PART II. Case Studies

Experimental Computation and Visual Theorems: Part I: The Computer as Collaborator

Jonathan Borwein FRSC FAAAS FAA FBAS FAMS

(With Aragón, Bailey, P. Borwein, Skerritt, Straub, Tam, Wan, Zudilin, ...)





Centre for Computer Assisted Research Mathematics and its Applications The University of Newcastle, Australia



http://carma.newcastle.edu.au/meetings/evims/ http://www.carma.newcastle.edu.au/jon/visuals-ext-abst.pdf

For 2016 Presentations

Revised 13-05-16

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Visual Theorems

PART II. Case Studies

Other References

Prepared for ACMES, May 12–15, 2016



registration program talks events accommodation travel maps

Computationally Assisted Mathematical Discovery and Experimental Mathematics



12-15 May 2016, London, Ontario, Canada,

to gather evidence in support of specific mathematical assertions that may themselves arise

ACMES will be held at Western University in London. ON, Canada from May 12-14, 2016.

Invited Speakers

- University of Newcastle (CARMA Institute) · Nel J.A. OEIS Foundation, and Rulgers (Dept. of Mathematics) Sloane
- Emest Davis New York University
- David
- Lila Kari University of Waterloo University of Toronto
- · David H.
- Balley

Key Participants

- Yuri V. St. Peteraburg Department of Steklov Matiyasevich Sciences, Institute of Mathematics
- Branden Department of Philosophy Northeastern University
- and Religion.

Program Committee









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Visual Theorems

www.carma.newcastle.edu.au/walks

(Dept. of Computer Science) (Dept. of Chemistry)

(Dept. of Computer Science)

- University of California, Davis (Lawrence Berkeley National Lab.)

(Dept. of Science and Technology

PART II. Case Studies

Other References

Jacques Hadamard, A Universal Mathematician (1998)



"The object of mathematical rigor is to sanction and legitimize the conquests of intuition, and there was never any other object for it."–JSH (1865-1963) last dozen of the first hundred of his year", said at the celebration of Hadamard's centenary:

The taupin who saw Jacques Hadamard enter the lecture theatre, found a teacher who was active, alive, whose reasoning combined exactness and dynamism. Thus the lecture became a struggle and an adventure. Without rigour suffering, the importance of intuition was restored to us, and the better students were delighted. For the others, the intellectual life was less comfortable, but so exciting... And then, above all, we knew quite well that with such a guide we never risked going under [II.5, p. 8].

Mandelbrojt recalled at the same jubilee:

For several years, Hadamard also gave lectures at the *Collège de France*: lectures which were long, hard, infinitely interesting. He never tried to hide the difficulties, on the contrary he brought them out. The audience thought together with him; these lectures provoked creativity. The day after a lecture by Hadamard was rich, full and all day long one thought about the ideas.

It was in these lectures that I learnt the secrets of the function $\zeta(s)$ of Riemann, it was there that I understood the significance of analytic continuation, of quasi-analyticity, of Dirichlet series, of the role of functional calculus in the calculus of variations [II.5, p. 25-27].

PART II. Case Studies

EXTENDED ABSTRACT

Long before current graphic, visualisation and geometric tools were available, John E. Littlewood (1885-1977) wrote in his delightful *Miscellany*¹:

A heavy warning used to be given [by lecturers] that pictures are not rigorous; this has never had its bluff called and has permanently frightened its victims into playing for safety. Some pictures, of course, are not rigorous, but I should say most are (and I use them whenever possible myself). [p. 53]

¹J.E. Littlewood, *A mathematician's miscellany*, London: Methuen (1953); Littlewood, J. E. and Bollobás, Béla, ed., *Littlewood's miscellany*, Cambridge University Press, 1986.

PART II. Case Studies

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Over the past decade, the role of visual computing in my own research has expanded dramatically.

In part this was made possible by the increasing speed and storage capabilities—and the growing ease of programming—of modern multi-core computing environments [BMC].

¹J.E. Littlewood, *A mathematician's miscellany*, London: Methuen (1953); Littlewood, J. E. and Bollobás, Béla, ed., *Littlewood's miscellany*, Cambridge University Press, 1986.

But, at least as much, it has been driven by my group's paying more active attention to the possibilities for graphing, animating or simulating most mathematical research activities.

²See http://www.carma.newcastle.edu.au/jon/Completion.pdf and http://www.carma.newcastle.edu.au/jon/dr-fields11.pptx.

Jonathan Borwein (University of Newcastle, Australia)

But, at least as much, it has been driven by my group's paying more active attention to the possibilities for graphing, animating or simulating most mathematical research activities.

- I first briefly discuss both visual theorems and experimental computation.
- I then turn to dynamic geometry (iterative reflection methods [AB]) and matrix completion problems (applied to protein conformation [ABT]).² (Case studies I)

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- I then turn to dynamic geometry (iterative reflection methods [AB]) and matrix completion problems (applied to protein conformation [ABT]).² (Case studies I)
- After an algorithmic interlude (Case studies II), I end with description of work from my group in probability (behaviour of short random walks [BS, BSWZ]) and transcendental number theory (normality of real numbers [AB3]). (Case studies III)

²See http://www.carma.newcastle.edu.au/jon/Completion.pdf and http://www.carma.newcastle.edu.au/jon/dr-fields11.pptx.

Digital Assistance

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My plans



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Other References

My plans



While all this work involved significant, often threaded [BSC], numerical- symbolic computation, I shall focus on the visual components.

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My plans



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I will make a sample of the on-line presentation, based in part on:

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Other References

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- What makes most sense for the audience
- My inclinations on the day
- How I manage my time

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My plans



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JMB was among roughly 60 new 2015 Fellows of the American Mathematical Society. He was cited "For contributions to nonsmooth analysis and classical analysis as well as experimental mathematics and visualization of mathematics."

PART II. Case Studies

Tools and Mathematics



J. Monaghan, L. Trouche, J.M. Borwein <u>Tools and Mathematics</u>

Instruments for learning

Series: Mathematics Education Library

- > The only book on the topic of tools and mathematics education
- Comprehensive coverage from pre-history to future directions in the field
- Content divided equally among the areas of curriculum, assessment, and policy design

This book is an exploration of tools and mathematics and issues in mathematics education related to tool use. The book has four parts. The first part sets the scene with a reflection on doing a mathematical task with different tools, a mathematical's account of tool use in his work and historical considerations of tool use. The second part opens with a broad review of technology and intellectual trends, circa 1970, and continues with three case studies of approaches in mathematics education and the place of tools in these approaches. The third part considers issues related to mathematics in the real world; and teachers' use of technology. The final part looks to the future and digital tools: task design; the importance of artefacts in gameplay; and new forms of activity via connectivity.



1st ed. 2016, XXI, 481 p. 133 illus., 92 illus. in color.



