

How the synthesis of MATH + AI will affect your career in STEM

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The Singularity in Mathematics

- Over the last year mathematicians have begun to prove theorems using Human-AI collaborations.
- On **Sep. 8th**, OpenAI released a 166 page paper that solves a famous conjecture about the equations that model fluid flow.
 - The **sole author** of this paper was a large language model (LLM).
- On **Oct 6th**, OpenAI released 372 papers¹ proving theorems about significant open problems across a wide range of mathematics.
- This singularity has forever changed mathematics and all math-adjacent research and development.
 - Most important development **since the enlightenment (1685-1730)**.
 - It will have a **profound impact** on your career in STEM.

**To take advantage of these developments you need
to know more math (not less)!**

¹10% hit rate

Four Ways to do Mathematics using Computers

(I) Since 1945, **numerical computation** for solutions of

- 1 physics-based mathematical modeling
- 2 differential equations
- 3 optimization problems
- 4 large scale linear algebraic systems and eigen-problems

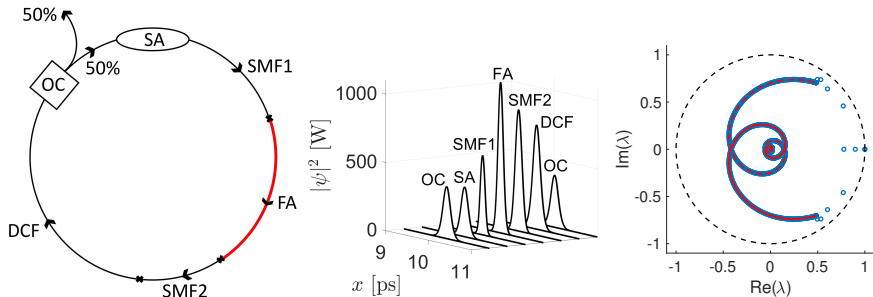


Figure: **Left:** Laser ring. **Center:** Pulse evolution. **Right:** Stability Spectrum

Four Ways to do Mathematics using Computers

(II) Since 2012, machine learning for

- 1 Problems for which we do not have mathematical models
 - Simplest case: fitting a line to data using **least squares** (1805)
- 2 Learning functions from data using **neural networks**
 - Face recognition in computer vision
- 3 **Reduced models** to speed up traditional numerical computations
 - Fast algorithms to train data for classifying erosion of wind turbines

Supported by a backbone from traditional numerical computation

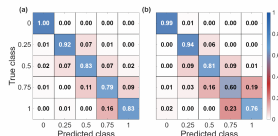
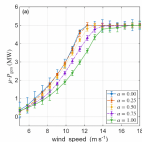
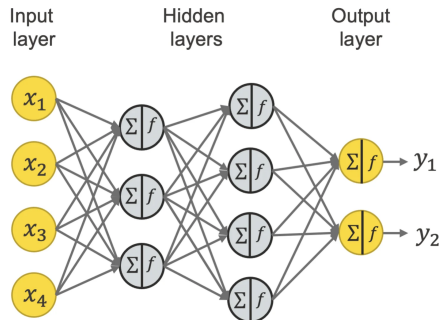


Figure: **Left:** Eroded blade **Center:** Reduced Model **Right:** Erosion Classification

What is a neural network?



- 1 Neural networks map inputs x to outputs y
- 2 The output of each layer is obtained by summing weighted inputs
- 3 Any $y = f(x)$ can be approximately represented by a neural network
- 4 Weights are optimized using training data $\{(x_i, y_i) \mid i = 1 \dots N\}$

Four Ways to do Mathematics using Computers

(III) Since 2025, **large language models** for theorem proving based on

- 1 Probabilistic text completion
- 2 Chain of thought reasoning
- 3 Reinforcement (goal oriented) learning
- 4 Agentic AI

