Tools for modern scientific computing

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Section 1

Computing in science

Introduction

Excerpt from scientific production code

```
if str(some_list)!="[]":
```

perform some computation

Golden maxim for today

When an engineer is wrong — the people suffer, when a scientist is wrong — the truth suffers.

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Calculations in high energy physics



Fig. 1 Estimated CPU required by the CMS (top) and ATLAS (bottom) experiments for LHC and HL-LHC [6, 7]



Source: Hennessy, John L., and David A. Patterson. Computer architecture: a quantitative approach. Elsevier, 2011. 6th edition.



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten New plot and data collected for 2010-2021 by K. Rupp



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ML4Science

Artificial-intelligence models require the vast computing power of supercomputers, such as this one at the University of California, San Diego.

Garbage in, garbage out: mitigating risks and maximizing benefits of AI in research

Brooks Hanson, Shelley Stall, Joel Cutcher-Gershenfeld, Kristina Vrouwenvelder, Christopher Wirz, Yuhan (Douglas) Rao & Ge Peng

GROWING AI USE IN EARTH AND SPACE SCIENCE

A rising proportion of abstracts for the annual meeting of the American Geophysical Union mention artificial intelligence (AI) or machine learning (ML) — a trend seen across all areas of geoscience.





At tools are being used to assess environmental observations, such as this satellite image of agricultural land in Bolivia that was once a forest

Patents in quantum computing

Figure 2



Number of DOCDB patent families per earliest publication year in the field of quantum computing

Source: authors' calculations

Quantum computing

Insight report

Quantum computing versus machine learning

Figure 16

Number of inventions per earliest publication year related to quantum computing and artificial intelligence/machine learning



Source: authors' calculation

CO2 consumption by astrophysicists The Ecological Impact of High-performance Computing in Astrophysics

Simon Portegies Zwart

¹Leiden Observatory, Leiden University, PO Box 9513, 2300 RA, Leiden, The Netherlands ¹



Daily Sea Surface Temperature, World (60°S-60°N, 0-360°E)

Dataset: NOAA OISST V2.1 | Image Credit: ClimateReanalyzer.org, Climate Change Institute, University of Maine



Are there slow and fast programming languages

- Yes: slow Python, C++; fast Python, C++
- No: there are slow and fast computer systems.





Scientific software engineering matters

Section 2

What do we do?

Dark matter detectorDEAP-3600



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Gravitational waves



Virgo detector



Measurement of first black hole coalescence with LIGO

Satellite imagery



Sentinel-2

Quantum computing



Section 3

Quantum computing

LUMI-Q

European quantum computers. EUROHPC-2022-CEI-QC-01



Spectral information processing with quantum neural networks

Manish Gupta, Piotr Gawron, Co-operation ESA's Φ-Lab — AstroCeNT





Unsupervised quantum machine learning for Earth observations

Piotr Gawron with IITiS PAN, CSGroup and CNES





Fig. 1. Illustration of the proposed hybrid contrastive learning framework.





Section 4

Julia



Julia is

- fast, compiled on the fly,
- high-level,
- expressive
- programming language
- designed for scientific computing.

Example of an optimisation problem

$$\begin{array}{ll} \min & 12x + 20y\\ \text{s.t.} & 6x + 8y \geq 100\\ & 7x + 12y \geq 120\\ & x \geq 0\\ & y \in [0,3] \end{array}$$

Example of an optimisation problem

1 using JuMP	
1 using HiGHS	
model = A JuMP Model Feasibility problem with: Variables: 0 Model mode: AUTOMATIC CachingOptimizer state: EMPTY_Of Solver name: HiGHS	PTIMIZER
<pre>1 model = Model(<u>HiGHS</u>.Optimizer)</pre>	
	x
1 @variable(<u>model</u> , <u>x</u> >= 0)	
	y
1 @variable(<u>model</u> , 0 <= <u>y</u> <= 3)	
	12x + 20y
1 Gobjective(model, Min, 12x + 20v)	

 $6x + 8y \ge 100$

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Example of an optimisation problem

 $7x + 12y \ge 120$

1 @constraint(model, c2, 7x + 12y >= 120)

1 print(model)

Min 12 x + 20 y Subject to c1 : 6 x + 8 y \ge 100 c2 : 7 x + 12 y \ge 120 x \ge 0 y \ge 0 y \le 3