D Springer

PART II. Case Studies

Key References and URLS

- F. ARAGON AND J.M. BORWEIN, "Global convergence of a non-convex Douglas-Rachford iteration." J. Global Optim. **57**(3) (2013), 753–769.
- F. ARAGON, D. H. BAILEY, J.M. BORWEIN AND P.B. BORWEIN, "Walking on real numbers." *Mathematical Intelligencer.* **35**(1) (2013), 42–60.



F. ARAGON, J. M.BORWEIN, AND M. TAM, "Douglas-Rachford feasibility methods for matrix completion problems.*ANZIAM Journal*, **55** (4) (2014), 299–326. Available at http://arxiv.org/abs/1308.4243.



J.M. BORWEIN AND A. STRAUB, "Mahler measures, short walks and logsine integrals." *Theoretical Comp Sci.* Special issue on *Symbolic and Numeric Computation.* **479** (1) (2013), 4-21. DOI: http://link.springer.com/article/10.1016/j.tcs.2012.10.025.



J.M. BORWEIN, M. SKERRITT AND C. MAITLAND, "Computation of a lower bound to Giuga's primality conjecture." *Integers* **13** (2013). Online Sept 2013 at #A67, http://www.westga.edu/~integers/cgi-bin/get.cgi.



J.M. BORWEIN, A. STRAUB, J. WAN AND W. ZUDILIN (with an Appendix by Don Zagier), "Densities of short uniform random walks." *Can. J. Math.* **64**(5), (2012), 961-990. http://dx.doi.org/10.4153/CJM-2011-079-2.

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PART II. Case Studies

Other References

...and 3D?



NAMS 2005. KnotPlot in a Cave

Considerable obstacles generally present themselves to the beginner, in studying the elements of Solid Geometry, from the practice which has hitherto uniformly prevailed in this country, of never submitting to the eye of the student, the figures on whose properties he is reasoning, but of drawing perspective representations of them upon a plane.

I hope that I shall never be obliged to have recourse to a perspective drawing of any figure whose parts are not in the same plane.—Augustus De Morgan

In Adrian Rice, "What Makes a Great Mathematics Teacher?" MAA Monthly, 1999.

PART II. Case Studies

Contents



PART I: Visual TheoremsVisual theorems

- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

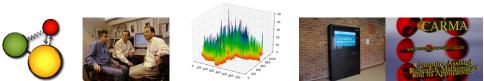
- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

PART II. Case Studies

Visual Theorems:

Animation, Simulation and Stereo ...

See http://vis.carma.newcastle.edu.au/: Stoneham movie



Cinderella, 3.14 min of Pi, Catalan's constant and Passive 3D

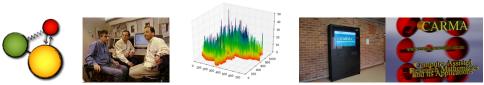
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Visual Theorems:

Animation, Simulation and Stereo ...

See http://vis.carma.newcastle.edu.au/: Stoneham movie

The latest developments in computer and video technology have provided a multiplicity of computational and symbolic tools that have rejuvenated mathematics and mathematics education. Two important examples of this revitalization are experimental mathematics and visual theorems — ICMI Study **19** (2012)



Cinderella, 3.14 min of Pi, Catalan's constant and Passive 3D

PART II. Case Studies

Contents



PART I: Visual Theorems

Visual theorems

Large matrices

- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

PART II. Case Studies

Visualising large matrices

Large matrices often have structure that pictures will reveal but which numeric data may obscure.

• The picture shows a 25×25 *Hilbert* matrix on the left and on the right a matrix required to have 50% sparsity and non-zero entries random in [0, 1].

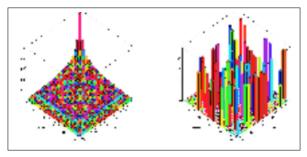


Figure: The Hilbert matrix (L) and a sparse random matrix (R)

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MATLAB's first symbolic example

Visualising large matrices

The 4×4 Hilbert matrix is

PART II. Case Studies

MATLAB's first symbolic example

Visualising large matrices

The 4×4 Hilbert matrix is

 $\begin{bmatrix} 1 & 1/2 & 1/3 & 1/4 \\ 1/2 & 1/3 & 1/4 & 1/5 \\ 1/3 & 1/4 & 1/5 & 1/6 \\ 1/4 & 1/5 & 1/6 & 1/7 \end{bmatrix}$

Hilbert matrices are notoriously unstable numerically. The left of the Figure shows the inverse of the 20×20 Hilbert matrix computed *symbolically exactly*. The middle shows enormous *numerical errors* if one uses 10 digit precision, and the right even if one uses 20 digits.

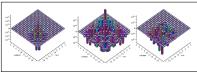


Figure: Inverse 20×20 Hilbert matrix (L) and 2 numerical inverses (R)

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

PART II. Case Studies

Visualising large polynomials

Large polynomials also often have structure that pictures will reveal but which



Table: 192-degree minimal polynomial for optical aberration correction, with up to 85 digit coefficients found by multipair PSLQ.

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Visualising large polynomials

Large polynomials also often have structure that pictures will reveal but which



Table: 192-degree minimal polynomial for optical aberration correction, with up to 85 digit coefficients found by multipair PSLQ.

 $\begin{array}{c} 1.70, 71, 200005, 726, 90, 200, MSO 400, 900, 911, 550, 140, 705, 500, 231, 000, 731, 734, 800, 700, MS, 147, 706, 101, 900, 110, 700, 147, 700, 101, 700, 147, 710, 147, 710, 145, 148, 700, 741, 740,$

Table: Some large coefficients

PART II. Case Studies

Poisson & Crandall

for aberration correction



References

- D.H. Bailey, J.M. Borwein, R.E. Crandall and I.J. Zucker, "Lattice sums arising from the Poisson equation." *Journal of Physics A*, 46 (2013) #115201 (31pp).
- D.H. Bailey, J.M. Borwein, and J. Kimberley, "Discovery and computation of large Poisson polynomials." *Experimental Mathematics*, Accepted, May 2016.
- G. Savin and D. Quarfoot, "On attaching coordinates of Gaussian prime torsion points of y² = x³ + x to Q(i)," 2010.
 www.math.utah.edu/~savin/EllipticCurvesPaper.pdf³

³Found from one 12 digit coefficient <u>387221579866</u>.

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

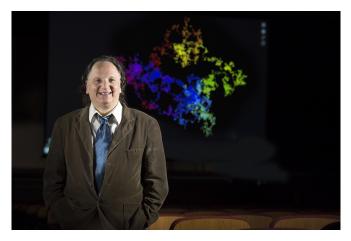
- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

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PART II. Case Studies

Other References

Me and my collaborators



MAA 3.14

http://www.carma.newcastle.edu.au/jon/pi-monthly.pdf

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PART II. Case Studies

2012 walk on π (went *viral*)

Biggest mathematics picture ever?

