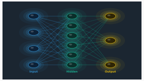

THE FIVE PILLARS

The Code of the Universe

From Classical Mathematics to Large Language Models

UAE Mathematics Conference 2026 · Prof. Jörg Osterrieder

Why Should You Care About Math?

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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.

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2017 → Now

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

Local Impact

Dubai's autonomous metro runs on optimization. Abu Dhabi's Falcon LLM uses every pillar we will cover today.

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

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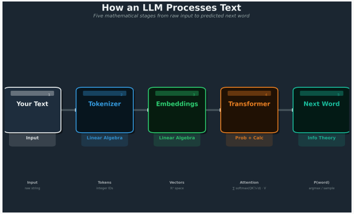

Token processing pipeline

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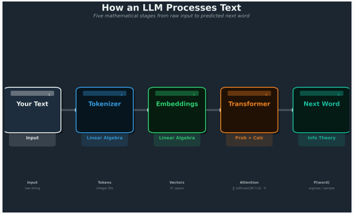

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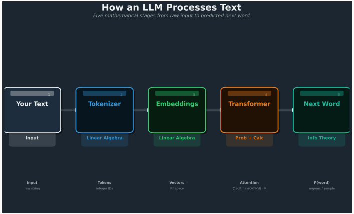

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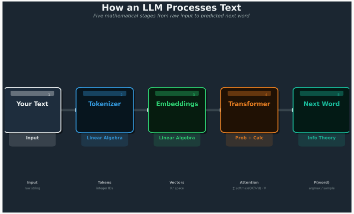

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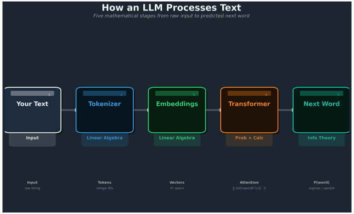
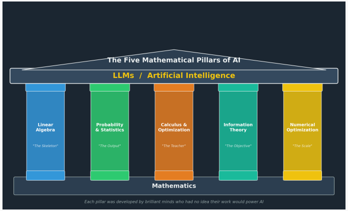
5. Optimizers like Adam make trillion-parameter training practical — Optimization



Token processing pipeline

The Five Pillars of AI Mathematics



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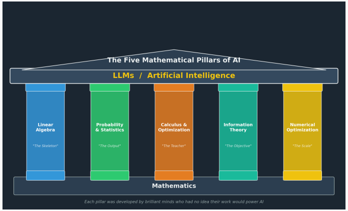

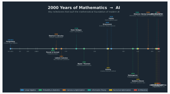

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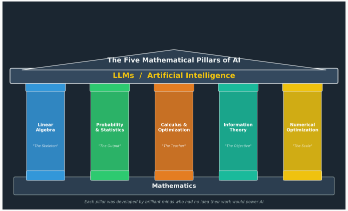

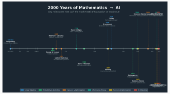

Each pillar was developed by brilliant minds who had no idea their work would power AI. We will visit each one, meet the mathematicians who built it, and show exactly where it appears inside a modern LLM.

Interactive Demos: How LLMs Work

Demo 1

3Blue1Brown — "Large Language Models explained briefly" (∼5 min). Visual walkthrough: tokenization, embeddings, attention, next-token prediction.

`https://www.youtube.com/watch?v=LPZh9BOjkQs`

Demo 2

Transformer Explainer — type text, see tokens → embeddings → attention → prediction in a live GPT-2 model.

