

# Why Should You Care About Math?

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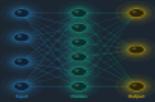
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**The secret?** Every breakthrough in AI is built on math that already existed — most of it centuries old. Today we’ll trace **five mathematical ideas** from ancient history to the AI running on your phone right now.



THE FIVE PILLARS

# The Code of the Universe

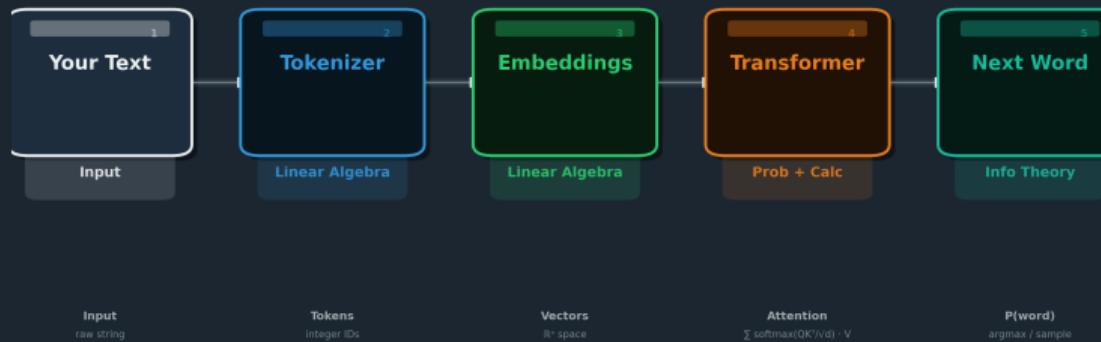
From Classical Mathematics to Large Language Models

The Five Mathematical Ideas Inside Every AI You Use

# LLM Token Processing Pipeline

## How an LLM Processes Text

Five mathematical stages from raw input to predicted next word



# What Happens When You Ask ChatGPT a Question?

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1. Your words become vectors, then giant matrices multiply — Linear Algebra

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4. The goal: minimize surprise (cross-entropy) — Information Theory
5. Optimizers like Adam make trillion-parameter training possible — Optimization

# How LLMs Work — Visual Intro

## Live Interactive Demo

3Blue1Brown — “Large Language Models explained briefly” (~5 min)

