

Why Should You Care About Math?

Why Should You Care About Math?

4,000 YEARS

Babylonians solved quadratics. Greeks proved theorems. Newton invented calculus to predict planets.

Why Should You Care About Math?

4,000 YEARS

Babylonians solved quadratics. Greeks proved theorems. Newton invented calculus to predict planets.

HIDDEN POWER

GPS needs relativity. Spotify uses linear algebra.
Your phone camera runs Fourier transforms.

Why Should You Care About Math?

4,000 YEARS

Babylonians solved quadratics. Greeks proved theorems. Newton invented calculus to predict planets.

HIDDEN POWER

GPS needs relativity. Spotify uses linear algebra. Your phone camera runs Fourier transforms.

2017 → Now

One paper — “*Attention Is All You Need*” — launched ChatGPT, Claude, Gemini, and a \$3 trillion industry.

Why Should You Care About Math?

4,000 YEARS

Babylonians solved quadratics. Greeks proved theorems. Newton invented calculus to predict planets.

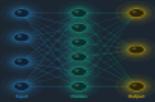
HIDDEN POWER

GPS needs relativity. Spotify uses linear algebra. Your phone camera runs Fourier transforms.

2017 → Now

One paper — “*Attention Is All You Need*” — launched ChatGPT, Claude, Gemini, and a \$3 trillion industry.

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

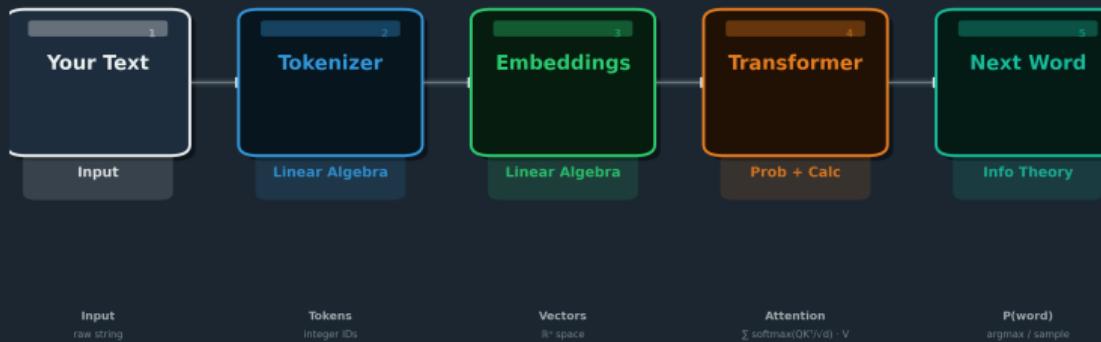
From Classical Mathematics to Large Language Models

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?

What Happens When You Ask ChatGPT a Question?

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

What Happens When You Ask ChatGPT a Question?

1. Your words become vectors, then giant matrices multiply — Linear Algebra
2. It computes probabilities for every possible next word — Probability

What Happens When You Ask ChatGPT a Question?

1. Your words become vectors, then giant matrices multiply — Linear Algebra
2. It computes probabilities for every possible next word — Probability
3. It learned from trillions of examples using derivatives — Calculus

What Happens When You Ask ChatGPT a Question?

1. Your words become vectors, then giant matrices multiply — Linear Algebra
2. It computes probabilities for every possible next word — Probability
3. It learned from trillions of examples using derivatives — Calculus
4. The goal: minimize surprise (cross-entropy) — Information Theory

What Happens When You Ask ChatGPT a Question?

1. Your words become vectors, then giant matrices multiply — Linear Algebra
2. It computes probabilities for every possible next word — Probability
3. It learned from trillions of examples using derivatives — Calculus
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>

