

Solving PDEs with Newton's Method

Daniel Platt
CUHK Shenzhen, 10 Dez 2024

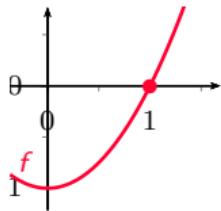
Newton's method is a way for finding zeros of functions: starting from an approximate zero, one iteratively improves it, and in favourable situations finds an exact zero. The same works for elliptic partial differential equations: one first obtains an approximate solution to the equation, and then iteratively uses the linearisation of the equation to improve the solution. In many cases one can prove that this provides an exact solution. I will introduce this technique and review two applications:(1) using pen and paper techniques to construct minimal surfaces, i.e. surfaces with minimal surface tension (joint work with S. Dwivedi and T. Walpuski); (2) using machine learning to construct the approximate solution with the goal of finding harmonic vector fields (joint work with M. Douglas, Y. Qi, R. Barbosa).

Solving PDEs with Newton's Method

1. Newton's method
2. Past research: pen and paper
3. Current research: a numerically verified proof
4. Future research: where to go from here

Newton's method

Toy example:
find zero of
 $f(x) = x^2 - 1$



1. Approximate solution $x_a = 1.01 \Rightarrow$

$$\begin{aligned}f(x) &= f(x_a) + f'(x_a)(x - x_a) + \frac{1}{2}f''(x_a)(x - x_a)^2 \\&= 0.0201 + \underbrace{2.02(x - x_a)}_{=\mathcal{L}(x-x_a)} + \underbrace{(x - x_a)^2}_{=\mathcal{N}(x-x_a)}\end{aligned}$$

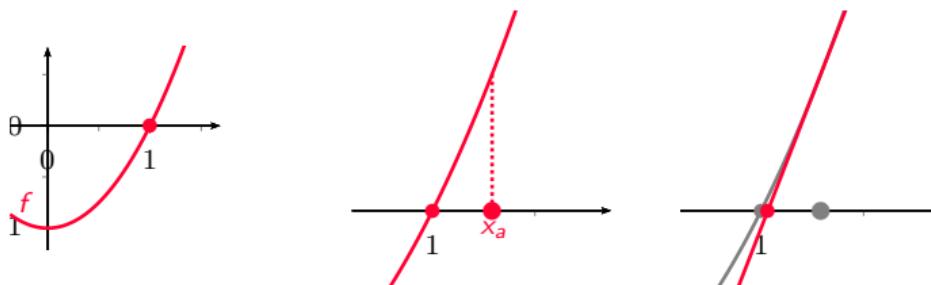
2. Linear estimate: $\|\mathcal{L}^{-1}\| = 1/2.02$
3. Non-linear estimate: $|\mathcal{N}(a) - \mathcal{N}(b)| = |a^2 - b^2| \leq (|a| + |b|) \cdot |a - b|$
4. $x \mapsto -\mathcal{N}\mathcal{L}^{-1}(x) - f(x_a)$ is a contraction on the set $(-1/2, 1/2)$

$$|\mathcal{N}\mathcal{L}^{-1}(a) - \mathcal{N}\mathcal{L}^{-1}(b)| < 0.49 \cdot |a - b|$$

\Rightarrow Fixed point theorem: ex. fixed point y such that $y = -\mathcal{N}\mathcal{L}^{-1}(y) - f(x_a)$
 $\Rightarrow y = \mathcal{L}(x - x_a)$ has $\mathcal{L}(x - x_a) = -\mathcal{N}(x - x_a) - f(x_a) \rightsquigarrow$ solution