`https://poloclub.github.io/transformer-explainer/`

PILLAR 1

Linear Algebra

The Skeleton of AI

P1 2000 Years of Linear Algebra

Hermann Grassmann

P1

2000 Years of Linear Algebra

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

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1844 Grassmann publishes vector spaces — almost universally ignored

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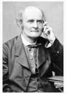


Arthur Cayley

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

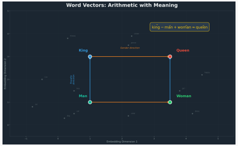
1844 Grassmann publishes vector spaces — almost universally ignored

1858 Cayley invents matrix theory — while working as a lawyer

P1

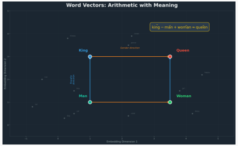
Words as Vectors

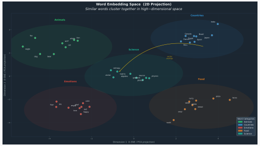
AI Connection



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

P1 Words as Vectors AI CONNECTION





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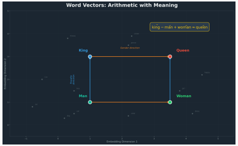
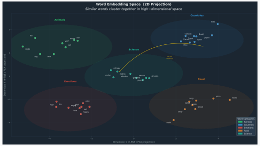




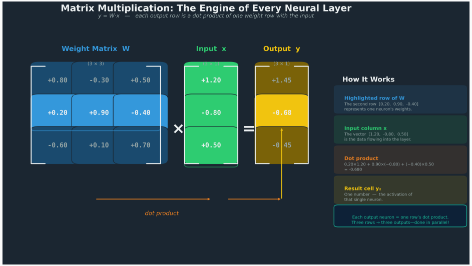
$$\vec{king} - \vec{man} + \vec{woman} \approx \vec{queen}$$

Mikolov et al., 2013 — Word2Vec: meaning encoded as geometry. GPT-3 uses 12,288-dimensional vectors; modern LLMs use comparable or larger spaces.

The Engine: Matrix Multiplication

P1

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

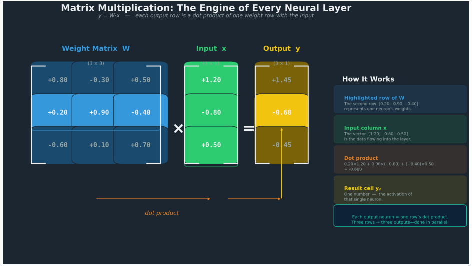


Matrix multiplication visualized

P1 The Engine: Matrix Multiplication

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

Every layer: multiply input vector by weight matrix, add bias. A neural network is this operation repeated hundreds of times.



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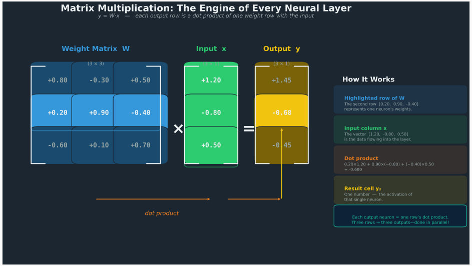
∼1.8T

PARAMETERS IN GPT-4 (ESTIMATED)



Matrix multiplication visualized

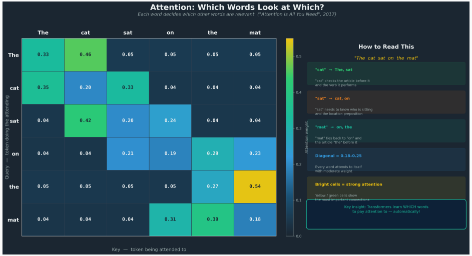
Attention = Three Matrix Multiplies

BREAKTHROUGH

P1

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

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



Attention weight heatmap

P1 Attention = Three Matrix Multiplies BREAKTHROUGH

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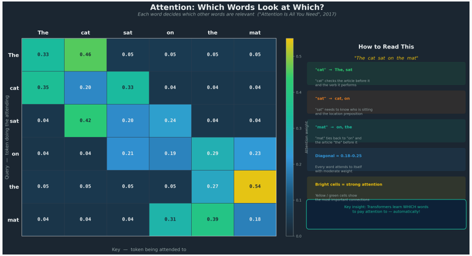

Attention weight heatmap

Three matrices. That’s all attention is. Cayley’s 1858 invention, applied to language — and it changed the world.