Supported by a backbone of neural networks

Theorem 1.1. *For every $\nu > 0$ there exist a force $f \in C_c^\infty(\mathbb{R}^3 \times (0, \infty); \mathbb{R}^3)$, a compact set $K \subset \mathbb{R}^3$, and smooth velocity and pressure fields u, p on $\mathbb{R}^3 \times [0, 1)$ satisfying*

$$\partial_t u + (u \cdot \nabla)u - \nu \Delta u + \nabla p = f, \quad \nabla \cdot u = 0, \quad u(\cdot, 0) = 0, \quad (1.1)$$

such that $\text{supp } u(\cdot, t) \cup \text{supp } p(\cdot, t) \subset K$ for every $0 \leq t < 1$,

$$\sup_{0 \leq t < 1} \|u(t)\|_{L^2(\mathbb{R}^3)} < \infty, \quad \limsup_{t \uparrow 1} \|u(t)\|_{L^\infty(\mathbb{R}^3)} = \infty.$$

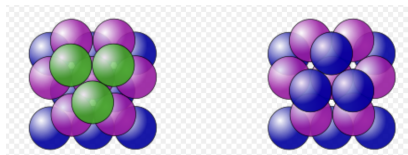
Consequently, there is no smooth solution (u, p) on $\mathbb{R}^3 \times [0, \infty)$ with the same force and initial datum whose kinetic energy is uniformly bounded $\sup_{t \geq 0} \frac{1}{2} \int_{\mathbb{R}^3} |u(x, t)|^2 dx < \infty$.

Figure: **Counterexample to Navier-Stokes Conjecture**

Four Ways to do Mathematics using Computers

(IV) Since 2014, **proof formalization** to certify automated proofs

- 1 1998-2014: Flyspeck Project to certify partially-automated proof of Kepler Conjecture



- 2 2023: Reliable proof certification using Lean programming language

$$\mathbf{x} \cdot \mathbf{y} \leq \|\mathbf{x}\| \|\mathbf{y}\|$$

```
-- Cauchy-Schwarz inequality for real inner products. -/
lemma real_inner_mul_inner_self_le (x y : F) : ⟨x, y⟩_R * ⟨x, y⟩_R ≤ ⟨x, x⟩_R * ⟨y, y⟩_R :=
calc ⟨x, y⟩_R * ⟨x, y⟩_R ≤ ‖⟨x, y⟩_R‖ * ‖⟨y, x⟩_R‖ :
  by { rw [real_inner_comm y, ← norm_mul], exact le_abs_self _ }
... ≤ ⟨x, x⟩_R * ⟨y, y⟩_R :| @inner_mul_inner_self_le R _ _ _ x y
```

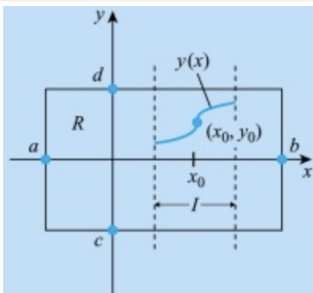
- 3 2026: LLM's translate human/AI proofs to Lean

Existence and Uniqueness Theorem for ODE's

Theorem

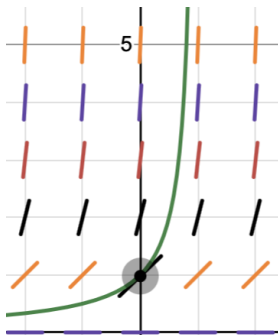
$$\begin{aligned}\frac{dy}{dx} &= f(x, y) \\ y(x_0) &= y_0\end{aligned}$$

Suppose the f and $\frac{\partial f}{\partial y}$ are continuous in a rectangle about (x_0, y_0) . Then there is a unique solution $y = y(x)$ in some interval about x_0 .



Blow up of Solution to an ODE

$$\frac{dy}{dx} = y^2$$



$$y = \frac{1}{1-x}$$

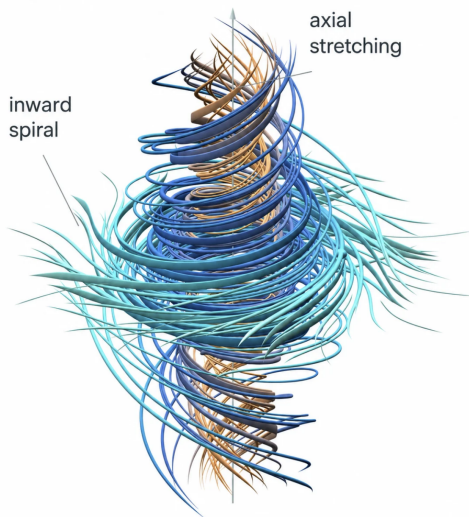
Clay Millenium Problem on the Navier-Stokes Equations