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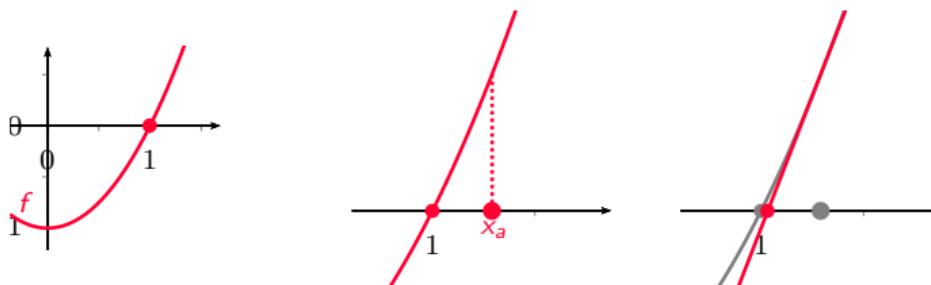
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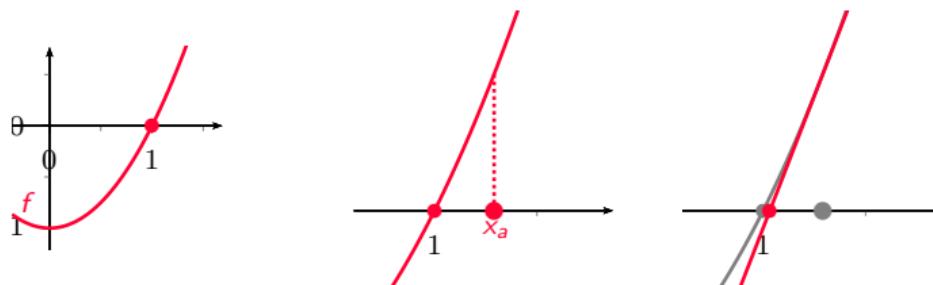
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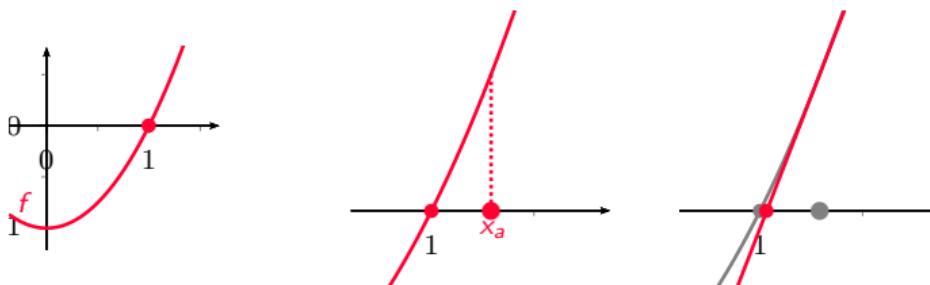
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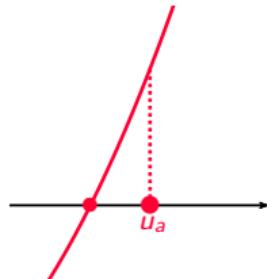
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Newton's method for elliptic PDEs

Elliptic PDE \mathcal{F} for function u



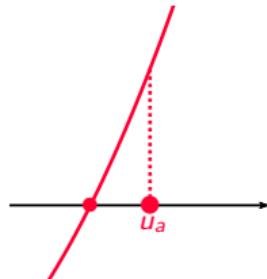
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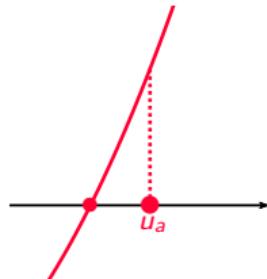
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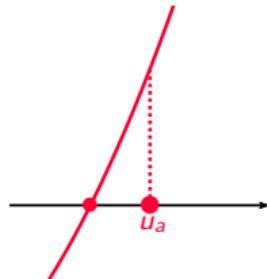
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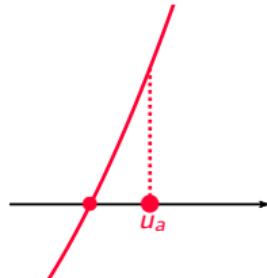
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Past research: pen and paper