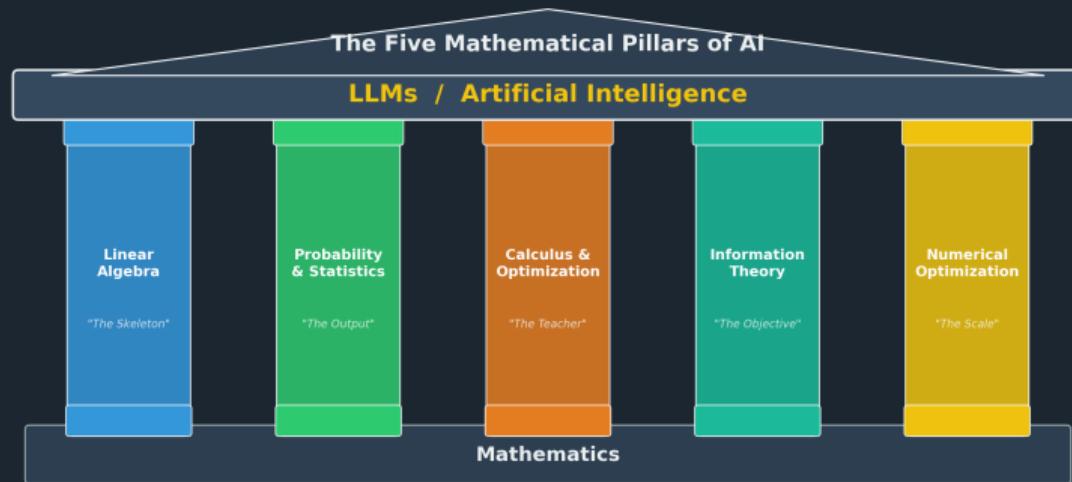
AnimatedLLM — Step by Step

Live Interactive Demo

Step-by-step animation of text generation & training

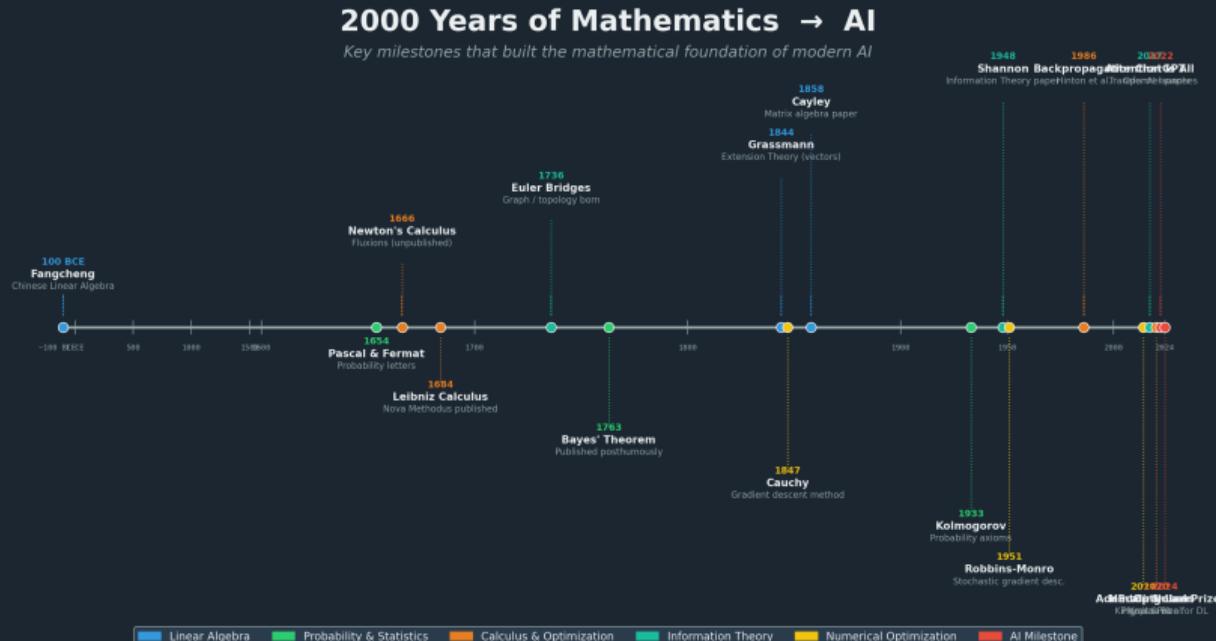
<https://animatedllm.github.io/>

The Five Pillars of AI Mathematics

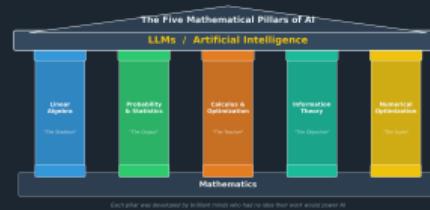


Each pillar was developed by brilliant minds who had no idea their work would power AI

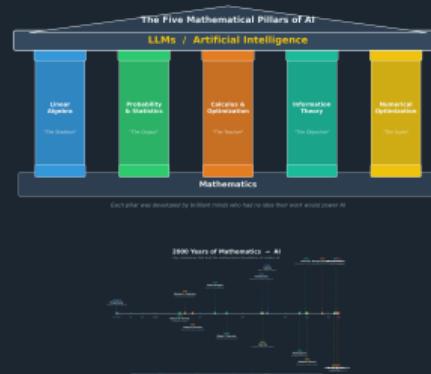
Mathematical Timeline: 100 BCE to 2024



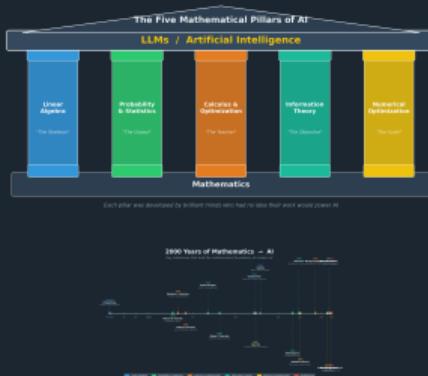
The Five Pillars



The Five Pillars



The Five Pillars



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

PILLAR 1

Linear Algebra

The Skeleton of AI

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

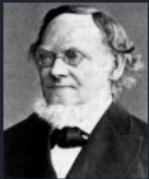


Hermann Grassmann

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

1844 Grassmann publishes vector spaces — universally ignored

2000 Years of Linear Algebra



Hermann Grassmann

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

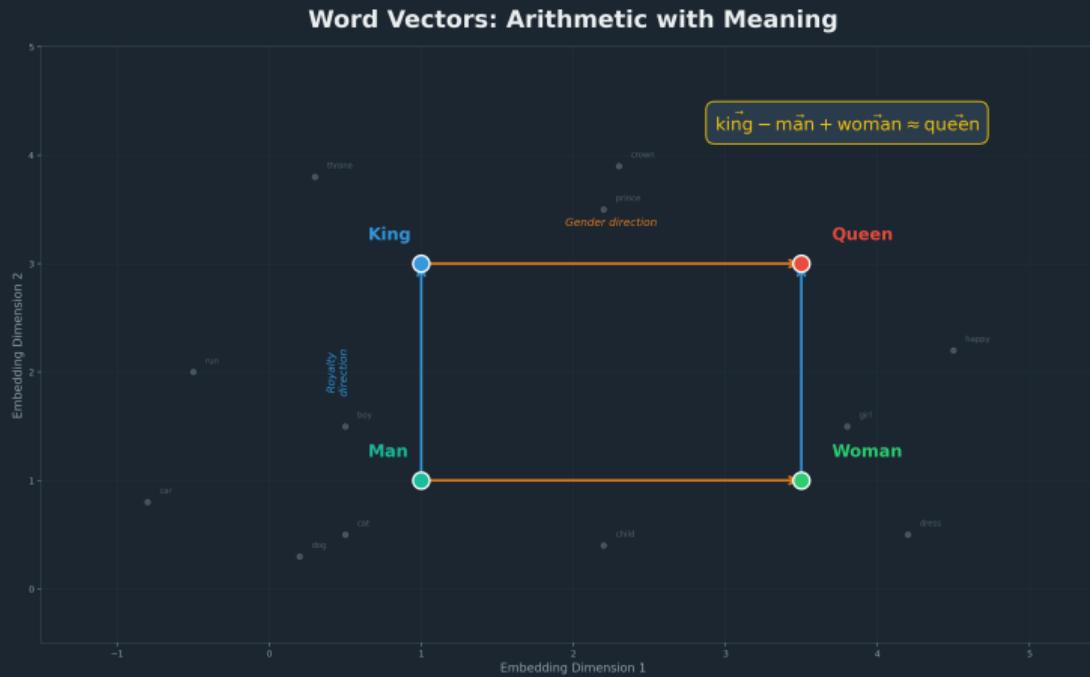
1844 Grassmann publishes vector spaces — universally ignored