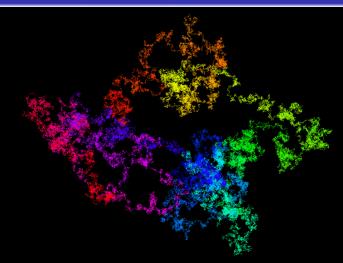


Figure: Walk on first 100 billion base-4 digits of π (normal?).

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Visual Theorems

www.carma.newcastle.edu.au/walks

(108 gigapixels)

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PART II. Case Studies

2012 walk on π (went viral)

Biggest mathematics picture ever? Computation: took roughly a month

> where several parts of the algorithm were run in parallel with 20 threads on CARMA's MacPro cluster.

Figure: Walk on first 100 billion base-4 digits of π (normal?). http://gigapan.org/gigapans/106803

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Digital Assistance

PART II. Case Studies

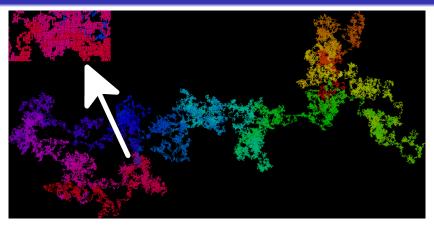
Outreach:

images and animations led to high-level research which went viral

PART II. Case Studies

Outreach:

images and animations led to high-level research which went viral



- 100 billion base four digits of π on Gigapan
- Really big pictures are often better than movies (NASA and AMS)

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Other References

My number-walk collaborators



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Other References

My short-walk collaborators



James Wan



Armin Straub



Wadim Zudilin

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PART II. Case Studies

Other References

My short-walk collaborators



James Wan

• Plus Dirk Nuyens





Armin Straub

and Don Zagier, ...



Wadim Zudilin

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

PART II. Case Studies

Some early conclusions:

So I am sure they get made

Key ideas: randomness, normality of numbers, planar walks, and fractals



How not to experiment

PART II. Case Studies

Some early conclusions:

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How not to experiment

Maths can be done *experimentally* (it is fun)

- using computer algebra, numerical computation and graphics: SNaG
- computations, tables and pictures are experimental data
- but you can not stop thinking

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- and what you know you can usually use
- you do not need to know much before you start research (as we shall see)

PART II. Case Studies

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DHB and JMB, Exploratory Experimentation in Mathematics (2011), www.ams.org/notices/20110/rtx111001410p.pdf

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

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When I have clarified and exhausted a subject, then I turn away from it, in order to go into darkness again; the never-satisfied man is so strange if he has completed a structure, then it is not in order to dwell in it peacefully, but in order to begin another.

I imagine the world conqueror must feel thus, who, after one kingdom is scarcely conquered, stretches out his arms for others.



Carl Friedrich Gauss (1777-1855)

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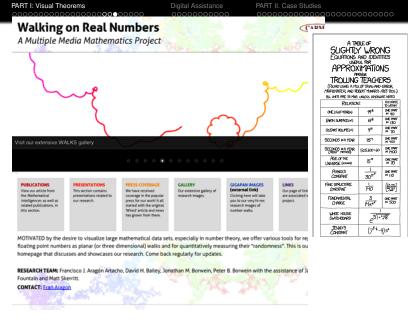
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Carl Friedrich Gauss (1777-1855)

- In an 1808 letter to his friend Farkas (father of Janos) Bolyai
- Archimedes, Euler, Gauss are the big three



Almost all I mention in Part III is accessible at

http://carma.newcastle.edu.au/walks/

Jonathan Borwein (University of Newcastle, Australia)

Other References

A TREE OF SLIGHTLY WRONG EQUITIONS AND IDENTITIES

APPROXIMATIONS

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PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

- Digital Assistance
 - Digital Assistance
 - Simulation in Mathematics
- PART II. Case Studies
 - Ia. Iterated reflections
 - Ib: Protein conformation
 - Ila: 100 digit challenge
 - Ilb: Polylogarithms
- Other References

PART II. Case Studies

Computer Assisted Research Maths: what it is?

Experimental mathematics is the use of a computer to run computations—sometimes no more than trial-and- error tests—to look for patterns, to identify particular numbers and sequences, to gather evidence in support of specific mathematical assertions that may themselves arise by computational means, including search.

Computer Assisted Research Maths: what it is?

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Like contemporary chemists — and before them the alchemists of old—who mix various substances together in a crucible and heat them to a high temperature to see what happens, today's experimental mathematicians put a hopefully potent mix of numbers, formulas, and algorithms into a computer in the hope that something of interest emerges. (JMB-Devlin, Crucible 2008, p. 1)

Quoted in International Council on Mathematical Instruction
 Study 19: On Proof and Proving, 2012

PART II. Case Studies

Experimental Mathematics: Integer Relation Methods

Secure Knowledge without Proof. Given real numbers β , α_1 , α_2 , ..., α_n , Helaman Ferguson's integer relation method (PSLQ), finds a nontrivial linear relation of the form

 $a_0\beta + a_1\alpha_1 + a_2\alpha_2 + \dots + a_n\alpha_n = 0, \tag{1}$

where a_i are integers—if one exists and provides an exclusion bound otherwise.



PROFILE: HELAMAN FERGUSON Carving His Own Unique Niche, In Symbols and Stone

By refusing to choose between mathematics and art, a self-described "misfit" has found the place where parallel careers meet

CMS D. Borwein Prize: Madelung



PART II. Case Studies

Experimental Mathematics: Integer Relation Methods

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where a_i are integers—if one exists and provides an exclusion bound otherwise.

If a₀ ≠ 0 then (1) assures β is in rational vector space generated by {α₁, α₂,..., α_n}.



Carving His Own Unique Niche, In Symbols and Stone

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CMS D. Borwein Prize: Madelung



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Experimental Mathematics: Integer Relation Methods

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where a_i are integers—if one exists and provides an exclusion bound otherwise.

- If a₀ ≠ 0 then (1) assures β is in rational vector space generated by {α₁, α₂,..., α_n}.
- $\beta = 1, \alpha_i = \alpha^i$ means α is algebraic of degree *n*



PROFILE: HELAMAN FERGUSON Carving His Own Unique Niche, In Symbols and Stone

By refusing to choose between mathematics and art, a self-described "misfit" has found the place where parallel careers meet

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PART II. Case Studies

Experimental Mathematics: Integer Relation Methods

Secure Knowledge without Proof. Given real numbers β , α_1 , α_2 , ..., α_n , Helaman Ferguson's integer relation method (PSLQ), finds a nontrivial linear relation of the form

 $a_0\beta + a_1\alpha_1 + a_2\alpha_2 + \dots + a_n\alpha_n = 0, \tag{1}$

where a_i are integers—if one exists and provides an exclusion bound otherwise.