- ▶ M-theory: $\mathbb{R}^4 \times M^7$ where M is Ricci-flat, used to model gravity
 - ▶ particles \leftrightarrow 3-dim minimal submanifolds in M
 - ▶ Conjecture (2016), proved in Dwivedi, Platt and Walpuski, 2023:
ex. M with arbitrarily small minimal submanifolds
 - ▶ Definition: minimal submanifold \leftrightarrow locally area minimising
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Normal vector fields $n \leftrightarrow$ submanifolds near u_a^t
 $u_a + n$ minimal surface $\Leftrightarrow \mathcal{F}(n) = \text{res} + \mathcal{L}(n) + \mathcal{A}(n) = 0$
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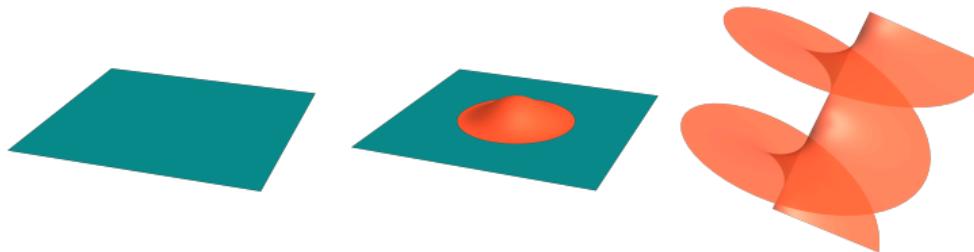
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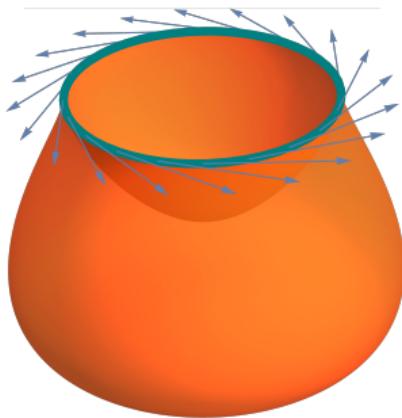
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Current research: a numerically verified proof

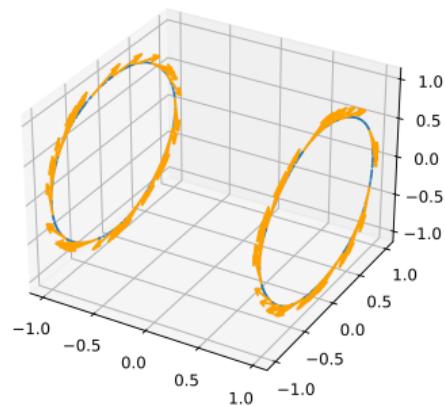
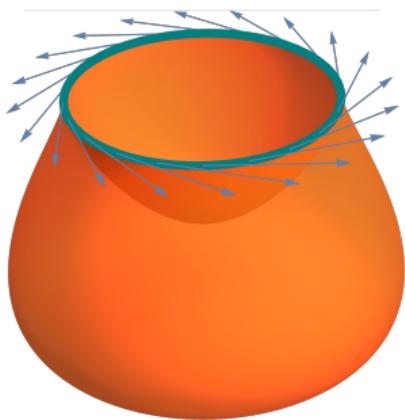
- ▶ Conjecture (2017): ex. 3-dim minimal submanifold L in Ricci-flat M^6 that has a nowhere vanishing vector field u with $\Delta u = 0$



1. Approximate solution u_a , neural network $u_a : L \rightarrow \mathbb{R}^3$
cf. Aslan, Platt and Sheard, 2023; Douglas, Platt and Qi, 2024; Ewert, Magruder, Maiboroda, Shen, Singh and Platt, 2024
Loss function: $x_1, \dots, x_{1000} \in L$, $\text{loss} = \sum_{i=1}^{1000} |\Delta u_a(x_i)|^2$

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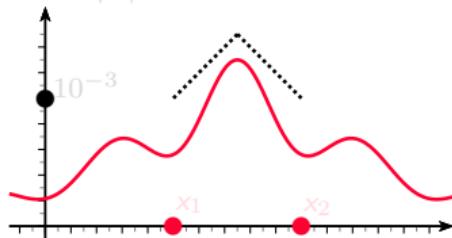
Current research: a numerically verified proof

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Know $|\Delta u_a| \leq 10^{-3}$ is x_1, \dots, x_{1000} , how about in between?