1858 Cayley invents matrix theory — while working as a lawyer

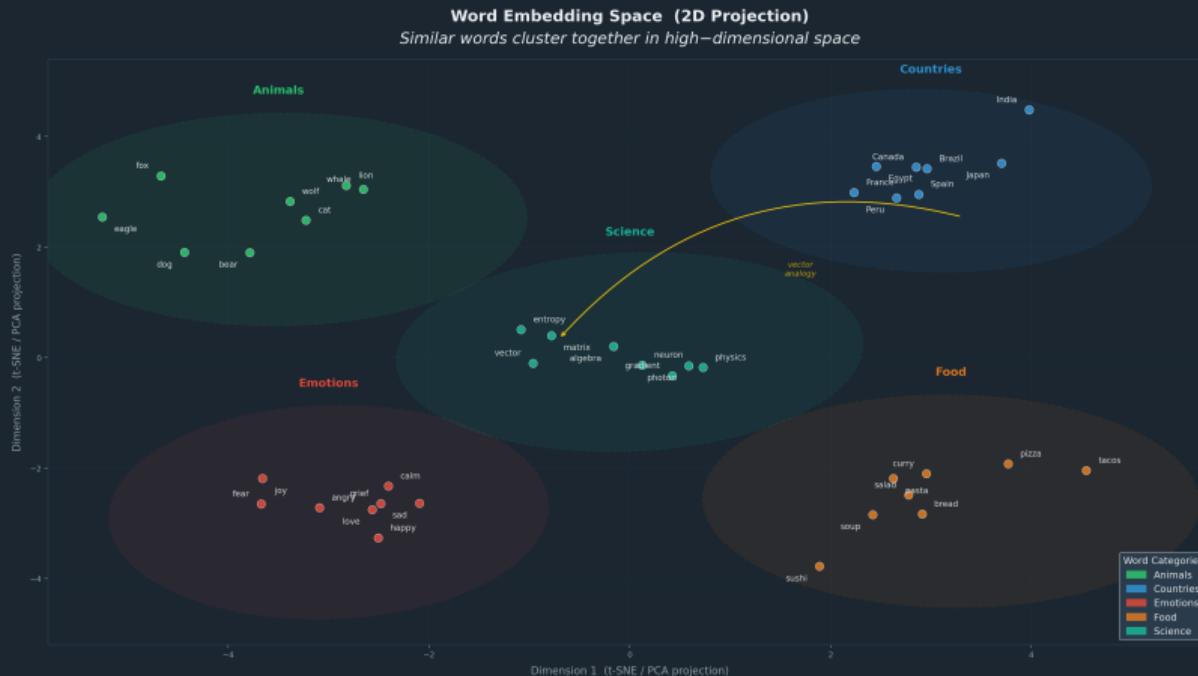


Arthur Cayley

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



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



Words as Vectors

AI CONNECTION



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

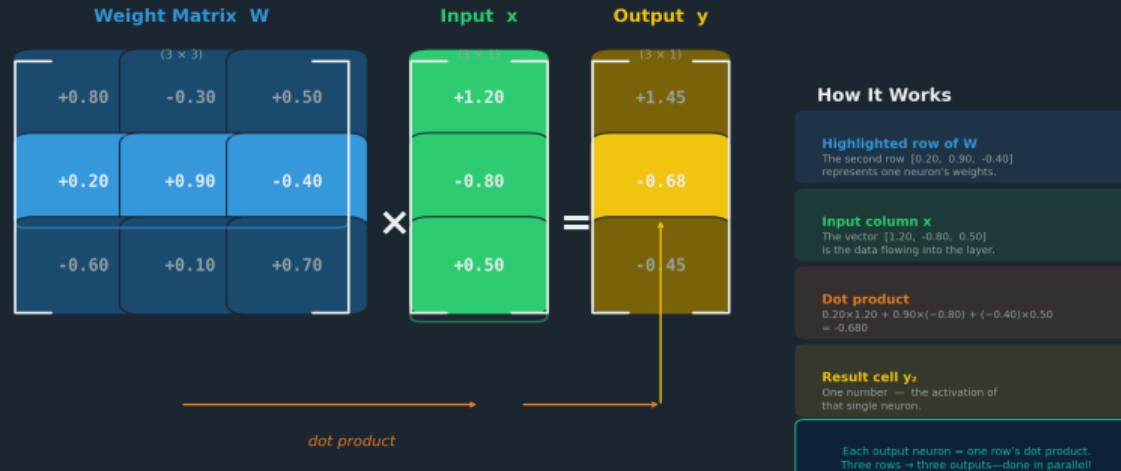


Mikolov et al., 2013 — Word2Vec: meaning encoded as geometry.

Matrix Multiplication: The Core Operation

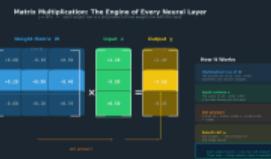
Matrix Multiplication: The Engine of Every Neural Layer

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



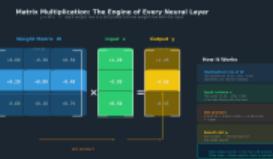
The Engine: Matrix Multiplication

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



The Engine: Matrix Multiplication

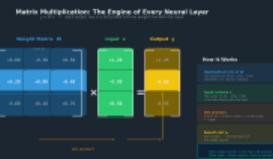
$$\text{output} = W \cdot \vec{x} + \vec{b}$$