- If a₀ ≠ 0 then (1) assures β is in rational vector space generated by {α₁, α₂,..., α_n}.
- $\beta = 1, \alpha_i = \alpha^i$ means α is algebraic of degree *n*
- 2000 Computing in Science & Engineering: PSLQ one of top 10 algorithms of 20th century

(2001 CISE article on Grand Challenges (JB-PB))



PROFILE: HELAMAN FERGUSON Carving His Own Unique Niche, In Symbols and Stone

By refusing to choose between mathematics and art, a self-described "misfit" has found the place where parallel careers meet

CMS D. Borwein Prize: Madelung



PART II. Case Studies

PSLQ in action

In all serious computations of π from 1700 (by John Machin) until 1980 some version of a *Machin formula* was used. These write

$$\arctan(1) = a_1 \cdot \arctan\left(\frac{1}{p_1}\right) + a_2 \cdot \arctan\left(\frac{1}{p_2}\right) + \dots + a_n \cdot \arctan\left(\frac{1}{p_n}\right)$$
 (2)

for rationals $a_1, a_2, ..., a_n$ and integers $p_1, p_2, ..., p_n > 1$. Recall the Taylor series $\arctan(x) = \sum_{n=0}^{\infty} \frac{(-1)^n}{2n+1} x^{2n+1}$. Combined with (2) this computes $\pi = 4 \arctan(1)$ efficiently, especially if the p_n are not too small.

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$$\pi = 16 \arctan\left(\frac{1}{5}\right) - 4 \arctan\left(\frac{1}{239}\right)$$

while Euler discovered

$$\arctan(1) = \arctan\left(\frac{1}{2}\right) + \arctan\left(\frac{1}{5}\right) + \arctan\left(\frac{1}{8}\right).$$
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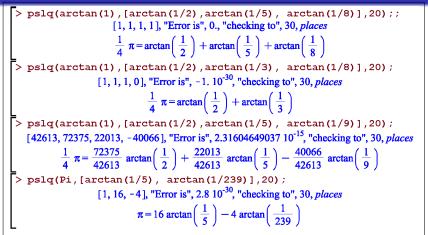
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- I have a function 'pslq' in *Maple*. When input data for PSLQ it *predicts* an answer to the precision requested. And checks it to ten digits more (or some other precision).
- This makes the code a real experimental tool as it predicts and confirms.

PART II. Case Studies

PSLQ in action

prepping for class



• The third shows that when no relation exists the code may find a good approximation but using very large rationals.

PART II. Case Studies

PSLQ in action

prepping for class

pslq(arctan(1), [arctan(1/2), arctan(1/5), arctan(1/8)], 20);; [1, 1, 1, 1], "Error is", 0., "checking to", 30, places $\frac{1}{4}\pi = \arctan\left(\frac{1}{2}\right) + \arctan\left(\frac{1}{5}\right) + \arctan\left(\frac{1}{8}\right)$ > pslq(arctan(1),[arctan(1/2),arctan(1/3), arctan(1/8)],20); [1, 1, 1, 0], "Error is", -1.10^{-30} , "checking to", 30, places $\frac{1}{4}\pi = \arctan\left(\frac{1}{2}\right) + \arctan\left(\frac{1}{2}\right)$ > pslq(arctan(1),[arctan(1/2),arctan(1/5), arctan(1/9)],20); [42613, 72375, 22013, -40066], "Error is", 2.31604649037 10⁻¹⁵, "checking to", 30, places $\frac{1}{4}\pi = \frac{72375}{42613} \arctan\left(\frac{1}{2}\right) + \frac{22013}{42613} \arctan\left(\frac{1}{5}\right) - \frac{40066}{42613} \arctan\left(\frac{1}{9}\right)$ > pslq(Pi,[arctan(1/5), arctan(1/239)],20); [1, 16, -4], "Error is", 2.8 10⁻³⁰, "checking to", 30, *places* $\pi = 16 \arctan\left(\frac{1}{5}\right) - 4 \arctan\left(\frac{1}{239}\right)$

- The third shows that when no relation exists the code may find a good approximation but using very large rationals.
- So it diagnoses failure because it uses large coefficients and because it is not true to the requested 30 places.

Visual Theorems

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
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Digital Assistance

- Digital Assistance
- Simulation in Mathematics

PART II. Case Studies

- Ia. Iterated reflections
- Ib: Protein conformation
- Ila: 100 digit challenge
- Ilb: Polylogarithms
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PART II. Case Studies

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PART II. Case Studies

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- Specialized Packages or General Purpose Languages such as Fortran, C++, Python, CPLEX, PARI, SnapPea, and MAGMA.

PART II. Case Studies

Digital Assistance

- Web Applications such as: Sloane's Encyclopedia of Integer Sequences, the Inverse Symbolic Calculator, Fractal Explorer, Jeff Weeks' Topological Games, or Euclid in Java.⁴
 - Most of the functionality of the ISC is built into the "identify" function *Maple* starting with version 9.5. For example, identify (4.45033263602792) returns $\sqrt{3} + e$. As always, the experienced will extract more than the novice.

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PART II. Case Studies

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- Web Databases including Google, MathSciNet, ArXiv, GitHub, Wikipedia, MathWorld, MacTutor, Amazon, Wolfram Alpha, the DLMF (all formulas of which are accessible in MathML, as bitmaps, and in T_EX) and many more that are not always so viewed.

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PART II. Case Studies

Digital Assistance

All entail *data-mining*. Franklin argues *"exploratory experimentation"* facilitated by *"widening technology"*, as in finance, pharmacology, astrophysics, medicine, and biotechnology, is leading to a reassessment of what legitimates experiment; in that a *"local model"* is not now prerequisite. Sørenson says *experimental mathematics* is following similar tracks.

These aspects of exploratory experimentation and wide instrumentation originate from the philosophy of (natural) science and have not been much developed in the context of experimental mathematics. However, I claim that e.g. the importance of wide instrumentation for an exploratory approach to experiments that includes concept formation also pertain to mathematics.

PART II. Case Studies

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PART II. Case Studies

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In consequence, boundaries between mathematics and natural sciences and between inductive and deductive reasoning are blurred and getting more so.

I leave the philosophically-vexing if mathematically-minor question as to if genuine *mathematical experiments* exist even if one embraces a fully idealist notion of mathematical existence. They sure feel like they do.