~ AI safety, robustness of AI systems

$f = \Delta u_a$, if $|\nabla f| < 1$ and $\text{dist}(x_1, x_2) < 10^{-3}$,
then $|f| < 2 \cdot 10^{-3}$ between x_1 and x_2



How to apply to curved space? Estimate distances between points?

~ topological data analysis

2. Estimate for $||\Delta^{-1}||$

cf. Dwivedi, Platt and Walpuski, 2023; Galdeano, Platt, Tanaka and Wang, 2023;
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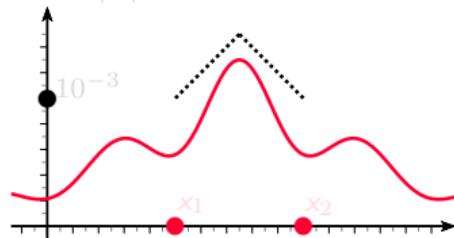
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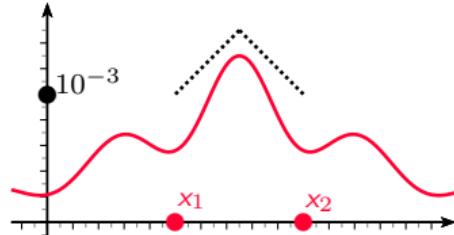
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~ AI safety, robustness of AI systems

$f = \Delta u_a$, if $|\nabla f| < 1$ and $\text{dist}(x_1, x_2) < 10^{-3}$,
then $|f| < 2 \cdot 10^{-3}$ between x_1 and x_2



How to apply to curved space? Estimate distances between points?

~ topological data analysis

2. Estimate for $||\Delta^{-1}||$

cf. Dwivedi, Platt and Walpuski, 2023; Galdeano, Platt, Tanaka and Wang, 2023;
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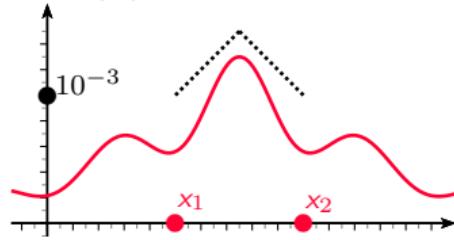
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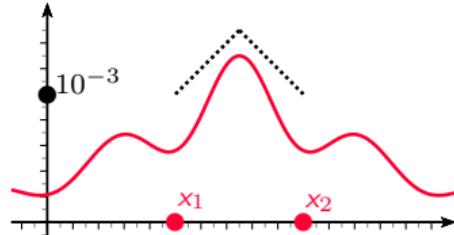
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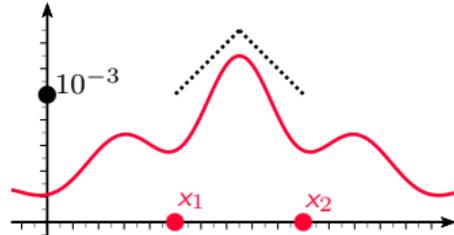
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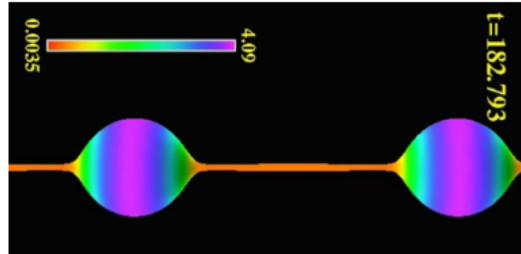
Future research: more numerically verified proofs

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Examples with $\mathcal{L} = \Delta$

1. Conjecture (1993): ex. Ricci-flat metric on $S^1 \times \mathbb{R}^4$ that is not constant in the S^1 -direction (cf. Albertini, Platt and Wiseman, 2024)
2. Conjecture (2021): ex. minimal surface in 2D without symmetry
3. Theorem (Calabi-Yau 1978): ex. Ricci-flat metric on the space $\{(x, y, z, u) \in \mathbb{CP}^3 : x^4 + y^4 + z^4 + u^4 = 0\}$
How close is a given computer approximation of this metric?