Every layer: multiply input vector by weight matrix

The Engine: Matrix Multiplication

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



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

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

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



Attention = Three Matrix Multiplies

BREAKTHROUGH

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

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



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

PILLAR 2

Probability & Statistics

The Language of Uncertainty

Born from Gambling



Blaise Pascal

Born from Gambling

1654 Pascal & Fermat exchange letters about a gambling problem

ORIGIN



Blaise Pascal



Fermat



Bayes



Kolmogorov

Born from Gambling

1654 Pascal & Fermat exchange letters about a gambling problem 



Blaise Pascal

1763 Bayes' theorem published posthumously



Fermat



Bayes



Kolmogorov

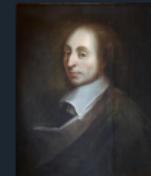
Born from Gambling

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

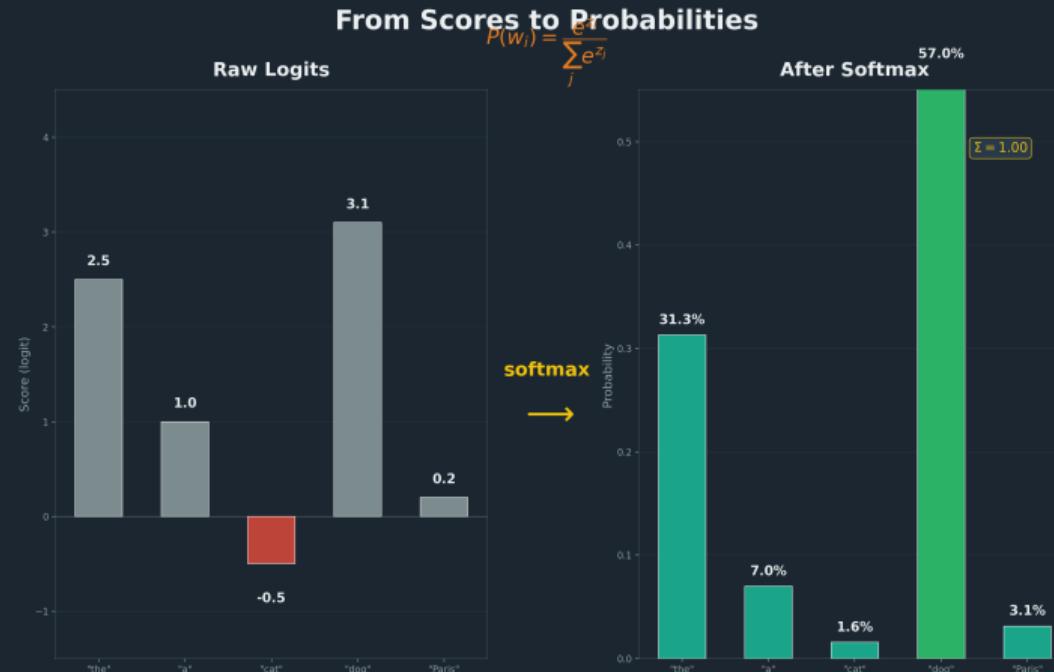


Bayes



Kolmogorov

Softmax: From Logits to Probabilities



Turning Scores into Probabilities



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

Turning Scores into Probabilities



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

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

Turning Scores into Probabilities



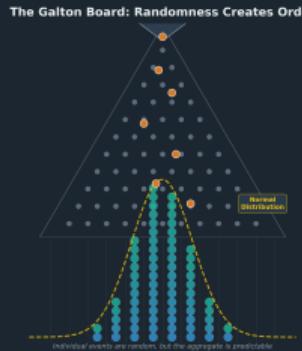
$$P(w_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

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



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

Randomness Creates Order

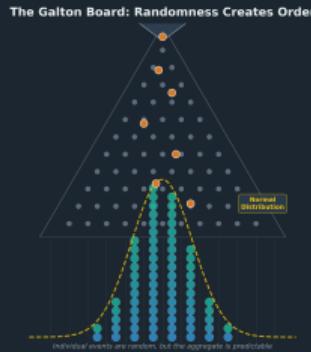


Individual events are random.

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

The Calculus Wars

ORIGIN



Newton (1666)



Leibniz (1684)

The Calculus Wars

ORIGIN



Newton (1666)



Leibniz (1684)



Principia Mathematica, 1713 ed.

The Calculus Wars

ORIGIN



Newton (1666)



Leibniz (1684)



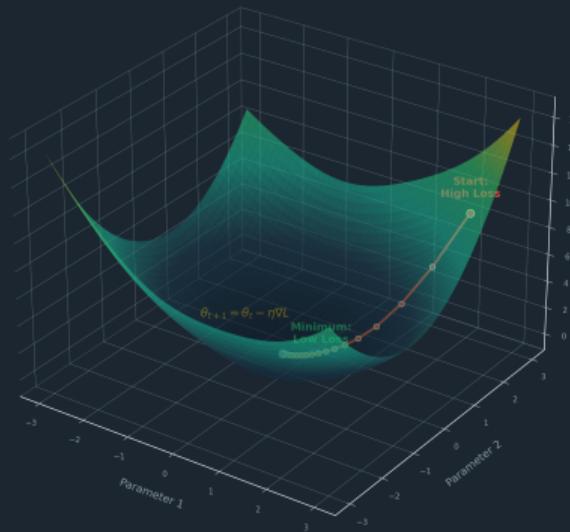
Principia Mathematica, 1713 ed.

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

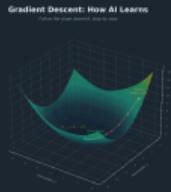
Gradient Descent on a Loss Surface

Gradient Descent: How AI Learns

Follow the slope downhill, step by step

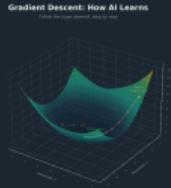


Gradient Descent: How AI Learns



Cauchy (1847)

