Mulțumesc din suflet pentru acest titlu

Response to Award of DSc(*h.c.*) by West University of Timișoara

James Davenport

University of Bath

5 September 2019

SYmbolic and
Numeric
Algorithms for
Scientific
Computation

SYNASC

SYmbolic [Algebra] and
Numeric [Arithmetic]
Algorithms [Precise Methods] for
Scientific [which includes Engineering]
Computation

Computation

Most people think of numbers [Arithmetic] when they think of computers.

"We may say most aptly that the Analytical Engine weaves algebraical patterns just as the Jacquard loom weaves flowers and leaves" — Ada, Countess Lovelace [Ada43].

The first theses in computer algebra date back to 1953 — a very good year.

The International Mathematical Olympiad, which started in Romania in 1959, separates Algebra from Arithmetic (Number Theory), but real life, and this conference, are not so binary.

The real distnction is that arithmetic deals with particular numbers, and algebra with generalities: so $3^2 + 4^2 = 5^2$ is a statement about a particular right-angled

Precision

Computing, whether symbolic or numeric, requires precision of statement.

Mathematician local: "in a suitably chosen open set"

Computer global definition

Computers do not have a "choose context" instruction.

This can lead to problems where different open subsets might give incompatible results, and even paradoxes. Hence our Paris work, published in SYNASC [CDKS12]. The algebra of contexts is necessary to make sure the arithmetic is correct.

Computation in the real world

I am a happy computer science professor. When I flew here, I trusted my life to a University of Bath spinout company, and to my former students who work there. This company is responsible for the software of the UK's National Air Traffic Services: over a million hours without a software fault.

- At SYNASC 2016, I learned about Line 14 of the Paris Métro, which by now has operated for twenty years without a software error.
- Crash-proof software for heart pacemakers [And17]
- But 500,000 Americans had their pacemakers recalled for security reasons [The17]

Surely this takes a great deal of testing?

Testing is like arithmetic: a specific case. "All cases that might arise in 20 years" is a tall order: both numerically, and would you believe such a list?

What is needed is algebra, or what people call "formal methods" in software. Very pleased to see (and speak at) FROM 2019, the Working Formal Methods Symposium 2019, just held in conjunction with SYNASC 2019.

One of the aims of our recent "Symbolic Computation and Satisfiability Checking" (SC^2) project [ABB+16, DEG+19] (SC^2 2016 was with SYNASC 2016) was to extend the scope of formal methods from Boolean logic ("There is no train in the next block") [Coo42] to numerical statements ("the next train is 6km ahead travelling at 150km/h").

Converting this from pure science to engineering proven software might make our railway tracks 30% more efficient!

Artificial Intelligence

SYNASC now has a flourishing Artificial Intelligence track.
Artificial Intelligence is much in the news currently. But most commentators are referring to one particular type of AI — Machine Learning (really "Pattern Recognition"): multi-layer neural nets trained on big data to recognize patterns.
This is the same sort of stimulus/response functionality that our right brain hemispheres carry out. But [Len19], there is also the work that our left brain hemispheres do.

Artificial Intelligence Compared

(In Mathematics, of course)

Right Brain Deepmind (Google) looked at GCSE, an examination taken by all 16-year olds in England, with Machine Learning (ML). It got the worst form of failure, achieved by less than the bottom 10% of English children [New19, SGHK19].

Left Brain Todai Robot project [AMIA14] was studying entrance to Japanese universities, especially in mathematics.

1. Uses ML to read the exam paper,
2. ML with linguistics to understand the text,
3. domain-specific reasoners,
4. complex program ML with linguistics to "write" the answer.

! Todai Robot couldn't quite get into Tokyo University to study Mathematics, but could get into most other Japanese universities. Roughly Todai Robot was in the top 1%, but not the top 0.1%, of Japanese 17 year olds.

Domain-Specific Reasoners

The most successful domain-specific reasoner, in the sense of the one that solved the most problems in the Tokyo University entrance examination, was Real Algebraic Geometry — precisely the subject of several SYNASC papers, and Erika Ábrahám's invited talk at SYNASC 2017.

There are other domain-specific reasoners in the Todai Robot project, building on various bits of Algebra and Arithmetic such as SYNASC represents.