- The Navier-Stokes Equations **model flow of fluids** like water and air.
- Partial differential equation for unknown **fluid velocity** $\mathbf{u} = \mathbf{u}(\mathbf{x}, t)$

$$\frac{\partial \mathbf{u}}{\partial t} = \nu \nabla^2 \mathbf{u} - (\mathbf{u} \cdot \nabla) \mathbf{u} - \frac{1}{\rho} \nabla p + \frac{1}{\rho} \mathbf{f}$$
$$\nabla \cdot \mathbf{u} = 0 \quad [\text{Incompressible fluid}]$$

- ν is viscosity, ρ is density, p is pressure, $\mathbf{f}$ is external force
- Del operator: $\nabla = \frac{\partial}{\partial x} \mathbf{i} + \frac{\partial}{\partial y} \mathbf{j} + \frac{\partial}{\partial z} \mathbf{k}$
- NS equation is **nonlinear**, so solutions exhibit complex behaviour
 - e.g. turbulence
- **Applications:** aircraft design, weather prediction, blood flow
- **Clay \$1 million problem:** Can fluid velocity blow up in finite time?
- **Open AI Result:** Yes it can, if you choose right forcing function.

A Blow up Solution to Navier-Stokes Equations



A Blow up Solution to Navier-Stokes Equations

A cascade of vorticies

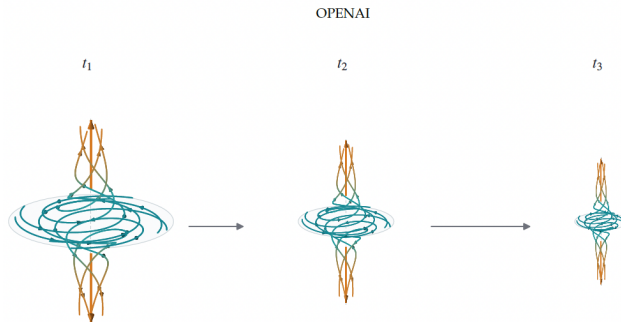


FIGURE 1. The central part of the inner core at successive times $t_1 < t_2 < t_3 < 1$. In this region, fluid spirals inward and flows axially on opposite sides of a dividing layer close to $z = 0$. As the singular time approaches, the region of intense flow shrinks and the velocity increases. Its radius shrinks faster than its height; this difference is exaggerated in the schematic.

A Blow up Solution to Navier-Stokes Equations

- Even if assume pressure and external forcing are smooth for $0 \leq t < 1$, there is a solution for which:
 - Fluid is motionless at $t = 0$
 - Fluid rotates faster and faster as $\mathbf{x} \rightarrow \mathbf{0}$ and $t \rightarrow 1$.
 - Speed $\rightarrow \infty$ at origin as $t \rightarrow 1$
 - Yet total energy is finite: $\iiint_{\mathbb{R}^3} \|u(\mathbf{x}, t)\|^2 d\mathbf{x} < \infty$ for all t
- The proof shows how to construct $\mathbf{u}$ but does not give a formula for it.
- **Basic Idea:**
 - ① Devise solution with these properties.
 - ② Plug it in to find external forcing function, $\mathbf{f}$, and
 - ③ **Arrange for $\mathbf{f}$ to be smooth.**

What does the Navier-Stokes Singularity Actually Mean?

- A fluid consists of billions of widely separated particles.
- However, for NS we assume that the fluid is a **continuum** (no gaps).
 - Mostly valid, except for rarefied gases and plasmas
 - Macroscopic quantities like velocity, density, pressure vary smoothly
- The fact the NS has a singular solution just confirms that the **equations are no longer valid** at the scale of individual molecules.
- Nevertheless, in theory one could perform a laboratory experiment to create a swirling flow that
 - becomes more and more concentrated about a single point,
 - rotates faster and faster,
 - but **never quite** blows up.
- Similar flows have been observed in numerical simulations.
- But that requires manufacturing very wierd forcing functions (or IC's).