Gradient Descent: How AI Learns



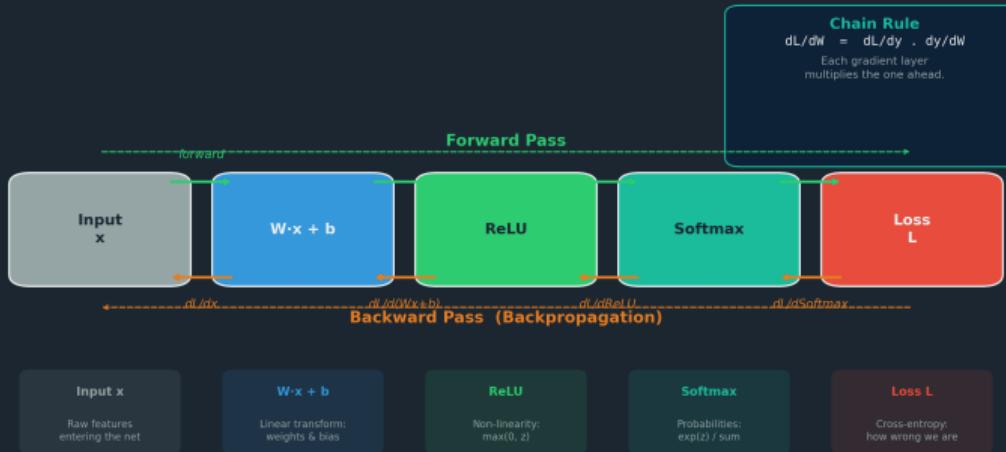
Cauchy (1847)

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)

Backpropagation = The Chain Rule

BREAKTHROUGH

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



Hinton (Nobel 2024)

The chain rule: derivatives flow backward through every layer

Backpropagation = The Chain Rule

BREAKTHROUGH

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



Hinton (Nobel 2024)

The chain rule: derivatives flow backward through every layer

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

Backpropagation = The Chain Rule

BREAKTHROUGH

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



Hinton (Nobel 2024)

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

Shannon: Father of Information Theory

ORIGIN

“Information is the resolution of uncertainty.”

— Claude Shannon



Claude Shannon

Shannon: Father of Information Theory

ORIGIN

“Information is the resolution of uncertainty.”

— Claude Shannon



Claude Shannon

1948: “A Mathematical Theory of Communication” —
invented the **bit**

Shannon: Father of Information Theory

ORIGIN

“Information is the resolution of uncertainty.”

— Claude Shannon



Claude Shannon

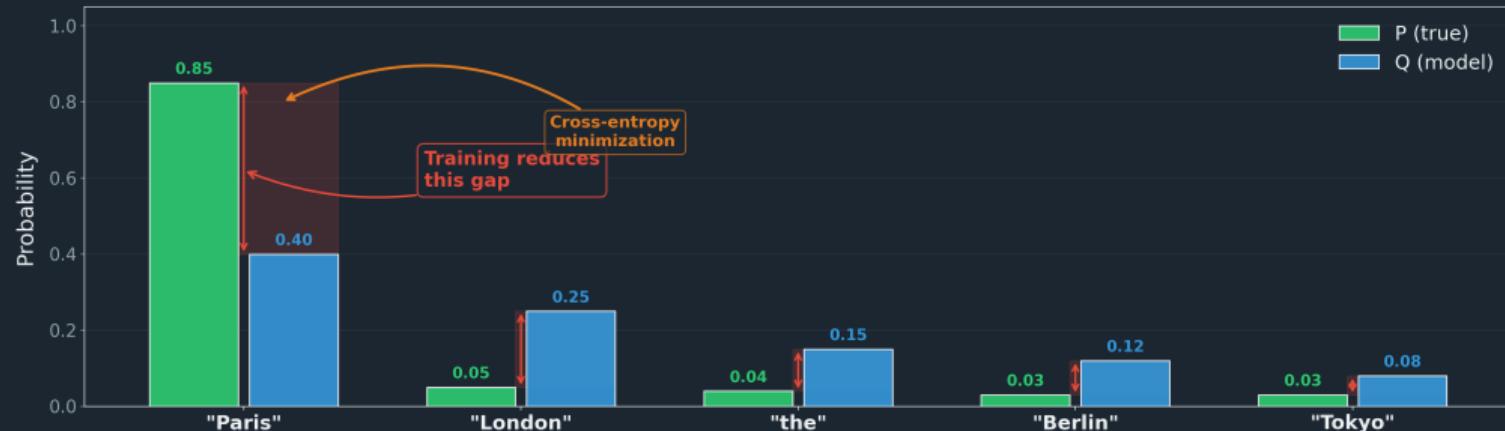
1948: “A Mathematical Theory of Communication” —
invented the **bit**

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

Cross-Entropy: Predicted vs True Distribution

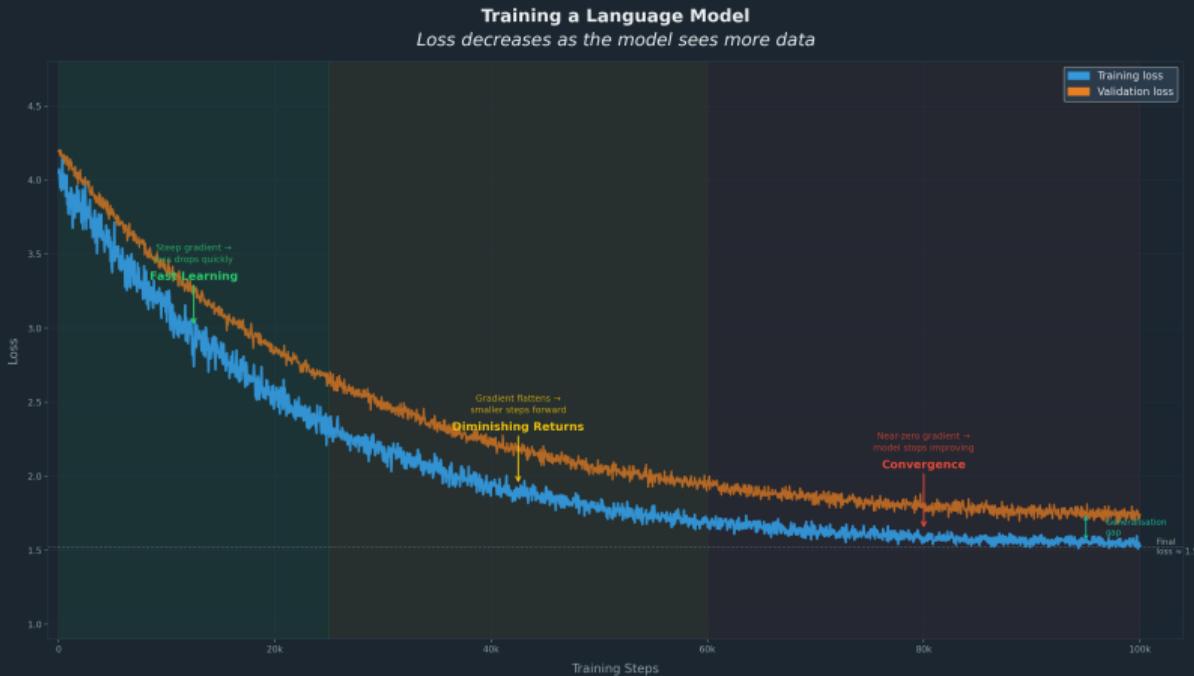
Cross-Entropy: Measuring Prediction Error

