD** vs **thread level** parallelism
- significantly faster on small multicore machines

Table: Speedup for four cores (c/f single core):

Digits	50	60	70	80	90
Speedup	1.1×	1.76×	1.55×	2.69×	2.80×

D5.7: Parallelise and assembly optimize FFT

FFT: Fast Fourier Transform

- Among the top 10 most important algorithms
- Key to fast arithmetic (integers, polynomials)
- Difficult to optimize: high memory bandwidth requirement

Earlier status:

- world leading **sequential** code in MPIR and FLINT;
- no parallel code.

D5.7: Parallelise and assembly optimize FFT

Achievements

- Parallelised Matrix Fourier implementation using OpenMP
- Assembly optimised butterfly operations in MPIR

Results:

- $\approx$ 15% speedup on Intel Haswell
- $\approx$ 20% speedup on Intel Skylake
- Significant speedups on multicore machines

Table: Speedup of large integer multiplication on 4/8 cores:

Digits	3M	10M	35M	125M	700M	3.3B	14B
4 cores	1.35×	2.67×	2.92×	2.92×	3.01×	2.95×	3.32×
8 cores	1.35×	3.56×	4.22×	4.36×	4.50×	4.31×	5.49×

Task 5.5: MPIR

MPIR : a library for big integer arithmetic

- Bignum operations: absolutly fundamental across all of computer algebra

D5.5: Assembly superoptimization

- MPIR contains assembly language routines for bignum operations
- $\rightsquigarrow$ hand optimised for every new microprocessor architecture
- $\rightsquigarrow \approx 3 - 6$ months of work for each arch.
- Superoptimisation: rearranges instructions to get optimal ordering

Earlier status:

  - No assembly code for recent (> 2012) Intel and AMD chips (Bulldozer, Haswell, Skylake, . . .)

D5.5: Assembly superoptimisation

Achievements

- A new assembly superoptimiser supporting recent instruction sets, including AVX
- Superoptimised handwritten assembly code for Haswell and Skylake
- Hand picked faster assembly code for Bulldozer from existing implementations

Results:

- Sped up basic arithmetic operations for Bulldozer, Skylake and Haswell
- Noticeable speedups for bignum arithmetic for all size ranges

D5.5: Assembly superoptimisation

Table: Speedups for bignum operations

Op	Mul (s)	Mul (m)	Mul (b)	GCD (s)	GCD (m)	GCD (b)
Haswell	1.18×	1.27×	1.29×	0.72×	1.45×	1.27×
Skylake	1.15×	1.20×	1.22×	0.84×	1.65×	1.32×

s = 512 bits, m = 8192 bits, big = 100K bits

No substantial speedups were found for the older, less sophisticated Bulldozer over existing assembly routines.

Task 5.6: Combinatorics

Perform a map/reduce operation on a very large set described recursively.

Large range of intensive applications in combinatorics:

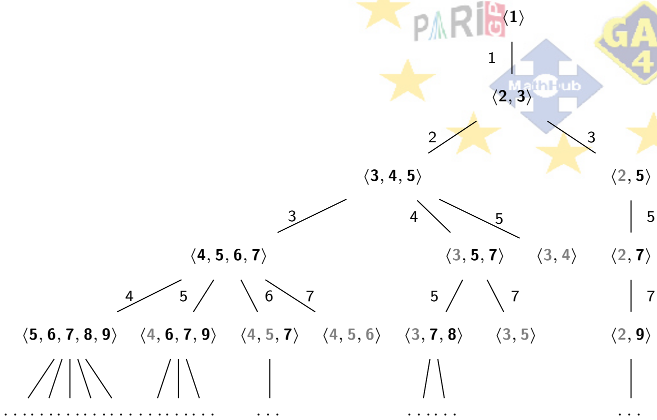
- Compute the cardinality, or more generally any kind of generating series
- Test a conjecture: i.e. find an element of S satisfying a specific property, or check that all of them do
- Count/list the elements of S having this property

Specificity of combinatorics:

- Typically the sets *doesn't fit in the computers* memory / disks and is enumerated on the fly (example of value: 10^{17} bytes).
- Easy to parallelize, if the set is flat (a list, a file, stored on a disk).

A Challenge: The tree of numerical semigroups

Extremely unbalanced. Need for an **efficient load balancing algorithm**.



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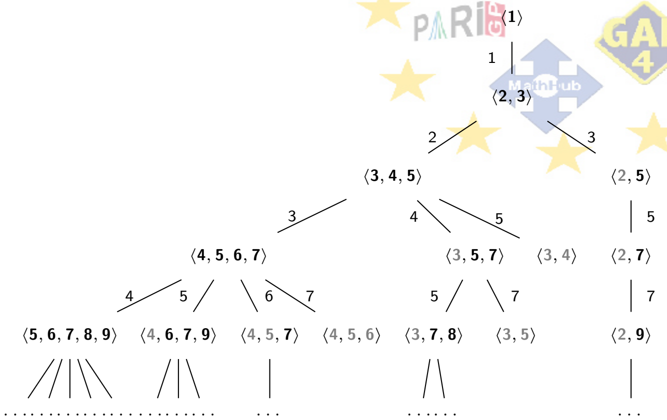


$\rightsquigarrow$ need for a high level task parallelization framework.

Work-Stealing System Architecture

A Python implementation

- Work stealing algorithm (Leiserson-Blumofe / Cilk)
- Esay to use, easy to call from sage
- Already, a dozen of use case
- Scale well with the number of CPU cores
- Reasonably efficient (knowing that this is Python code).