Visual Theorems

PART II. Case Studies

Top Ten Algorithms (20C):

all but one well used in CARMA

Algorithms for the Ages

"Great algorithms are the poetry of computation," says Francis Sullivan of the Institute for Defense Analyses' Center for Computing Sciences in Bowie, Maryland. He and Jack Dongarra of the University of Tennessee and Oak Ridge National Laboratory have put together a sampling that might have made Robert Frost beam with pride-had the poet been a computer jock. Their list of 10 algorithms having "the greatest influence on the development and practice of science and engineering in the 20th century" appears in the January/February issue of Computing in Science & Engineering. If you use a computer, some of these algorithms are no doubt crunching your data as you read this. The drum roll, please:

- 1. 1946: The Metropolis Algorithm for Monte Carlo. Through the use of random processes, this
 algorithm offers an efficient way to stumble toward answers to problems that are too complicated to
 solve exactly.
- 1947: Simplex Method for Linear Programming. An elegant solution to a common problem in planning and decision-making.
- 1950: Krylov Subspace Iteration Method. A technique for rapidly solving the linear equations that abound in scientific computation.
- 1951: The Decompositional Approach to Matrix Computations. A suite of techniques for numerical linear algebra.
- 1957: The Fortran Optimizing Compiler. Turns high-level code into efficient computer-readable code.
- 1959: QR Algorithm for Computing Eigenvalues. Another crucial matrix operation made swift and practical.
- 7. 1962: Quicksort Algorithms for Sorting. For the efficient handling of large databases.
- 1965: Fast Fourier Transform. Perhaps the most ubiquitous algorithm in use today, it breaks down waveforms (like sound) into periodic components.
- 1977: Integer Relation Detection. A fast method for spotting simple equations satisfied by collections of seemingly unrelated numbers.
- 10. **1987: Fast Multipole Method.** A breakthrough in dealing with the complexity of n-body calculations, applied in problems ranging from celestial mechanics to protein folding.

From Random Samples, Science page 799, February 4, 2000.

PART II. Case Studies

Experimental Mathematics: PSLQ is core to CARMA



Jonathan Borwein Keith Devlin

Experimentelle Mathematik

Eine beispielorientierte Einführung



Experimental Mathematics (2004-08, 2009, 2010)

Jonathan Borwein (University of Newcastle, Australia)

Visual Theorems

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
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- Computer assisted research



Digital Assistance

- Digital Assistance
- Simulation in Mathematics

PART II. Case Studies

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Simulation in *pure* mathematics

Pure mathematicians have not often though of simulation as a relevant tool.

The *cardioid* in the Figure below came from a scatter plot while trying to determine for which complex numbers z = b/a a continued fraction due to Ramanujan, $\Re(a,b)$, converged.

PART II. Case Studies

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It is given for complex numbers a and b by

$$\mathscr{R}(a,b) = \frac{a}{1 + \frac{b^2}{1 + \frac{4a^2}{1 + \frac{9b^2}{1 + \frac{9b^2}{1 + \frac{b^2}{1 + \frac{b^2}{$$

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PART II. Case Studies

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We eventually determined from highly sophisticated arguments that:

Visual Theorems

Theorem

Digital Assistance

PART II. Case Studies

Other References

Simulation in pure mathematics

(Six formulae for
$$\mathscr{R}(a,a), a > 0$$
)
 $\mathscr{R}(a,a) = \int_0^\infty \frac{\operatorname{sech}\left(\frac{\pi x}{2a}\right)}{1+x^2} dx$
 $= 2a \sum_{k=1}^\infty \frac{(-1)^{k+1}}{1+(2k-1)a}$
 $= \frac{1}{2} \left(\Psi\left(\frac{3}{4} + \frac{1}{4a}\right) - \Psi\left(\frac{1}{4} + \frac{1}{4a}\right) \right)$
 $= \frac{2a}{1+a} {}_2F_1\left(\frac{\frac{1}{2a} + \frac{1}{2}, 1}{\frac{1}{2a} + \frac{3}{2}}\right) - 1$
 $= 2\int_0^1 \frac{t^{1/a}}{1+t^2} dt$
 $= \int_0^\infty e^{-x/a} \operatorname{sech}(x) dx.$

Jonathan Borwein (University of Newcastle, Australia)

PART II. Case Studies

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Simulation in pure mathematics

Here $_2F_1$ is the hypergeometric function. If you do not know ψ ('psi'), you can easily look it up once you can say 'psi'. Notice that

$$\mathscr{R}(a,a) = 2 \int_0^1 \frac{t^{1/a}}{1+t^2} dt$$

so that $R(1, 1) = \log 2$.

PART II. Case Studies

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PART II. Case Studies

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- After making no progress analytically, Crandall and I decided in 2003, taking a somewhat arbitrary criterion for convergence, to colour yellow points for which the fraction seemed to converge.
- We sampled one million points and reasoned a few thousand mis-categorisations would not damage the experiment.



Figure A pardial diagonared by aimulation

PART II. Case Studies

Other References

Simulation in pure mathematics

PART II. Case Studies

Simulation in pure mathematics

The Figure is so precise that we could identify the cardioid. It is the points where

 $\sqrt{|ab|} \leq \frac{|a+b|}{2}.$

PART II. Case Studies

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 $\sqrt{|ab|} \le \frac{|a+b|}{2}.$

Since for positive *a*, *b* the fraction satisfies

$$\mathscr{R}(\frac{a+b}{2},\sqrt{ab})=\frac{\mathscr{R}(a,b)+\mathscr{R}(b,a)}{2}$$

this gave us enormous impetus to continue our eventually successful hunt for a proof.

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

2 Digital Assistance

 Digital Assistance
 Simulation in Mathematics

 3 PART II. Case Studies

 Ia. Iterated reflections
 Ib: Protein conformation
 Ila: 100 digit challenge
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 4 Other References

, x Digital Assistance

PART II. Case Studies

Other References

Reflection methods

Let $S \subseteq \mathbb{R}^m$. The (nearest point or metric) projection onto *S* is the (set-valued) mapping,

 $P_S x := \operatorname*{arg\,min}_{s \in S} \|s - x\|.$

The reflection w.r.t. S is the (set-valued) mapping,

$$R_S := 2P_S - I.$$





x.

PART II. Case Studies

Other References

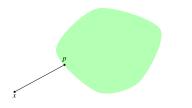
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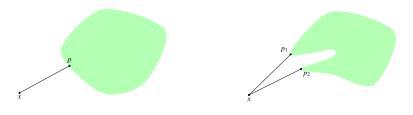
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PART II. Case Studies

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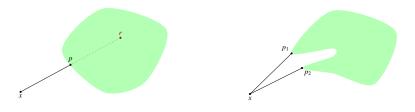
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PART II. Case Studies

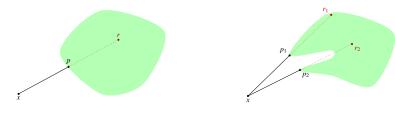
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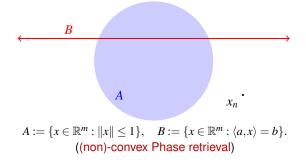
PART II. Case Studies

The Douglas-Rachford Algorithm (1956-1979-)

Theorem (Douglas-Rachford in finite dimensions)

Suppose $A, B \subseteq \mathbb{R}^m$ are closed and convex. For any $x_0 \in \mathbb{R}^m$ define

$$x_{n+1} := T_{A,B}x_n$$
 where $T_{A,B} := \frac{I + R_B R_A}{2}$.