1 optimize!(model)

```
Running HiGHS 1.6.0: Copyright (c) 2023 HiGHS under MIT licence terms
                                                                           0
Presolving model
2 rows, 2 cols, 4 nonzeros
2 rows, 2 cols, 4 nonzeros
Presolve : Reductions: rows 2(-0); columns 2(-0); elements 4(-0) - Not reduced
Problem not reduced by presolve: solving the LP
Using EKK dual simplex solver - serial
                  Objective Infeasibilities num(sum)
 Iteration
         O.
               0.000000000e+00 Pr: 2(220) 0s
         2
               2.0500000000e+02 Pr: 0(0) 0s
Model status : Optimal
Simplex iterations: 2
Objective value : 2.0500000000e+02
HiGHS run time
                             0.00
```

1 Enter cell code...

0

Lorenz system

1 using DifferentialEquations

```
1 using Plots
```

parameterized_lorenz! (generic function with 1 method)

 $\begin{array}{l} 1 \quad \mbox{inction parameterized_lorenz!(du, u, p, t)} \\ 2 \quad x, y, x = u \\ 3 \quad \sigma, \rho, \beta = p \\ 4 \quad \mbox{du[1]} = dx = \sigma * (y - x) \\ 5 \quad \mbox{du[2]} = dy = x * (\rho - z) - y \\ 6 \quad \mbox{du[3]} = dz = x * y - \beta * z \\ 7 \quad \mbox{end} \end{array}$

u0 = [1.0, 0.0, 0.0]1 u0 = [1.0, 0.0, 0.0]

tspan = (0.0, 100.0)

1 tspan = (0.0, 100.0)

p = [10.0, 28.0, 2.66667]

1 p = [10.0, 28.0, 8 / 3]

prob =

DDEFroblem with uType Vector{Float64} and tType Float64. timespan: (0.0, 100.0) u0: 3-element Vector{Float64}: 1.0 0.0 0.1 1 prob = ODEProblem(parameterized_lorenz!, <u>u0</u>,

tspan, p)

Lorenz system

sol =

	timestamp	value1	value2	value3
1	0.0	1.0	0.0	0.0
2	3.56786e-5	0.999643	0.000998805	1.78143e-8
3	0.000392465	0.996105	0.0109654	2.14696e-6
4	0.00326241	0.969359	0.0897706	0.000143802
5	0.00905808	0.924204	0.242289	0.00104616
6	0.0169565	0.880046	0.438736	0.00342426
7	0.02769	0.848331	0.691563	0.00848762
8	0.0418564	0.849504	1.01454	0.0182121
9	0.0602404	0.913907	1.44256	0.0366938
10	0.0836854	1.08886	2.05233	0.0740257
	more			

1 sol = solve(prob)



Calculations in high energy physics

Computing and Software for Big Science (2023) 7:10 https://doi.org/10.1007/s41781-023-00104-x

RESEARCH



Potential of the Julia Programming Language for High Energy Physics Computing

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Calculations in high energy physics



Fig.3 Comparison of C/C++, Python and Julia language performance for a set of short algorithms. OpenBLAS, together with NumPy in the Python case are used for matrix operation. The score is defined as the time to run the algorithm divided by the time to run the C version of the same algorithm

Quantum information

PLOS ONE

RESEARCH ARTICLE

QuantumInformation.jl—A Julia package for numerical computation in quantum information theory

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Calculation of cumulants

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EFFICIENT COMPUTATION OF HIGHER-ORDER CUMULANT TENSORS*

KRZYSZTOF DOMINO[†], PIOTR GAWRON[†], AND ŁUKASZ PAWELA[†]



FIG. 2. Computation time for cumulant tensors computed using the block structure and the proposed algorithm for different block sizes b, at n = 60.



FIG. 3. Computation time speedup of fourth cumulant tensor computed using the block structure and the proposed algorithm vs. the naive algorithm.



(a) Julia implementation of general algorithm (b) R implementation of general algorithm from [16].



FIG. 6. Computation time speedup of fourth cumulant tensor calculation using algorithm employing the block structure vs. algorithms from [16].

PhD opportunities

- Quantum computing for astronomy / astrophysics
- Neuromorphic computing
- Scientific software tools in Julia studying new computation methods
- Large scale computation workflows

Thank you





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