Machine Learning

The result of large amounts of computation on massive amounts of data, as the underlying Numerical Algorithms try to find distinguishing features. This is basically arithmetic, though one algebraic technique, automatic differentiation, is being used in places [BPRS18].

As such, while it is possible to say what such a Machine Learning system will do on a given piece of input, essentially a test, it is impossible with the current state of technology to make statements in general, essentially the equivalent of formal methods.

For Machine Learning to become truly acceptable, we will have to be able to apply Symbolic Computation to it, a topic of active research at Bath and elsewhere, and I hope to see results at future SYNASCs.

No to Machine Learning (Currently)?

Q Does this mean I am glad that the company I mentioned doesn't use machine learning?

A Not at all, for it is used extensively in the process of generating the formal proofs that underpin the safety of their products.

Note that it is *not* used in validating them.

Just as a trained mathematician reaches for the right lemmas, by pattern matching and without examining every lemma ever learned to decide if it is the right one, machine learning has a great rôle to play in equipping formal methods with a similar activity [KBKU13].

Such an interplay between machine learning and algebra has also been part of the SYNASC programme [HEDP16].

E. Ábrahám, B. Becker, A. Bigatti, B. Buchberger, A. Cimatti, J.H. Davenport, M. England, P. Fontaine, S. Forrest, D. Kroening, W. Seiler, and T. Sturm.
SC^2: Satisfiability Checking meets Symbolic Computation (Project Paper).
In *Proceedings CICM 2016*, pages 28–43, 2016.

Ada Augusta Countess of Lovelace.
Sketch of the Analytical Engine invented by Charles Babbage, by L.F. Menabrea of Turin, with notes on the memoir by the translator.
Taylor's Scientific Memoirs (Article XXIX), 3:666–731, 1843.

N.H. Arai, T. Matsuzaki, H. Iwane, and H. Anai.
Mathematics by Machine.
In K. Nabeshima, editor, *Proceedings ISSAC 2014*, pages 1–8, 2014.

J. Andronick.
Reasoning about Concurrency in High-Assurance, High-Performance Software Systems.
In L. de Moura, editor, *Proceedings CADE 2017*, pages 1–7, 2017.

A.G. Baydin, B.A. Pearlmutter, A.A. Radul, and J.M. Siskind.
Automatic differentiation in machine learning: a survey.
Journal of machine learning research, 18:1–43, 2018.

F. Chyzak, J.H. Davenport, C. Koutschan, and B. Salvy.
On Kahan's Rules for Determining Branch Cuts.
In D. Wang *et al.*, editor, *Proceedings SYNSAC 2012*, pages 47–51, 2012.

W.F. Cooke.
Telegraphic Railways or the Single Way.
Simpkin, Marshall & Co., 1842.

J.H. Davenport, M. England, A. Griggio, T. Sturm, and C. Tinelli.
Editorial: Symbolic Computation and Satisfiability Checking.
In J.H. Davenport, M. England, A. Griggio, T. Sturm, and C. Tinelli, editors, *Symbolic Computation and Satisfiability Checking*. Journal of Symbolic Computation (to appear), 2019.

Z. Huang, M. England, J.H. Davenport, and L.C. Paulson.
Using Machine Learning to Decide When to Precondition Cylindrical Algebraic Decomposition With Groebner Bases.
In *Proceedings SYNASC 2016*, pages 45–52, 2016.

D. Kühlwein, J.C. Blanchette, C. Kaliszyk, and J. Urban.
MaSh: machine learning for sledgehammer.
In International Conference on Interactive Theorem Proving, pages 35–50, 2013.

D. Lenat.
What AI Can Learn From Romeo & Juliet.
https://www.forbes.com/sites/cognitiveworld/2019/07/03/what-ai-can-learn-from-romeo--juliet/, 2019.

New Scientist.
DeepMind taught an AI to take a school maths exam — but it failed.
https://www.newscientist.com/article/2198761-deepmind-taught-an-ai-to-take-a-school-maths-e
2019.

D. Saxton, R. Grefenstette, F. Hill, and P. Kohli.
Analysing Mathematical Reasoning Abilities of Neural Models.
https://arxiv.org/abs/1904.01557, 2019.

The Guardian.
Hacking risk leads to recall of 500,000 pacemakers due to patient death fears.
https://www.theguardian.com/technology/2017/aug/31/hacking-risk-recall-pacemakers-patient-death-fears-fda-
2017.