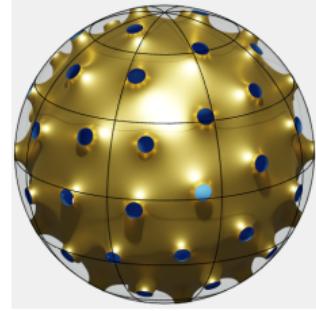
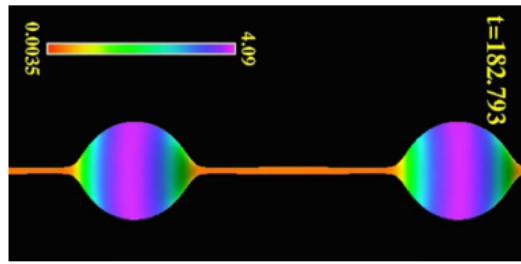
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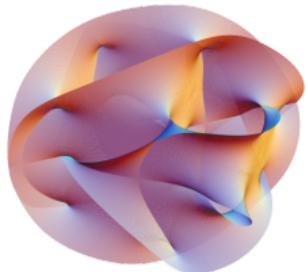
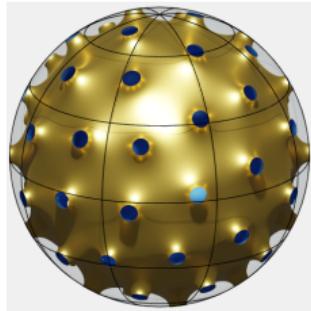
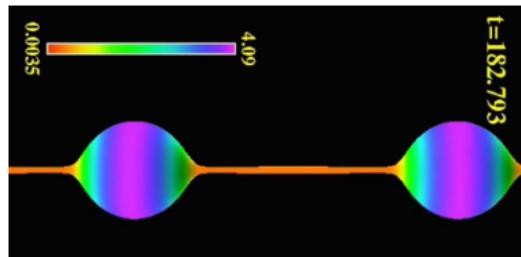
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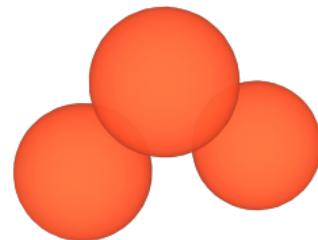


Future research: more conjecture generation using ML

1. Hilbert's 16th problem (1900): maximum number of connected components of algebraic surface in \mathbb{R}^3

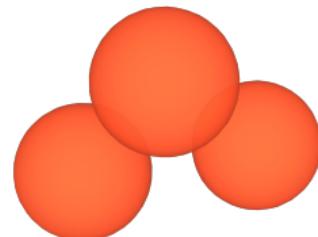
2. Conjecture (1981): maximum number of singularities of hypersurface?

3. Question (1931): is there a metric with positive curvature on $S^2 \times S^2$?

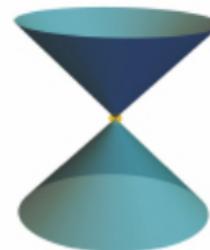


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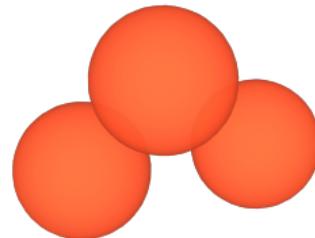
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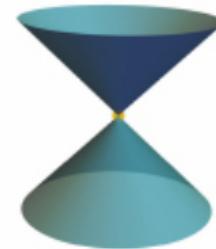
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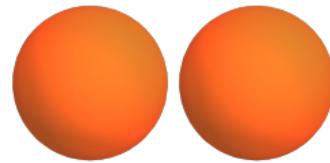
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Thank you for the attention!

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