<https://www.youtube.com/watch?v=LPZh9B0jkQs>

# Transformer Explainer — Live GPT-2

## Live Interactive Demo

Type text, see tokens → embeddings → attention → prediction

<https://poloclub.github.io/transformer-explainer/>

# 3D LLM Visualization

## Live Interactive Demo

3D walkthrough of every matrix operation in a GPT model

<https://bbycroft.net/llm>

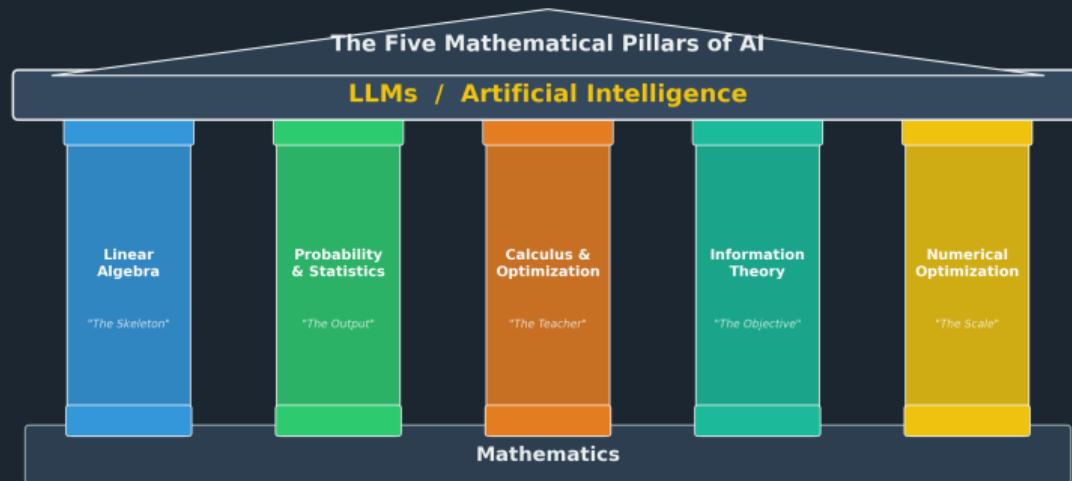
# AnimatedLLM — Step by Step

## Live Interactive Demo

Step-by-step animation of text generation & training

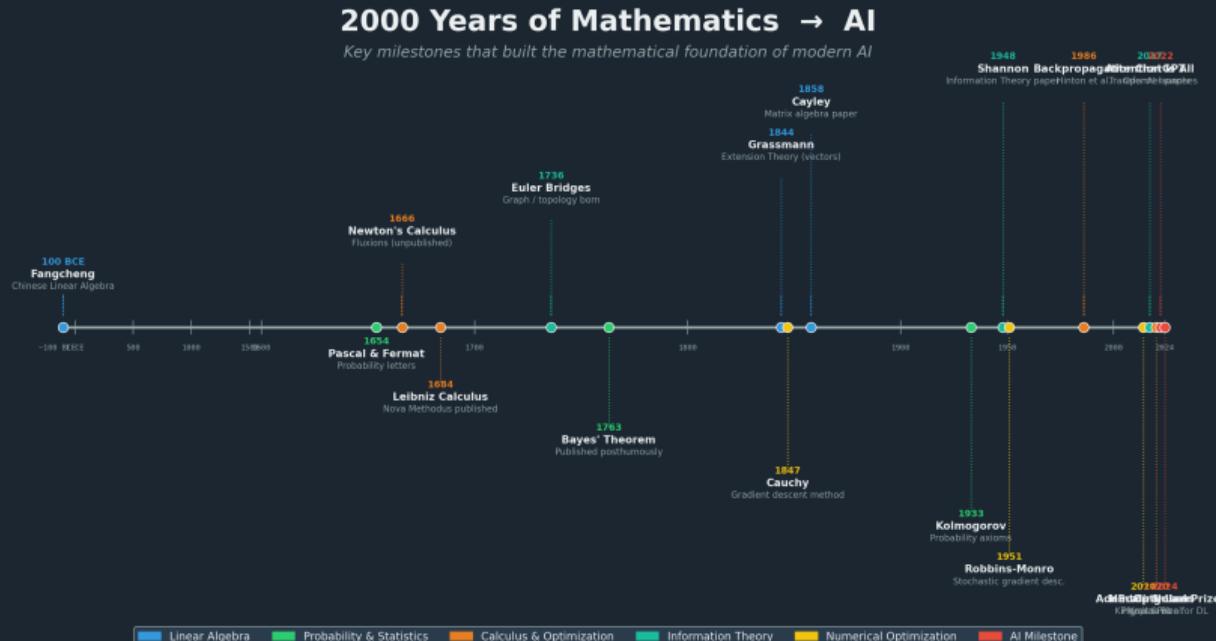
<https://animatedllm.github.io/>

# The Five Pillars of AI Mathematics

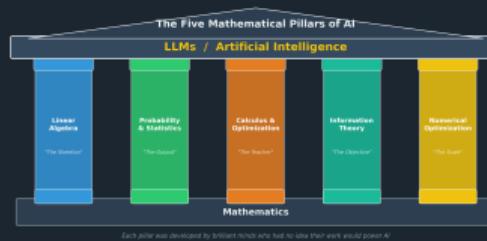


Each pillar was developed by brilliant minds who had no idea their work would power AI

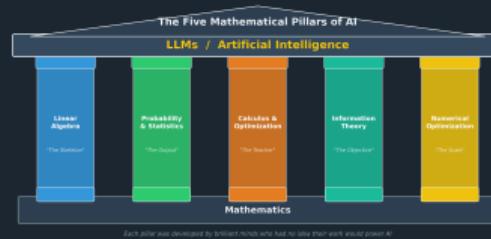
# Mathematical Timeline: 100 BCE to 2024



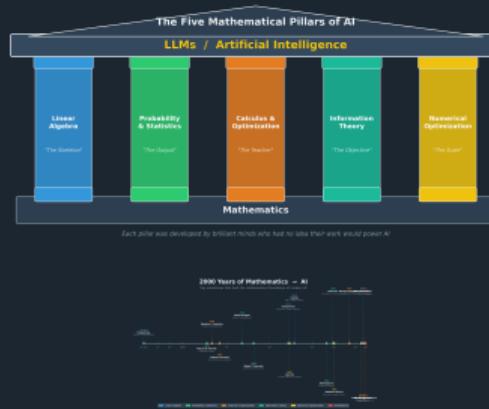
# The Five Pillars



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PILLAR 1

# Linear Algebra

The Skeleton of AI

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# 2000 Years of Linear Algebra



Hermann Grassmann

# 2000 Years of Linear Algebra



Hermann Grassmann

~100 BCE Chinese *Fangcheng* — solving systems with counting rods ORIGIN

# 2000 Years of Linear Algebra

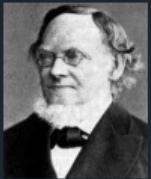


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1844 Grassmann publishes vector spaces — universally ignored

# 2000 Years of Linear Algebra



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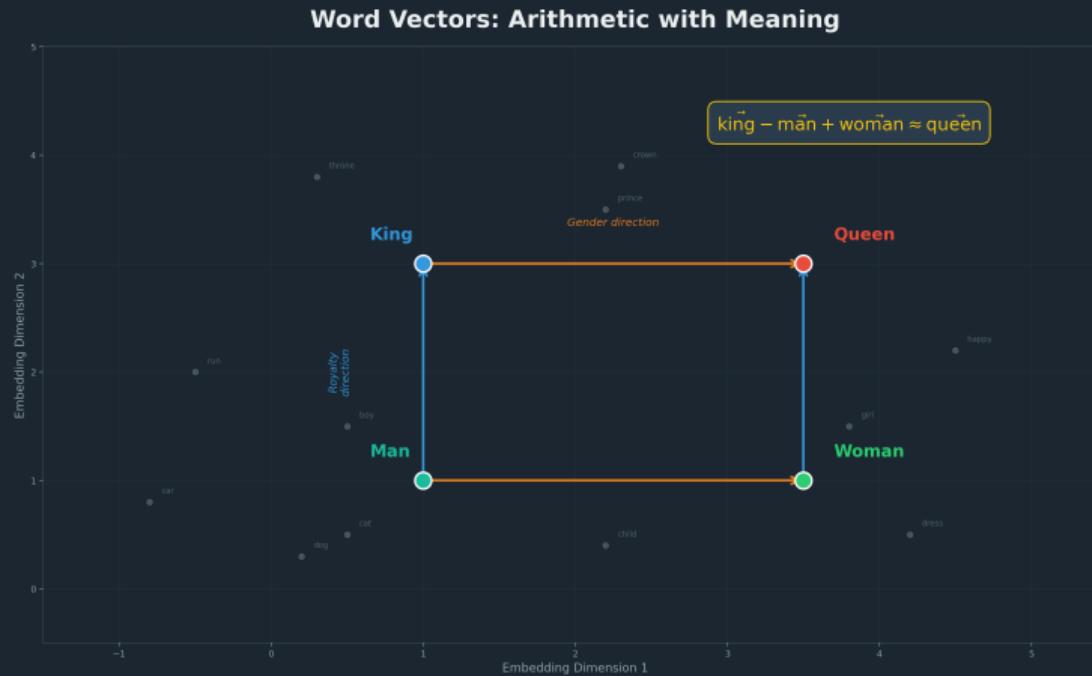
1844 Grassmann publishes vector spaces — universally ignored