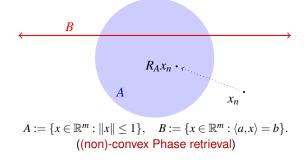
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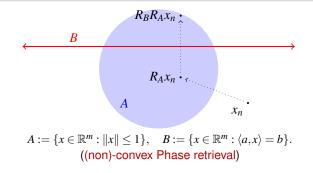
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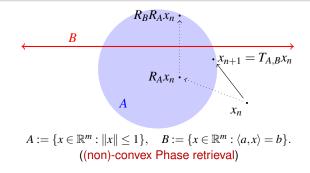
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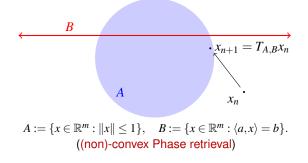
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PART II. Case Studies

ANIMATION

Works for *B* affine and *A* a 'sphere'

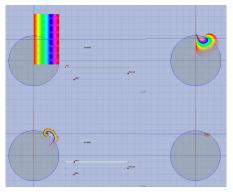
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ANIMATION

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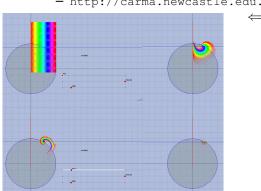


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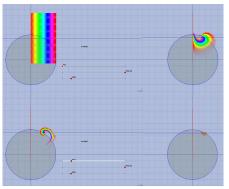
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- Much empirical evidence for this and other non-convex settings.
 - both numeric and geometric (Cinderella/SAGE)
 - http://carma.newcastle.edu.au/jon/expansion.html



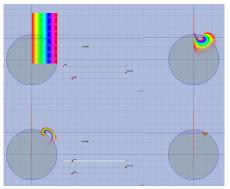
- 20000 starting points coloured by distance from *y*-axis
- after 0,7,14,21 steps
- a "generic visual theorem"?

ANIMATION

Works for *B* affine and *A* a 'sphere'

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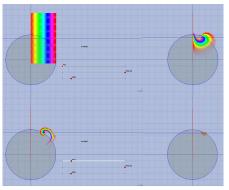
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 - showing global convergence off the (chaotic) y-axis?

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- 20000 starting points coloured by distance from *y*-axis
- after 0,7,14,21 steps
- a "generic visual theorem"?
 - showing global convergence off the (chaotic) y-axis?
- note the *error* from using only 14 digit computation.

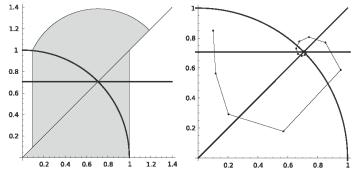
Digital Assistance

PART II. Case Studies

Other References

Works for *B* affine and *A* a 'sphere'

What we could prove (L) and what we could see (R)



2012 Proven region of convergence in grey 2014 Lyapunov function based proof of global convergence (Benoist)

PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research
- Digital Assistance

 Digital Assistance
 Simulation in Mathematics

 PART II. Case Studies

 Ia. Iterated reflections
 Ib: Protein conformation
 Ila: 100 digit appliance
 - IIb: Polylogarithms
 - Other References

PART II. Case Studies

Other References

Case study I:

Protein conformation determination

Proteins: large biomolecules comprising multiple amino acid chains.⁵



⁵RuBisCO (responsible for photosynthesis) has 550 amino acids (smallish).
⁶A coupling which occurs through space, rather than chemical bonds.

Jonathan Borwein (University of Newcastle, Australia)

Visual Theorems

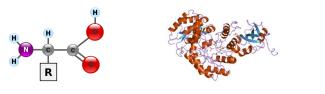
PART II. Case Studies

Other References

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Generic amino acid RuBisCO

Matt Tam

- Proteins participate in virtually every cellular process !
- Protein structure \rightarrow predicts how functions are performed.
- NMR spectroscopy (Nuclear Overhauser effect⁶) can determine a subset of interatomic distances without damage (under 6Å).

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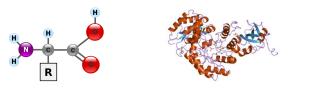
PART II. Case Studies

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A low-rank Euclidean distance matrix completion problem.

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PART II. Case Studies

Six Proteins

Numerics if reconstructed using reflection methods

We use only interatomic distances below 6Å typically constituting less than 8% of the total nonzero entries of the distance matrix.

Table. Six Proteins: average (maximum) errors from five replications.

Protein	# Atoms	Rel. Error (dB)	RMSE	Max Error
1PTQ	404	-83.6 (-83.7)	0.0200 (0.0219)	0.0802 (0.0923)
1HOE	581	-72.7 (-69.3)	0.191 (0.257)	2.88 (5.49)
1LFB	641	-47.6 (-45.3)	3.24 (3.53)	21.7 (24.0)
1PHT	988	-60.5 (-58.1)	1.03 (1.18)	12.7 (13.8)
1POA	1067	-49.3 (-48.1)	34.1 (34.3)	81.9 (87.6)
1AX8	1074	-46.7 (-43.5)	9.69 (10.36)	58.6 (62.6)

$$\begin{aligned} & \mathsf{Rel. error}(dB) := 10 \log_{10} \left(\frac{\|P_{C_2} P_{C_1} X_N - P_{C_1} X_N \|^2}{\|P_{C_1} X_N \|^2} \right), \\ & \mathsf{RMSE} := \sqrt{\frac{\sum_{i=1}^m \|\hat{p}_i - p_i^{rrue}\|_2^2}{\# \text{ of atoms}}}, \qquad \mathsf{Max} := \max_{1 \leq i \leq m} \|\hat{p}_i - p_i^{rrue}\|_2 \end{aligned}$$

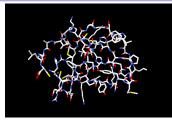
• The points $\hat{p}_1, \hat{p}_2, ..., \hat{p}_n$ denote the best fitting of $p_1, p_2, ..., p_n$ when rotation, translation and reflection is allowed.

Digital Assistance

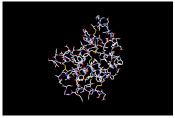
PART II. Case Studies

Other References

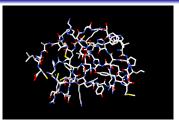
What do the reconstructions look like?



1PTQ (actual)



1POA (actual)



5,000 steps, -83.6dB (perfect)



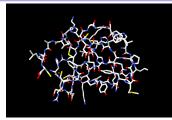
5,000 steps, -49.3dB (mainly good!)