How was the NS blow-up solution found?

Goal: Blow up with or without forcing on entire 3D space

LLM solution relied heavily on work of human mathematicians

Involved all four ways of doing math on a computer.

- 2014 Hou and Luo: Traditional numerical computation indicating blow up in cylindrical domain.
- 2022: Hou and Chen: Error estimates to prove Hou and Luo numerics really gives blow up.
- 2023: Cordoba and Martinez-Zoroa: Hard analysis to construct blow up with rough forcing for Euler.²
- 2026: Anandkumar : Physics-informed neural networks for stable singularities for Euler equation

²Euler equation is Navier-Stokes without viscosity.

How was the NS blow-up solution found?

- Aug 15, 2026: Buckmaster (NYU) and Apölge (Anthropic) use LLM's to prove blow up for Euler equation with smooth forcing based on ideas from Cordoba and Martinez-Zoroa and Anandkumar.

The first LLM generated proof Levent sent me was the most horrendous I have ever read; we verified it on Lean on Aug 22nd.

- Sep 8th 2026: After hearing of Buckmaster and progress, OpenAI
 - Launches 10,000 agents over 88 hours ($\approx$ \$15M) on NS blow up.
 - Announces proof of forced blow up for NS with Lean certification.
 - Open AI is sole author on this paper.
- October: Buckmaster states that the OpenAI proof treats viscosity term in NS using **same ideas** he and Apölge generated for Euler using LLMs **but in a very novel way.**

“The agents almost write in a foreign language to fill in all details of proof.”

What AI Proof Generation Teaches us about AI

AI systems are extremely powerful

Vast implications for science, engineering & society at large

Large Language Models

- Know almost everything humans have written
- Make connections that humans have **never** considered
- Thread their way through highly complex arguments
- Plan and organize their work
- Relentlessly pursue tasks
- Think super-fast, in parallel (agentic AI)
- Can be **interrogated**
- Are getting better and better at more and more intellectual tasks

AI increases human intelligence:

Our ability to learn, understand & deal with difficult situations

The events of 2026 raise many philosophical questions/debates

- What is human intelligence?
- What sort of intelligence does AI possess?
- What will AI **not** be able to do?
- What use is a Lean-certified theorem if no one understands it?
- Will we return to a **pre-enlightenment age**
 - Accepting received truths without understanding?
- How should mathematicians organize their communities in light of AI
- How should we train next generation of STEM professionals?

Math 2.0: What do Mathematicians do now?

What we have always done, but often in collaboration with AI and with more emphasis on conveying understanding.

- ① **Mathematical Modeling:** Applications $\rightarrow$ Math
- ② **Build Theory:** Like linear algebra, probability theory, group theory
- ③ **Theorem Proving:** Solve problems that arise in theory building
- ④ **Do Mathematics on Computers:** In Four⁺ Ways
- ⑤ **Develop Understanding:** Transmit to the STEM community
- ⑥ **Train Next Generation:** Engineers, scientists, mathematicians, ...
- ⑦ **Advance Applications:** This will **blossom** with help from AI.

Mathematicians will tackle much harder applied problems

How to take advantage of AI in your STEM career?

Prepare to add value to human and AI R&D

Focus on Fundamentals for First Two Years

- Develop strong fundamentals without relying on AI
 - Math
 - Physics
 - Coding
- Practice writing and editing without relying on AI
- Practice speaking in public
- Learn how to clearly explain technical subjects

How to take advantage of AI in your STEM career?

AI is rapidly impacting all math-adjacent fields

- People at the **edge of knowledge** are best positioned to leverage AI
 - Find something you are **passionate** about and become an expert at it
 - **Interrogate AI** to boost your expertise (use AI as a super tutor)
- Learn more math theory and get experience applying it in your field
 - Whenever you can, turn what you are doing into a math problem
 - Use AI to help solve the problem (Just-in-time math)
- Collaborate with AI on research with a human mentor

Embodied AI is here:

**Robotic systems are already revolutionizing
bench science and hands-on engineering**