KEY TAKEAWAYS

Linear Algebra

- Vectors represent meaning — words become geometry
- Matrices transform — every layer is a matrix multiply
- Attention is pure linear algebra — Q, K, V

PILLAR 2

Probability & Statistics

The Language of Uncertainty

P2

Born from Gambling

Blaise Pascal

P2

Born from Gambling

1654 Pascal & Fermat exchange letters about a gambling problem ORIGIN

Blaise Pascal

Fermat

Bayes

Kolmogorov

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1933 Kolmogorov writes the axioms — probability becomes rigorous

Blaise Pascal

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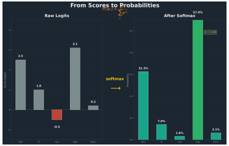
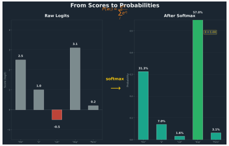
Turning Scores into Probabilities



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

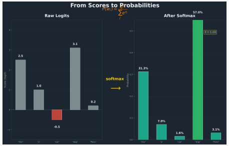
Turning Scores into Probabilities



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

50,000+ words. One probability each. Kolmogorov's axioms in action: all positive, all sum to 1.

P2 Turning Scores into Probabilities



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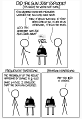
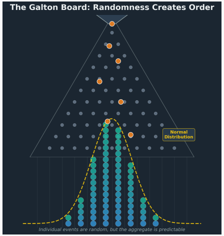


xkcd.com/1132 (CC BY-NC 2.5)

P2

Randomness Creates Order



Galton board (1889)

Individual events are random. Each ball bounces left or right at every peg. Yet the aggregate always forms a bell curve — the Central Limit Theorem made physical.

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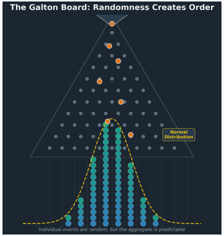

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Individual events are random. Each ball bounces left or right at every peg. Yet the aggregate always forms a bell curve — the Central Limit Theorem made physical.

LLMs show a similar pattern: each token is sampled from a probability distribution, but the sequence of samples produces coherent text. Randomness at the micro level, structure at the macro level.

KEY TAKEAWAYS

Probability & Statistics

- Probability is the output language of LLMs
- Softmax satisfies Kolmogorov's axioms — rigorously correct
- Randomness at micro level creates structure at macro level

PILLAR 3

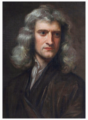
Calculus & Optimization

The Teacher

P3

The Calculus Wars

ORIGIN



Newton (1666)

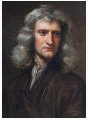
VS

Leibniz (1684)

P3

The Calculus Wars

ORIGIN



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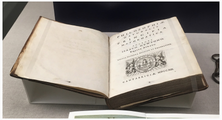

Principia, 1713 ed.

P3

The Calculus Wars

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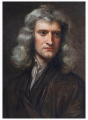

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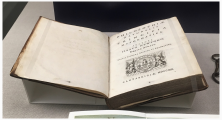
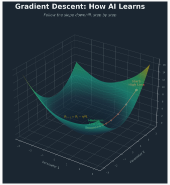


Principia, 1713 ed.

Both invented calculus independently. Newton accused Leibniz of plagiarism, then secretly wrote the Royal Society report exonerating himself. Modern historians agree: both were right. But we use Leibniz's notation: $\frac{dy}{dx}$

P3

Gradient Descent: How AI Learns



Augustin-Louis Cauchy (1847)

P3

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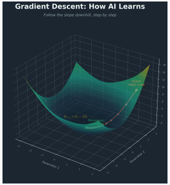


Augustin-Louis Cauchy (1847)

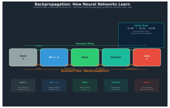
Blindfolded on a hill. Feel the slope under your feet. Step downhill. Repeat. That is gradient descent — and Cauchy invented it in 1847 for solving systems of equations.