1858 Cayley invents matrix theory — while working as a lawyer

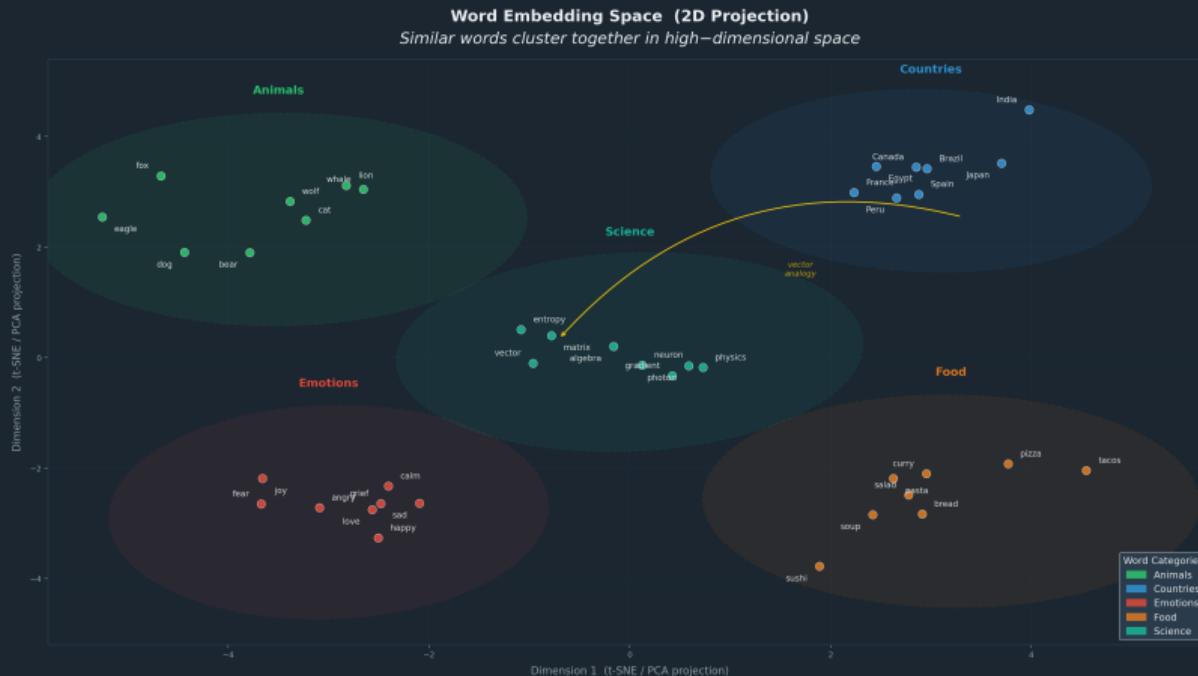


Arthur Cayley

## Word Vectors: King – Man + Woman = Queen



# 2D Word Embedding Space



# Words as Vectors

AI CONNECTION



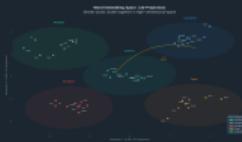
$$\vec{\text{king}} - \vec{\text{man}} + \vec{\text{woman}} \approx \vec{\text{queen}}$$

# Words as Vectors

AI CONNECTION

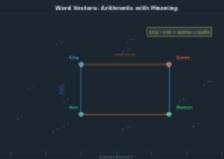


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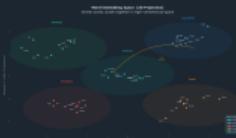


# Words as Vectors

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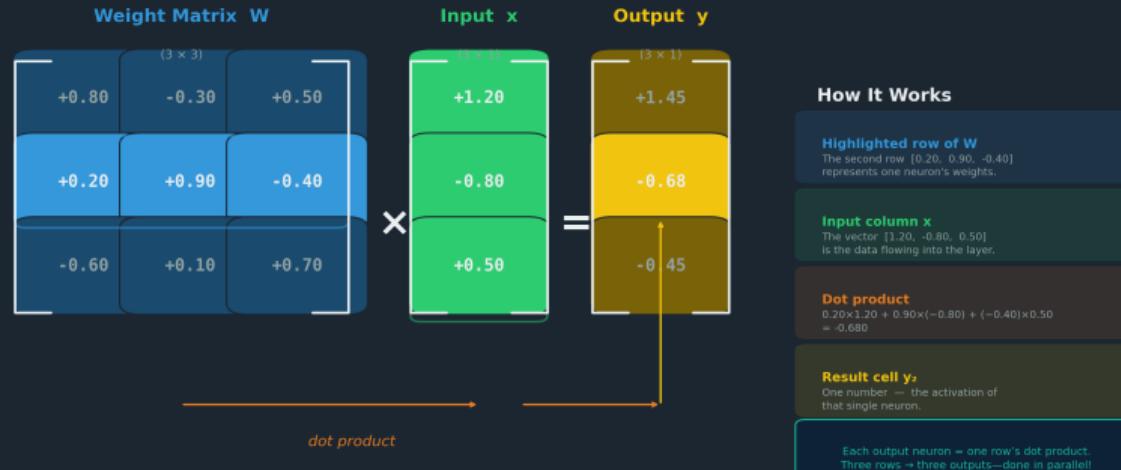


Mikolov et al., 2013 — Word2Vec: meaning encoded as geometry.