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

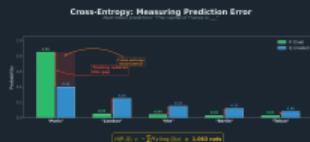
AI CONNECTION



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

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.

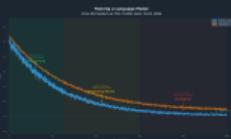
Cross-Entropy: The LLM Loss Function

AI CONNECTION



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

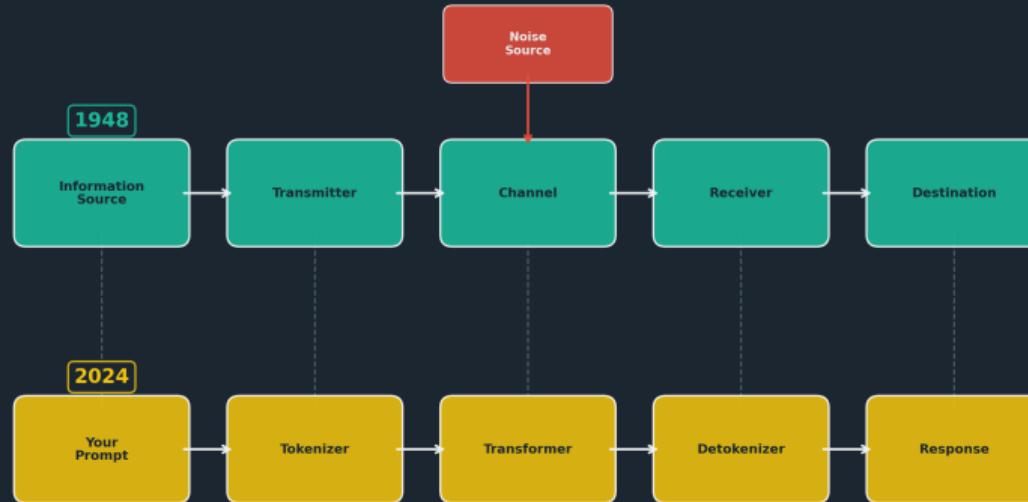
Shannon's 1948 formula IS the training objective of every LLM.