Digital Assistance

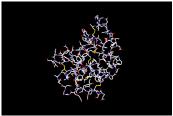
PART II. Case Studies

Other References

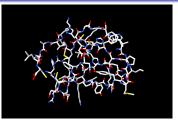
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5,000 steps, -49.3dB (mainly good!)

• The picture of 'failure' suggests many strategies

Jonathan Borwein (University of Newcastle, Australia)

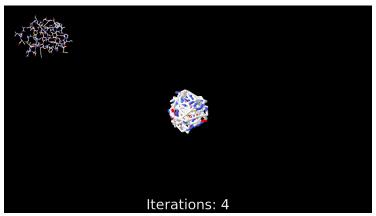
Visual Theorems

Digital Assistance

PART II. Case Studies

Other References

What do reconstructions look like?



Video: First 3,000 steps of the 1PTQ reconstruction.

At http://carma.newcastle.edu.au/DRmethods/1PTQ.html

PART II. Case Studies

Other References

What do the Reconstructions Look Like?

An optimised implementation gave a ten-fold speed-up.

PART II. Case Studies

Other References

What do the Reconstructions Look Like?

An optimised implementation gave a ten-fold speed-up. This allowed for the following experiment to be performed:

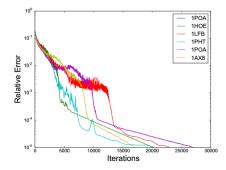


Figure: Relative error by iterations (vertical axis logarithmic).

PART II. Case Studies

Other References

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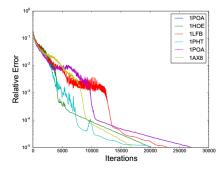


Figure: Relative error by iterations (vertical axis logarithmic).

- For < 5,000 iterations, the error exhibits non-monotone oscillatory behaviour. It then decreases sharply. Beyond this progress is slower.
- Is early termination to blame? Terminate when error < -100dB.

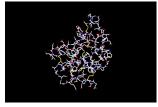
Digital Assistance

PART II. Case Studies

Other References

A More Robust Stopping Criterion

The "un-tuned" implementation (from previous slide):



1POA (actual)



5,000 steps (~2d), -49.3dB

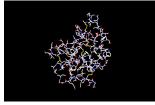
Digital Assistance

PART II. Case Studies

Other References

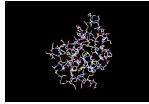
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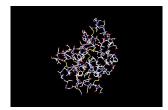
The optimised implementation:



1POA (actual)



5,000 steps (~2d), -49.3dB



28,500 steps (~1d), -100dB (perfect!)

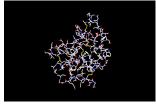
Digital Assistance

PART II. Case Studies

Other References

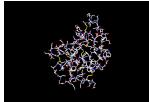
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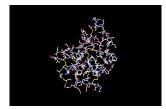
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Similar results observed for the other test proteins.

Jonathan Borwein (University of Newcastle, Australia)

Visual Theorems

PART II. Case Studies

What do reconstructions look like?

There are many projection methods, so why use Douglas-Rachford?

Douglas-Rachford reflection method reconstruction:



500 steps, -25 dB.



1,000 steps, -30 dB.



2,000 steps, -51 dB.



5,000 steps, -84 dB.

Alternating projection method reconstruction:



500 steps, -22 dB.



1,000 steps, -24 dB.



2,000 steps, -25 dB.



5,000 steps, -28 dB.

PART II. Case Studies

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5,000 steps, -28 dB.

• Yet MAP works very well for optical abberation correction (Hubble, amateur telescopes). Why?

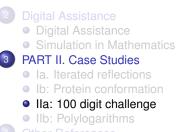
PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
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Other References

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"If anyone gets 50 digits in total, I will be impressed."

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"If anyone gets 50 digits in total, I will be impressed."

- To his surprise, a total of **94** teams, representing 25 different nations, submitted results. Twenty of these teams received a full 100 points (10 correct digits for each problem).
- Bailey, Fee and I quit at 85 digits!

PART II. Case Studies

SKIP

The hundred digit challenge

The problems and solutions are dissected most entertainingly in

[1] F. Bornemann, D. Laurie, S. Wagon, and J. Waldvogel (2004)."The Siam 100-Digit Challenge: A Study In High-accuracy Numerical Computing", SIAM, Philadelphia.

PART II. Case Studies

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PART II. Case Studies

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Success in solving these problems required a broad knowledge of mathematics and numerical analysis, together with significant computational effort, to obtain solutions and ensure correctness of the results. As described in [1] the strengths and limitations of Maple, Mathematica, MATLAB (The 3Ms), and other software tools such as PARI or GAP, were strikingly revealed in these ventures.

Almost all of the solvers relied in large part on one or more of these three packages, and while most solvers attempted to confirm their results, there was no explicit requirement for proofs to be provided.

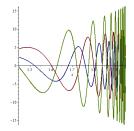
PART II. Case Studies

Trefethen's problem #9

The integral

$$I(\alpha) = \int_0^2 [2 + \sin(10\alpha)] x^{\alpha} \sin\left(\frac{\alpha}{2 - x}\right) dx$$

depends on the parameter α . What is the value $\alpha \in [0,5]$ at which $I(\alpha)$ achieves its maximum?



Integrands for some α

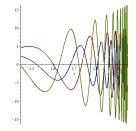
PART II. Case Studies

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Integrands for some α

I(α) is expressible in terms of a *Meijer-G function* —a special function with a solid history that we use below.

$$I(\alpha) = 4 \sqrt{\pi} \Gamma(\alpha) G_{2,4}^{3,0} \left(\frac{\alpha^2}{16} \middle| \frac{\frac{\alpha+2}{2}}{\frac{1}{2}}, \frac{\frac{\alpha+3}{2}}{2} \right) [\sin(10\alpha) + 2].$$

- Unlike most contestants, *Mathematica* and *Maple* will figure this out; help files or a web search then inform the scientist.
- This is another measure of the changing environment. It is usually a good idea—and not at all immoral—to data-mine.

PART II. Case Studies

ANIMATION

Trefethen's problem #10

A particle at the center of a 10×1 rectangle undergoes Brownian motion (i.e., 2-D random walk with infinitesimal step lengths) till it hits the boundary. What is the probability that it hits at one of the ends rather than at one of the sides?

Walking in a 10×5 box



PART II. Case Studies

Trefethen's problem #10

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ANIMATION

Hitting the Ends. Bornemann [1] starts his remarkable solution by exploring *Monte-Carlo methods*, which are shown to be impracticable.

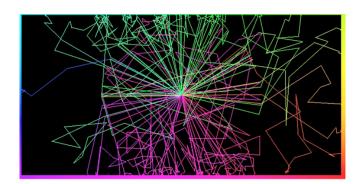
- He reformulates the problem *deterministically* as the value at the center of a 10 × 1 rectangle of an appropriate harmonic measure of the ends, arising from a 5-point discretization of Laplace's equation with Dirichlet boundary conditions.
- This is then solved by a well chosen *sparse Cholesky* solver. A reliable numerical value of $3.837587979 \cdot 10^{-7}$ is obtained and the problem is solved *numerically* to the requisite ten places.
- This is the warm up....