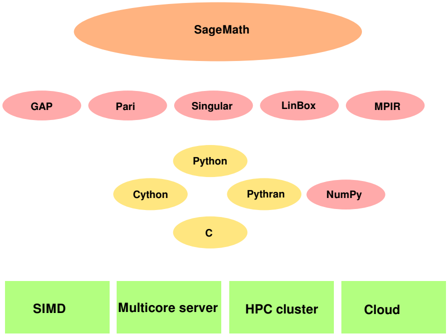
References

- Trac Ticket 13580 `http://trac.sagemath.org/ticket/13580`

- *Exploring the Tree of Numerical Semigroups* Jean Fromentin and Florent Hivert `https://hal.inria.fr/UNIV-ROUEN/hal-00823339v3`

Task 5.7: Pythran

Pythran: a Python to C compiler



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- High performance is achieved mostly by the C language

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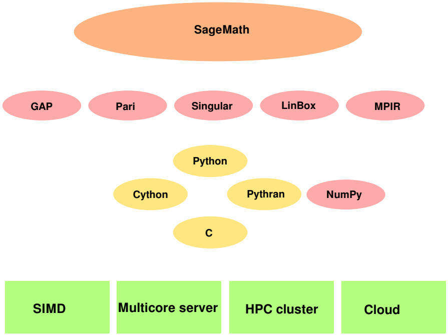

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- High performance is achieved mostly by the C language
- Python to C compilers:

  Cython: general purpose

  Pythran: narrower scope, better at optimizing Numpy code (Linear algebra)

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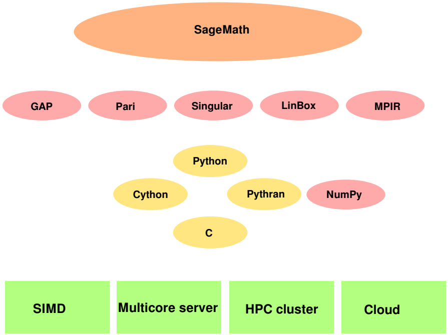
Pythran: a Python to C compiler



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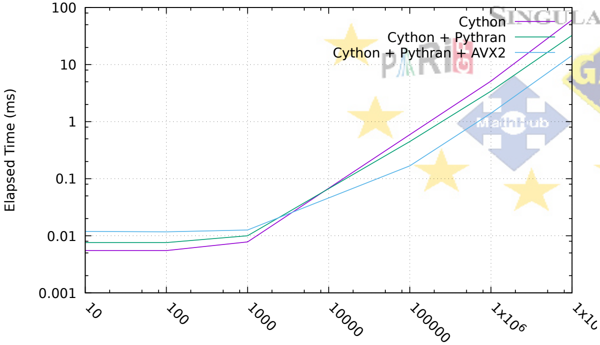
Goal: Implement the convergence

D5.4 Improve Pythran typing system

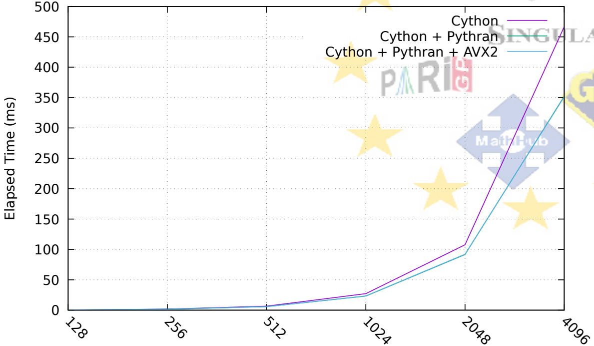
D5.2 Make Cython use Pythran backend to optimize Numpy code

D5.2: Make Cython use Pythran backend for NumPy code




```
import numpy
cimport numpy
def float_comp (numpy.ndarray[numpy.float_t , ndim=1] a,
                numpy.ndarray[numpy.float_t , ndim=1] b):
    return numpy.sqrt(numpy.sqrt(a*a+b*b))
```

D5.2: Make Cython use Pythran backend for NumPy code




```
def harris(numpy.ndarray[numpy.float_t, ndim=2] I):
  cdef int m = I.shape[0]
  cdef int n = I.shape[1]
  cdef numpy.ndarray[numpy.float_t,ndim=2] dx = (I[1:,:] - I[:m-1,:])[:,1:]
  cdef numpy.ndarray[numpy.float_t,ndim=2] dy = (I[:,1:] - I[:,:n-1])[1:,:]
  cdef numpy.ndarray[numpy.float_t, ndim=2] A = dx * dx
  cdef numpy.ndarray[numpy.float_t, ndim=2] B = dy * dy
  cdef numpy.ndarray[numpy.float_t, ndim=2] C = dx * dy
  cdef numpy.ndarray[numpy.float_t, ndim=2] tr = A + B
  cdef numpy.ndarray[numpy.float_t, ndim=2] det = A * B - C * C
  return det - tr * tr
```

Task 5.8: SunGridEngine integeration in JupytherHub

Access to big compute

- Traditional access to supercomputers is difficult
- Notebooks are easy but run on laptops or desktops
- We need a way to connect notebooks to supercomputers

Sun Grid Engine

A job scheduler for Academic HPC Clusters

- Controls how resources are allocated to researchers
- One of the most popular schedulers

Achievements

- Developed software to run Jupyter notebooks on supercomputers
- Users don't need to know details. They just log in.
- Demonstration install at University of Sheffield

Progress report on other tasks

T5.1: Pari

- Generic parallelization engine is now mature, released (D5.10, due M24)

T5.2: GAP

- 6 releases were cut integrating contributions of D3.11 and D5.15
- Build system refactoring for integration of HPC GAP

T5.3: LinBox

- Algorithmic advances (5 articles) on linear algebra and verified computing
- Software releases and integration into SageMath