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



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

PILLAR 5

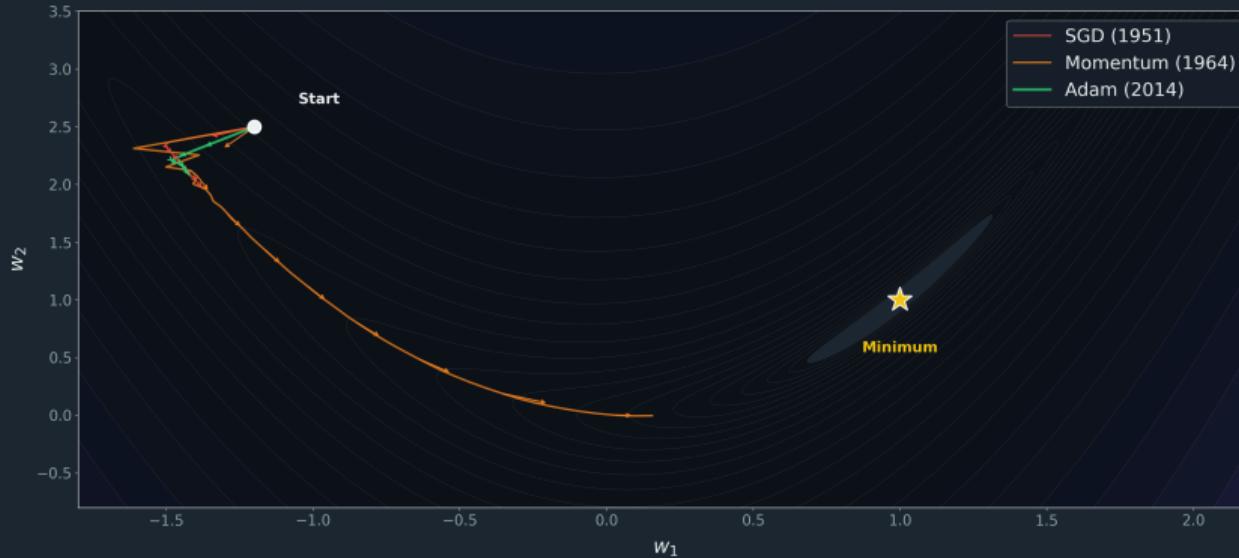
Numerical Optimization

Training at Scale

SGD to Momentum to Adam

The Evolution of Optimizers

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



The Evolution of Optimizers

DISCOVERY



The Evolution of Optimizers

DISCOVERY



1951: Robbins & Monro invent SGD

The Evolution of Optimizers

DISCOVERY



1951: Robbins & Monro invent SGD

1964: Polyak adds momentum

The Evolution of Optimizers

DISCOVERY



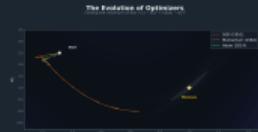
1951: Robbins & Monro invent SGD

1964: Polyak adds momentum

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

The Evolution of Optimizers

DISCOVERY



1951: Robbins & Monro invent SGD

1964: Polyak adds momentum

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

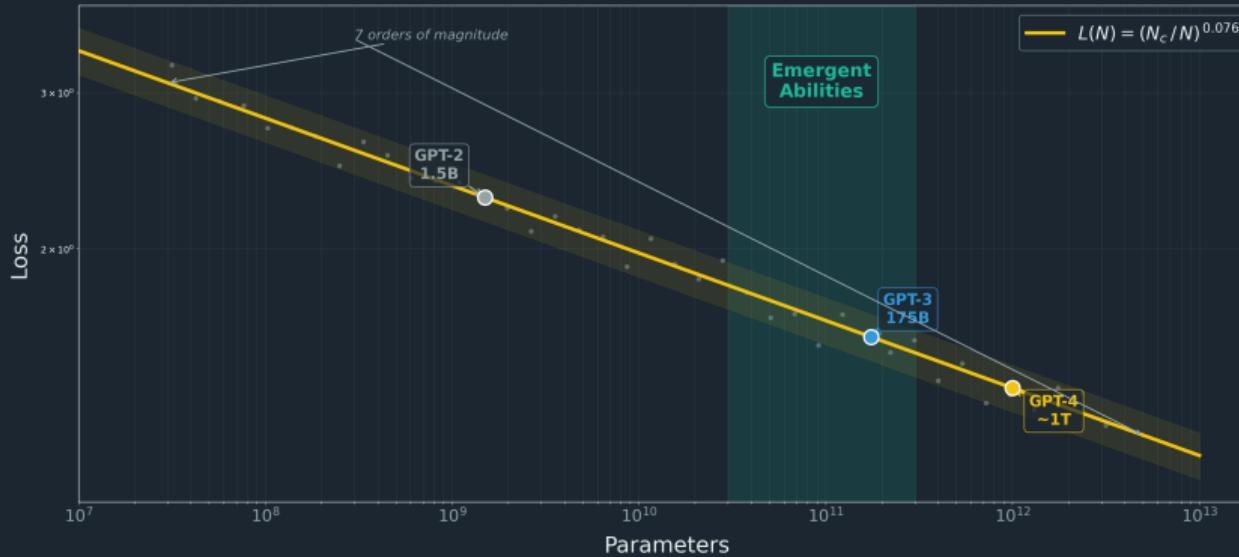


xkcd.com/1838 (CC BY-NC 2.5)

Neural Scaling Laws (Kaplan et al., 2020)

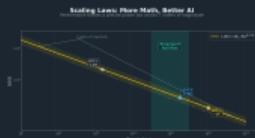
Scaling Laws: More Math, Better AI

Performance follows a precise power law across 7 orders of magnitude



More Math, Better AI

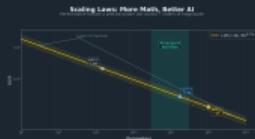
AI CONNECTION



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

More Math, Better AI

AI CONNECTION

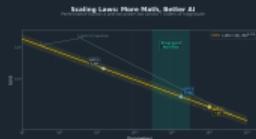


$$L(N) = \left(\frac{N_c}{N} \right)^{0.076}$$

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

More Math, Better AI

AI CONNECTION



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

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



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
Cross-disciplinary Interactions



■ Linear Algebra
bra Skeleton

■ Probability
Language

■ Calculus
Teacher

■ Info Theory
Objective

■ Optimization
Scale

Where All Five Pillars Meet



■ **Linear Alge-**
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

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

35/42

IMO GOLD MEDAL 2025

Gemini Deep Think — only 67 of
630 humans earned gold

What LLMs Can Actually Do

BREAKTHROUGH

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

35/42

IMO GOLD MEDAL 2025

Gemini Deep Think — only 67 of
630 humans earned gold

Nobel

CHEMISTRY 2024

AlphaFold solved 50-year protein
folding problem

What LLMs Can Actually Do

BREAKTHROUGH

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

35/42

IMO GOLD MEDAL 2025

Gemini Deep Think — only 67 of
630 humans earned gold

Nobel

CHEMISTRY 2024

AlphaFold solved 50-year protein
folding problem

92%

HUMANEVAL CODING

Claude on standard benchmark

What LLMs Can Actually Do

BREAKTHROUGH

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

35/42

IMO GOLD MEDAL 2025

Gemini Deep Think — only 67 of
630 humans earned gold

Nobel

CHEMISTRY 2024

AlphaFold solved 50-year protein
folding problem

92%

HUMANEVAL CODING

Claude on standard benchmark

These are not predictions. These already happened.

The Numbers Are Stupid Big

The Numbers Are Stupid Big

1.7T

PARAMETERS IN GPT-4

The Numbers Are Stupid Big

1.7T

PARAMETERS IN GPT-4

\$100M+

TRAINING COST

25,000 GPUs for 90 days

The Numbers Are Stupid Big

1.7T

PARAMETERS IN GPT-4

15T

TRAINING TOKENS

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

\$100M+

TRAINING COST

25,000 GPUs for 90 days

The Numbers Are Stupid Big

1.7T

PARAMETERS IN GPT-4

\$100M+

TRAINING COST

25,000 GPUs for 90 days

15T

TRAINING TOKENS

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

800M

WEEKLY CHATGPT USERS

1 in 10 humans on Earth (Oct 2025)

The Numbers Are Stupid Big

1.7T

PARAMETERS IN GPT-4

\$100M+

TRAINING COST

25,000 GPUs for 90 days

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.

Brilliant and Broken

“It solved an IMO problem but can’t count the letters in “strawberry.” Both true.”

Brilliant and Broken

“It solved an IMO problem but can’t count the letters in “strawberry.” Both true.”

Strawberry: Says there are 2 R’s in “strawberry”

9.11 vs 9.9: Many LLMs claim $9.11 > 9.9$

Brilliant and Broken

“It solved an IMO problem but can’t count the letters in “strawberry.” Both true.”

Strawberry: Says there are 2 R's in “strawberry”

9.11 vs 9.9: Many LLMs claim $9.11 > 9.9$

Mata v. Avianca: Lawyer fined \$5K for fake citations

Air Canada: Ordered to honor a hallucinated refund policy

Brilliant and Broken

“It solved an IMO problem but can’t count the letters in “strawberry.” Both true.”