# Matrix Multiplication: The Core Operation

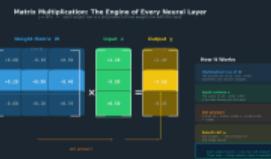
## Matrix Multiplication: The Engine of Every Neural Layer

$y = W \cdot x$  — each output row is a dot product of one weight row with the input



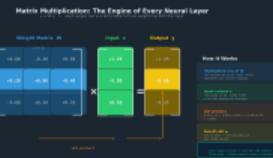
# The Engine: Matrix Multiplication

$$\text{output} = W \cdot \vec{x} + \vec{b}$$



# The Engine: Matrix Multiplication

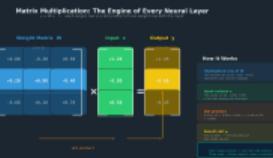
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Every layer: multiply input vector by weight matrix

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Every layer: multiply input vector by weight matrix

GPT-4: ~1.8 trillion such multiplications per token

# Attention Weight Heatmap

## Attention: Which Words Look at Which?

Each word decides which other words are relevant ("Attention Is All You Need", 2017)



# Attention = Three Matrix Multiplies

BREAKTHROUGH

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V$$

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$



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Three matrices. That's all attention is. Cayley's invention, applied to language.

PILLAR 2

# Probability & Statistics

The Language of Uncertainty

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# Born from Gambling



Blaise Pascal

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1654 Pascal & Fermat exchange letters about a gambling problem

ORIGIN



Blaise Pascal



Fermat



Bayes



Kolmogorov

# Born from Gambling

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Blaise Pascal

1763 Bayes' theorem published posthumously



Fermat



Bayes



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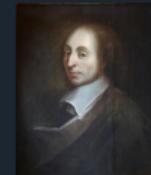
# Born from Gambling

1654 Pascal & Fermat exchange letters about a gambling problem

ORIGIN

1763 Bayes' theorem published posthumously

1933 Kolmogorov writes the axioms — probability becomes rigorous



Blaise Pascal



Fermat

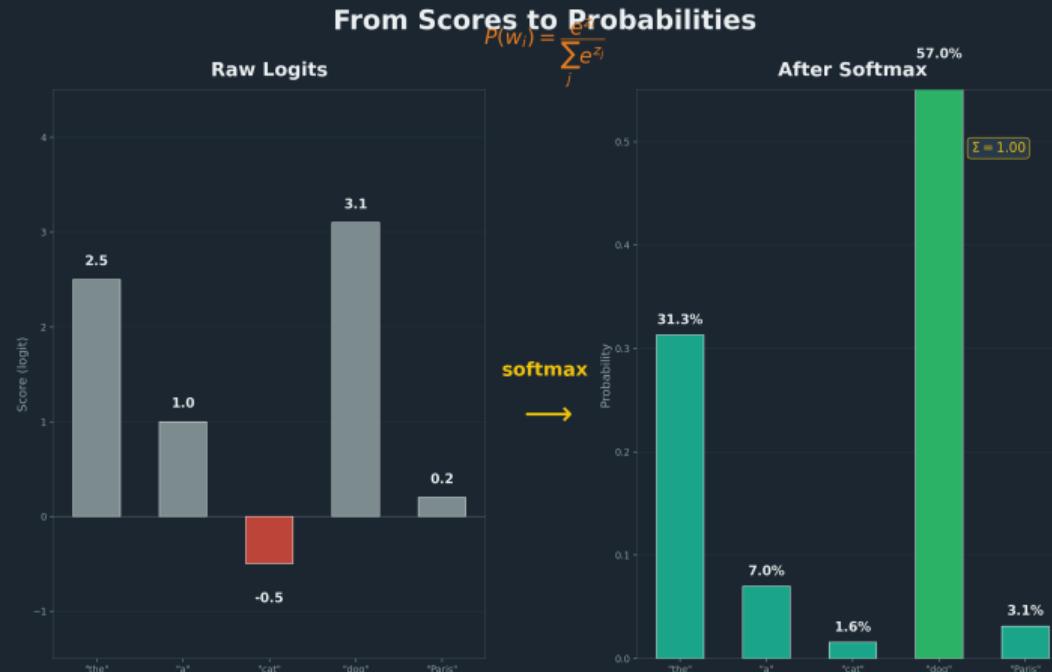


Bayes



Kolmogorov

# Softmax: From Logits to Probabilities



# Turning Scores into Probabilities



$$P(w_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

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50,000+ words. One probability each. Kolmogorov's axioms in action.

# Turning Scores into Probabilities



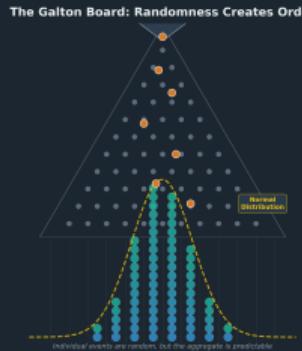
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xkcd.com/1132 (CC BY-NC 2.5)

# Randomness Creates Order

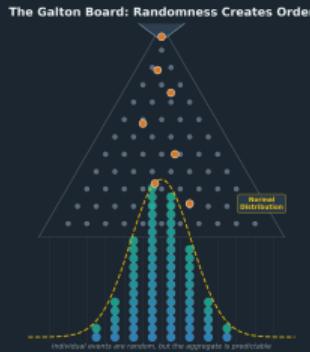


Individual events are random.

But the aggregate forms a pattern.

Wikimedia Commons (CC BY-SA 4.0)

# Randomness Creates Order



Wikimedia Commons (CC BY-SA 4.0)

Individual events are random.

But the aggregate forms a pattern.

LLMs work the same way: each token is sampled randomly, but the sequence is coherent.

PILLAR 3

# Calculus & Optimization

The Teacher

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# The Calculus Wars

ORIGIN



Newton (1666)



Leibniz (1684)

# The Calculus Wars

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Principia Mathematica, 1713 ed.