Walking in a $b \times a$ box

Digital Assistance

PART II. Case Studies

ANIMATION



PART II. Case Studies

Trefethen's problem #10

We may proceed to develop two analytic solutions, the *first* using *separation of variables* on the underlying PDE on a general $2a \times 2b$ rectangle. We learn that with $\rho := a/b$

$$p(a,b) = \frac{4}{\pi} \sum_{n=0}^{\infty} \frac{(-1)^n}{2n+1} \operatorname{sech}\left(\frac{\pi(2n+1)}{2}\rho\right).$$
 (5)

PART II. Case Studies

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 (5)

- Three terms yields 50 correct digits: p(10,1) = 0.00000038375879792512261034071331862048391007930055940724...
- The first term alone, $\frac{4}{\pi}$ sech(5π), gives the underlined digits.

PART II. Case Studies

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- The first term alone, $\frac{4}{\pi}$ sech(5π), gives the underlined digits.
- A second method using conformal mappings, yields

$$\operatorname{arccot} \rho = p(a,b) \frac{\pi}{2} + \operatorname{arg} \mathbf{K} \left(e^{ip(a,b)\pi} \right)$$
 (6)

where K is the complete elliptic integral of the first kind.

PART II. Case Studies

Trefethen's problem #10

• We have entered the wonderful world of modular functions

Jonathan Borwein (University of Newcastle, Australia) Visual Theorems www

PART II. Case Studies

Other References

Trefethen's problem #10

• We have entered the wonderful world of modular functions

Bornemann et al ultimately show that the answer is

$$p = \frac{2}{\pi} \arcsin(k_{100}) \tag{7}$$

where

$$k_{100} := \left(\left(3 - 2\sqrt{2} \right) \left(2 + \sqrt{5} \right) \left(-3 + \sqrt{10} \right) \left(-\sqrt{2} + \sqrt[4]{5} \right)^2 \right)^2,$$

is a singular value. [In general $p(a,b) = \frac{2}{\pi} \arcsin\left(k_{(a/b)^2}\right)$.]

PART II. Case Studies

Other References

Trefethen's problem #10

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is a singular value. [In general $p(a,b) = \frac{2}{\pi} \arcsin\left(k_{(a/b)^2}\right)$.]

- No one (except harmonic analysts perhaps) anticipated a closed form—let alone one like this.
- Can be done for some other shapes (perhaps, convex with piecewise smooth boundaries, starting at barycentre), and for self-avoiding walks.

Trefethen's problem #4

Digital Assistance

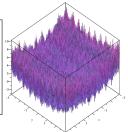
PART II. Case Studies

... zooming

What is the global minimum of the function

 $\exp(\sin(50x)) + \sin(60e^y) + \sin(70\sin x) + \sin(\sin(80y))$

 $-\sin(10(x+y)) + (x^2 + y^2)/4?$



Trefethen's problem #4

Digital Assistance

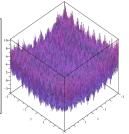
PART II. Case Studies

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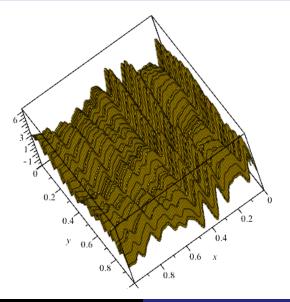


- Can be solved in a global optimization package or by a damped Newton method
- In Mathematica by NMinimize[f[x, y], x, y, Method -> "RandomSearch", "SearchPoints" -> 250, WorkingPrecision -> 20]
- In Maple by NLPSolve(f(x,y), x = -4 ... 4, y = -4 ... 4, initial point = {x = -.4, y = -.1});
- or by 'zooming' on $[-3,3] \times [-3,3]$.

PART II. Case Studies

Trefethen's problem #4

... zooming on [0,1]



PART II. Case Studies

Contents



PART I: Visual Theorems

- Visual theorems
- Large matrices
- Large polynomials
- My collaborators and π
- Early conclusions
- Experimental mathematics
- Computer assisted research

- Digital Assistance
 Digital Assistance
 Simulation in Math
 - Simulation in Mathematics



PART II. Case Studies

- Ia. Iterated reflections
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- Ila: 100 digit challenge
- Ilb: Polylogarithms
- Other References

PART II. Case Studies

Algorithm performance

a simulated interlude

Proposition (Polylogarithm computation)

(a) For s = n a positive integer,

$$\operatorname{Li}_{n}(z) = \sum_{m=0}^{\infty} \zeta(n-m) \frac{\log^{m} z}{m!} + \frac{\log^{n-1} z}{(n-1)!} (H_{n-1} - \log(-\log z)).$$
(8)

(b) For any complex order s not a positive integer,

$$\operatorname{Li}_{s}(z) = \sum_{m \ge 0} \zeta(s-m) \frac{\log^{m} z}{m!} + \Gamma(1-s)(-\log z)^{s-1}.$$
 (9)

Here $\zeta(s) := \sum_{n}^{-s}$ and continuations, $H_n := 1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n}$, and \sum' avoids the singularity at $\zeta(1)$. In (8), $|\log z| < 2\pi$ precludes use when $|z| < e^{-2\pi} \approx 0.0018674$. For small |z|, however, it suffices to use the definition

$$\mathrm{Li}_{s}(z) = \sum_{k=1}^{\infty} \frac{z^{k}}{k^{s}}.$$

(10)

Visual Theorems

PART II. Case Studies

Algorithm performance

- a simulated interlude
- We found (10) faster than (8) whenever |z| < 1/4, for precision from 100 to 4000 digits. We illustrate for Li₂ in the Figure.

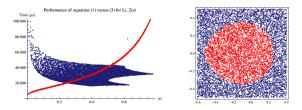


Figure: (L) Timing (8) (blue) and (10) (red).(R) blue region where (8) is faster.

PART II. Case Studies

Algorithm performance

a simulated interlude

- We found (10) faster than (8) whenever |z| < 1/4, for precision from 100 to 4000 digits. We illustrate for Li₂ in the Figure.
- Timings show microseconds required for 1,000 digit accuracy as the modulus goes from 0 to 1 with blue showing superior performance of (8). The region records 10,000 trials of random *z*, such that $-0.6 < \Re(z) < 0.4, -0.5 < \Im(z) < 0.5$.

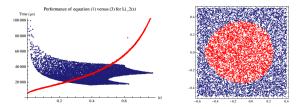


Figure: (L) Timing (8) (blue) and (10) (red).(R) blue region where (8) is faster.

PART II. Case Studies

Other References

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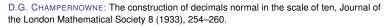
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