Strawberry: Says there are 2 R's in “strawberry”

9.11 vs 9.9: Many LLMs claim $9.11 > 9.9$

Mata v. Avianca: Lawyer fined \$5K for fake citations

Air Canada: Ordered to honor a hallucinated refund policy

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

The Race — Zero to Gold in 8 Years

The Race — Zero to Gold in 8 Years

2017 “Attention Is All You Need” paper 

The Race — Zero to Gold in 8 Years

- 2017 “Attention Is All You Need” paper 
- 2020 GPT-3 launches — 175 billion parameters

The Race — Zero to Gold in 8 Years

2017 “Attention Is All You Need” paper 

2020 GPT-3 launches — 175 billion parameters

Nov 2022 ChatGPT: 100M users in 2 months (Instagram took 2.5 years)

The Race — Zero to Gold in 8 Years

2017 “Attention Is All You Need” paper 

2020 GPT-3 launches — 175 billion parameters

Nov 2022 ChatGPT: **100M users in 2 months** (Instagram took 2.5 years)

Mar 2023 GPT-4 passes the bar exam 

The Race — Zero to Gold in 8 Years

2017 “Attention Is All You Need” paper 

2020 GPT-3 launches — 175 billion parameters

Nov 2022 ChatGPT: **100M users in 2 months** (Instagram took 2.5 years)

Mar 2023 GPT-4 passes the bar exam 

2024 Two Nobel Prizes go to AI work (Physics + Chemistry) 

The Race — Zero to Gold in 8 Years

2017 “Attention Is All You Need” paper 

2020 GPT-3 launches — 175 billion parameters

Nov 2022 ChatGPT: 100M users in 2 months (Instagram took 2.5 years)

Mar 2023 GPT-4 passes the bar exam 

2024 Two Nobel Prizes go to AI work (Physics + Chemistry) 

Jan 2025 DeepSeek R1 drops — Nvidia loses \$600B in one day

The Race — Zero to Gold in 8 Years

2017 “Attention Is All You Need” paper 

2020 GPT-3 launches — 175 billion parameters

Nov 2022 ChatGPT: 100M users in 2 months (Instagram took 2.5 years)

Mar 2023 GPT-4 passes the bar exam 

2024 Two Nobel Prizes go to AI work (Physics + Chemistry) 

Jan 2025 DeepSeek R1 drops — Nvidia loses \$600B in one day

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

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

- 5. Enter a Kaggle competition**

Real data, real problems, real community

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

5. Enter a Kaggle competition

Real data, real problems, real community

\$186K

ML ENGINEER MEDIAN SALARY

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

5. Enter a Kaggle competition

Real data, real problems, real community

\$186K

ML ENGINEER MEDIAN SALARY

Free tools: ChatGPT, Claude, GitHub Copilot
(free for students), Google Colab, Kaggle

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

5. Enter a Kaggle competition

Real data, real problems, real community

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

\$186K

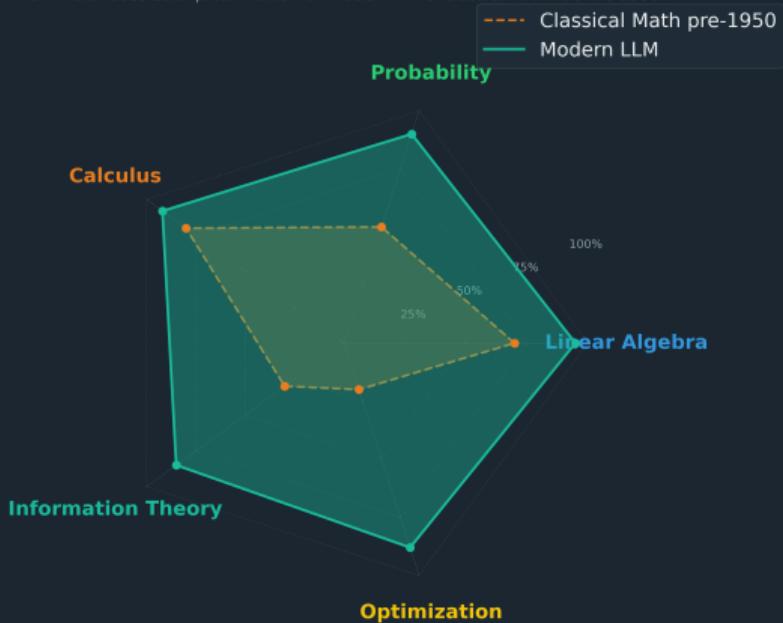
ML ENGINEER MEDIAN SALARY

Free tools: ChatGPT, Claude, GitHub Copilot
(free for students), Google Colab, Kaggle

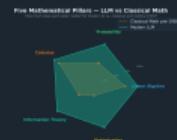
Five Pillars: Convergence Radar

Five Mathematical Pillars — LLM vs Classical Math

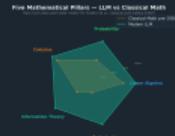
How much does each pillar matter for modern AI vs. classical work before 1950?



The Code Is Still Being Written

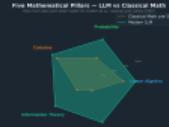


The Code Is Still Being Written



- AI / ML Engineer
- Data Scientist
- Research Mathematician
- Quantitative Analyst
- AI Safety Researcher

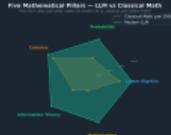
The Code Is Still Being Written



- AI / ML Engineer
- Data Scientist
- Research Mathematician
- Quantitative Analyst
- AI Safety Researcher

"The mathematicians who built these tools never imagined AI. The AI researchers who use them stand on 2000 years of shoulders."

The Code Is Still Being Written



- AI / ML Engineer
- Data Scientist
- Research Mathematician
- Quantitative Analyst
- AI Safety Researcher

"The mathematicians who built these tools never imagined AI. The AI researchers who use them stand on 2000 years of shoulders."

Thank you. Questions?