# The Calculus Wars

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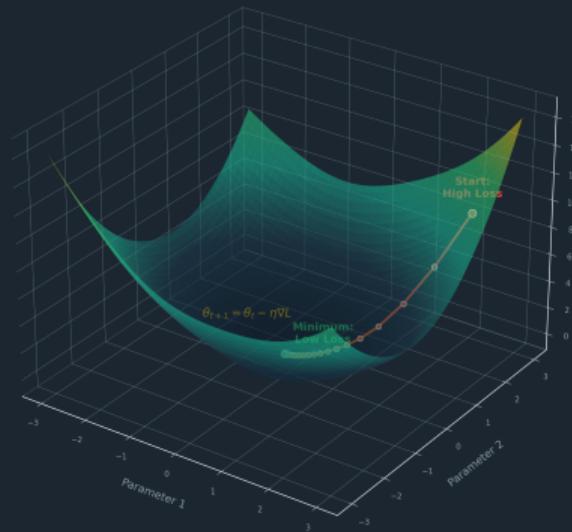
Principia Mathematica, 1713 ed.

Both invented calculus independently. We use Leibniz's notation:  $\frac{dy}{dx}$

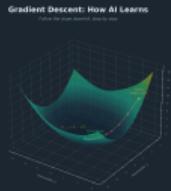
# Gradient Descent on a Loss Surface

## Gradient Descent: How AI Learns

Follow the slope downhill, step by step

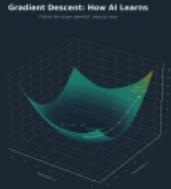


# Gradient Descent: How AI Learns



Cauchy (1847)

# Gradient Descent: How AI Learns



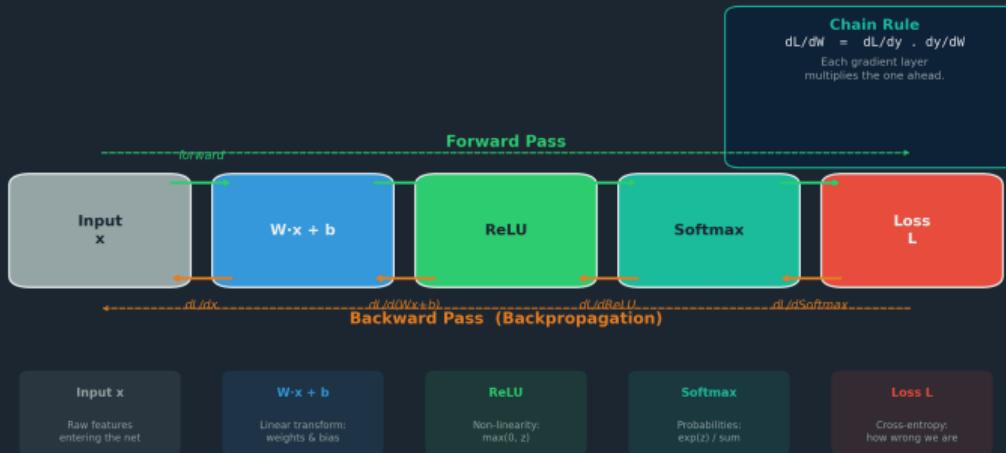
Cauchy (1847)

Cauchy invented this in 1847 — for tracking planetary orbits.

# Backpropagation: Forward and Backward Pass

## Backpropagation: How Neural Networks Learn

Forward pass computes predictions; backward pass propagates gradients via the chain rule



# Backpropagation = The Chain Rule

BREAKTHROUGH

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial y} \cdot \frac{\partial y}{\partial w}$$



Hinton (Nobel 2024)

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The chain rule: derivatives flow backward through every layer

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1986: Rumelhart, Hinton & Williams publish in *Nature*

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The chain rule: derivatives flow backward through every layer

1986: Rumelhart, Hinton & Williams publish in *Nature*

2024: Hinton wins the Nobel Prize in Physics

PILLAR 4

# Information Theory

The Objective Function

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# Shannon: Father of Information Theory

ORIGIN

*“Information is the resolution of uncertainty.”*

— Claude Shannon



Claude Shannon

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1948: “A Mathematical Theory of Communication” —

invented the **bit**

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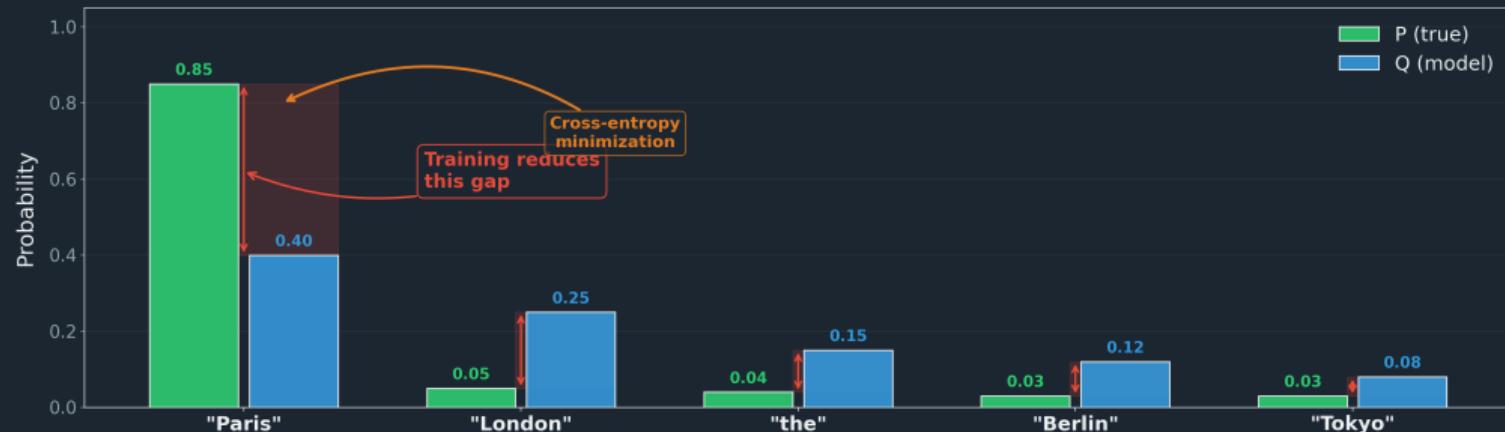
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**Fun fact:** Shannon juggled while riding a unicycle through Bell  
Labs

# Cross-Entropy: Predicted vs True Distribution

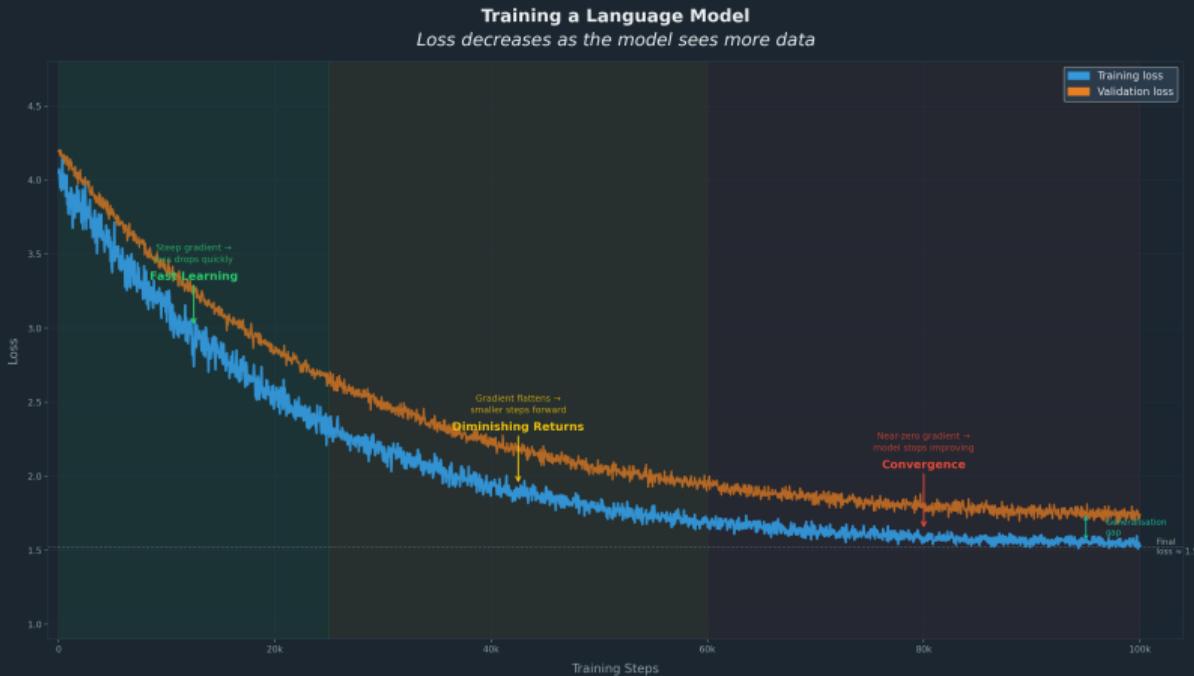
## Cross-Entropy: Measuring Prediction Error

Next token prediction: "The capital of France is \_\_"



$$H(P, Q) = - \sum P(x) \log Q(x) = 1.063 \text{ nats}$$

# Training Loss Curve Over Time



# Cross-Entropy: The LLM Loss Function

AI CONNECTION



$$H(P, Q) = -\sum_x P(x) \log Q(x)$$

# Cross-Entropy: The LLM Loss Function

AI CONNECTION



$$H(P, Q) = -\sum_x P(x) \log Q(x)$$

Shannon's 1948 formula IS the training objective of every LLM.

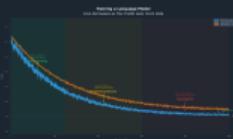
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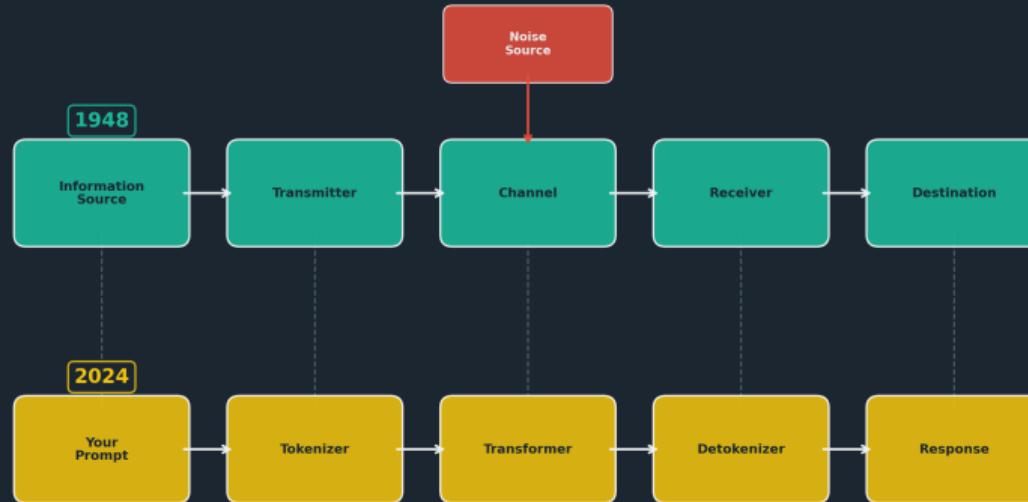
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Training loss decreasing over time

# Shannon's Communication Model as LLM Pipeline

**Shannon's Model → The LLM Pipeline**  
*The same architecture, 75 years apart*

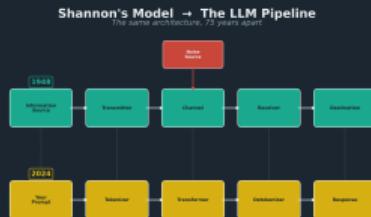


# Shannon's Model → The LLM Pipeline

Shannon's Model → The LLM Pipeline  
The Shannon Structure, 70 years apart



# Shannon's Model → The LLM Pipeline



Shannon designed this for telephone lines. 75 years later, it describes exactly how ChatGPT works.

PILLAR 5

# Numerical Optimization

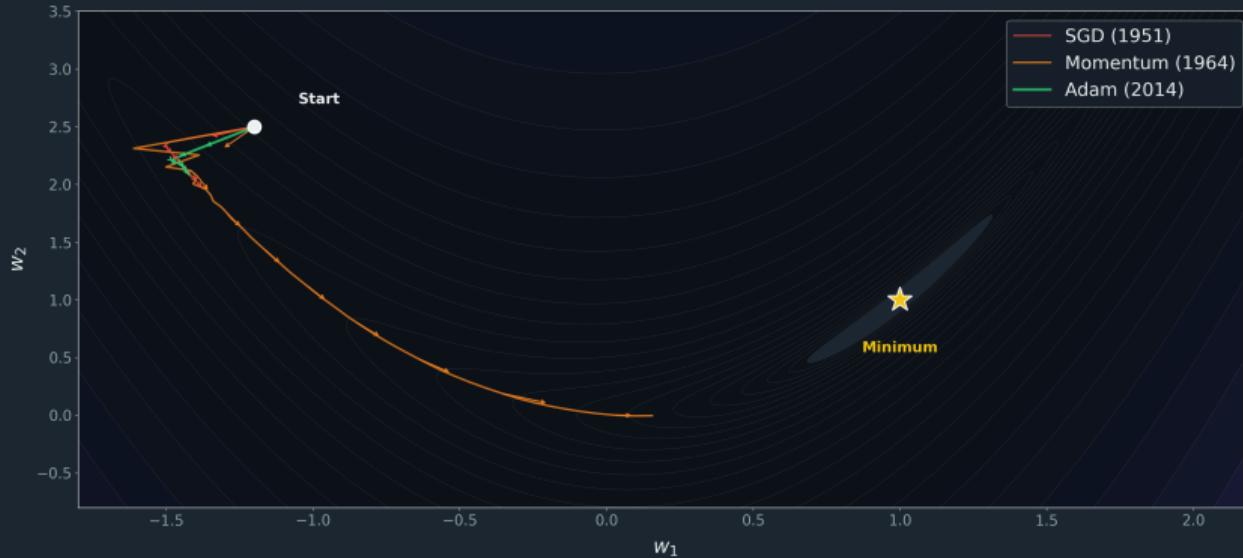
Training at Scale

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# SGD to Momentum to Adam

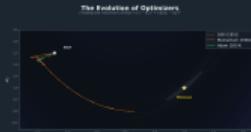
## The Evolution of Optimizers

Finding the minimum of  $f(w) = (1 - w_1)^2 + 10(w_2 - w_1^*)^2$



# The Evolution of Optimizers

DISCOVERY



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1951: Robbins & Monro invent SGD

# The Evolution of Optimizers

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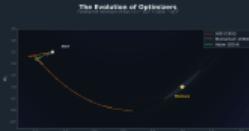


1951: Robbins & Monro invent SGD

1964: Polyak adds momentum

# The Evolution of Optimizers

DISCOVERY



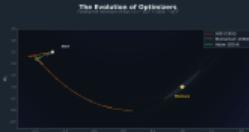
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2014: Kingma & Ba create Adam — **200,000+ citations**

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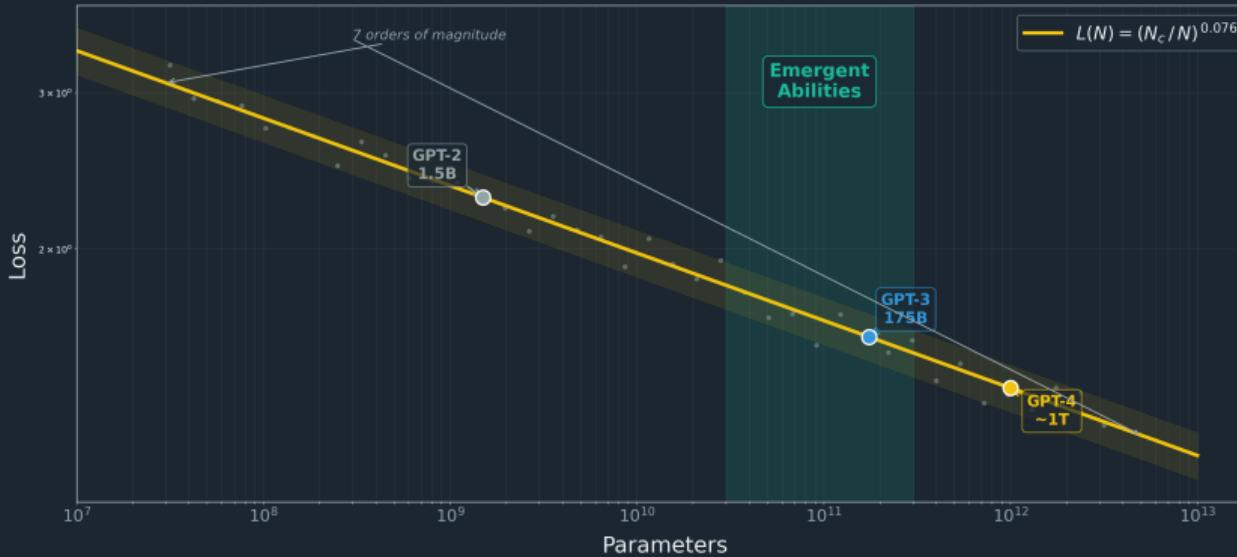


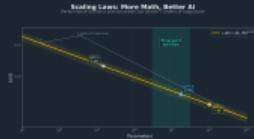
xkcd.com/1838 (CC BY-NC 2.5)

# Neural Scaling Laws (Kaplan et al., 2020)

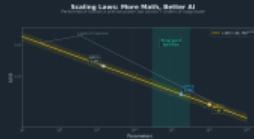
## Scaling Laws: More Math, Better AI

Performance follows a precise power law across 7 orders of magnitude



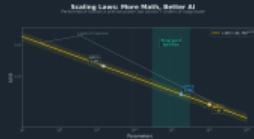


$$L(N) = \left( \frac{N_c}{N} \right)^{0.076}$$



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Kaplan et al., 2020 — why companies spend billions on bigger models.



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xkcd.com/2048 (CC BY-NC 2.5)

# All Five Pillars in One Forward-Backward Pass

## Where All Five Pillars Meet *Inside a single transformer layer*



# Where All Five Pillars Meet



# Where All Five Pillars Meet

Where All Five Pillars Meet



■ Linear Alge-  
bra      Skeleton

■ Probability  
Language

■ Calculus  
Teacher

■ Info Theory  
Objective

■ Optimiza-  
tion      Scale

# Where All Five Pillars Meet

Where All Five Pillars Meet



■ Linear Algebra  
bra      Skeleton

■ Probability  
Language

■ Calculus  
Teacher

■ Info Theory  
Objective

■ Optimization  
Scale

Five branches of pure mathematics, developed over 2000 years, all running simultaneously in a single forward-backward pass.

# What LLMs Can Actually Do

BREAKTHROUGH

*"An AI won a Nobel Prize and a Math Olympiad gold medal. In back-to-back years."*

# What LLMs Can Actually Do

BREAKTHROUGH

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**35/42**

IMO GOLD MEDAL 2025

Gemini Deep Think — only 67 of  
630 humans earned gold

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**Nobel**

CHEMISTRY 2024

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HUMAN EVAL CODING

Claude on standard benchmark

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HUMAN EVAL CODING

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These are not predictions. These already happened.

# The Numbers Are Stupid Big

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1.7T

PARAMETERS IN GPT-4

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**\$100M+**

TRAINING COST

25,000 GPUs for 90 days

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**15T**

TRAINING TOKENS

= 2,750 Wikipedias = 84,000 years of reading

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TRAINING TOKENS

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**800M**

WEEKLY CHATGPT USERS

1 in 10 humans on Earth (Oct 2025)

# The Numbers Are Stupid Big

**1.7T**

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TRAINING COST

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**15T**

TRAINING TOKENS

= 2,750 Wikipedias = 84,000 years of reading

**800M**

WEEKLY CHATGPT USERS

1 in 10 humans on Earth (Oct 2025)

**Plot twist:** DeepSeek R1 matched GPT-4 performance for **\$6 million**. Open source.

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**Why?** LLMs are statistical pattern completers, not fact databases. There is no internal fact-checker.

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Jul 2025 AI scores IMO gold medal (35/42)  AI CONNECTION

# What **YOU** Can Do Right Now

- 1. Get the GitHub Student Developer Pack**

Free Copilot, free cloud credits, free everything

- 2. Take the Kaggle Intro to ML course**

Free, hands-on, takes one weekend

- 3. Open Google Colab and run a notebook**

Free GPU, no setup, works in your browser

- 4. Try a HuggingFace model**

Thousands of pre-trained models, one line of code

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**The tools are free. The courses are free. What are you doing this weekend?**

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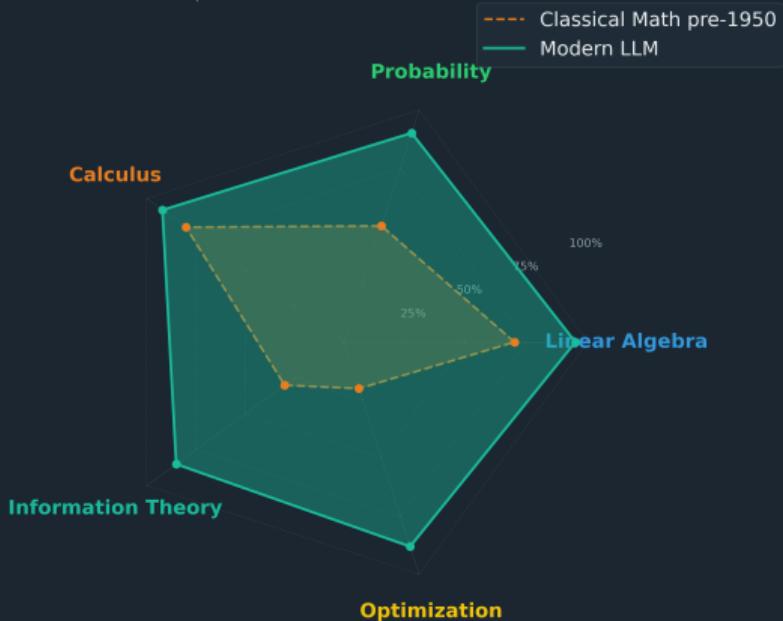
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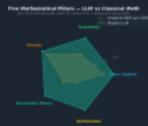
# Five Pillars: Convergence Radar

## Five Mathematical Pillars — LLM vs Classical Math

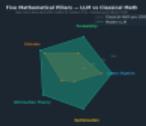
How much does each pillar matter for modern AI vs. classical work before 1950?



# The Code Is Still Being Written

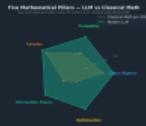


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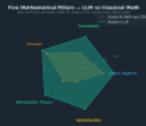
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**Thank you. Questions?**