P3

Backpropagation = The Chain Rule

BREAKTHROUGH

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



Geoffrey Hinton

P3 Backpropagation = The Chain Rule BREAKTHROUGH

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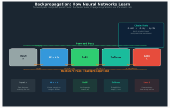

Geoffrey Hinton

NOBEL PHYSICS 2024

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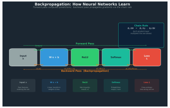

Geoffrey Hinton

NOBEL PHYSICS 2024

The chain rule: derivatives flow backward through every layer

P3 Backpropagation = The Chain Rule BREAKTHROUGH

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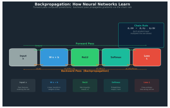


Geoffrey Hinton

NOBEL PHYSICS 2024

The chain rule: derivatives flow backward through every layer

1986: Rumelhart, Hinton & Williams publish in *Nature*. 2024: Hinton wins the Nobel Prize for foundational work in machine learning.

KEY TAKEAWAYS

Calculus & Optimization

- Derivatives tell the model which way to adjust
- The chain rule makes it scale to billions of parameters
- 350-year-old math powers every AI training run

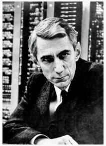
PILLAR 4

Information Theory

The Objective Function

P4

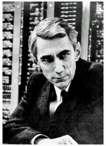
Shannon: Father of Information Theory



Claude Shannon

P4

Shannon: Father of Information Theory



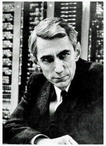
Claude Shannon

ORIGIN

> *"Information is the resolution of uncertainty."*
>
> — Claude Shannon

P4

Shannon: Father of Information Theory



Claude Shannon

ORIGIN

> *"Information is the resolution of uncertainty."*
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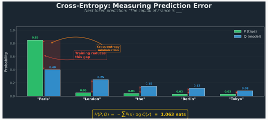
1948: *"A Mathematical Theory of Communication"* — invented the bit as the fundamental unit of information.

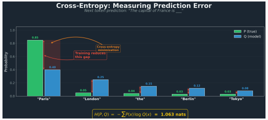
Fun fact: Shannon juggled while riding a unicycle through the halls of Bell Labs.

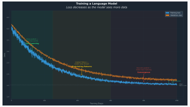
Cross-Entropy: The LLM Loss Function



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

Cross-Entropy: The LLM Loss Function



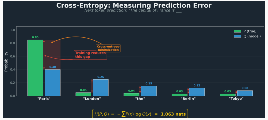


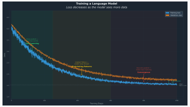
Training loss decreasing over time

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

Cross-Entropy: The LLM Loss Function

P4



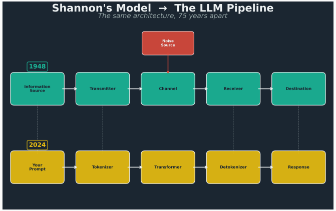


Training loss decreasing over time

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

Shannon's 1948 formula **IS** the training objective of every LLM. Minimize surprise: assign high probability to the correct next word.

P4 Shannon's Model → The LLM Pipeline



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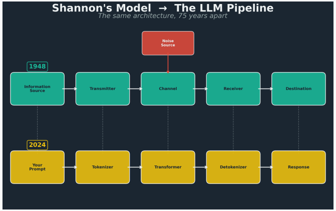
Shannon's Model $\longrightarrow$ The LLM Pipeline



Shannon (1948): Source $\longrightarrow$ Encoder $\longrightarrow$ Channel $\longrightarrow$ Decoder $\longrightarrow$ Destination

Modern LLM: User $\longrightarrow$ Tokenizer $\longrightarrow$ Transformer $\longrightarrow$ Output Layer $\longrightarrow$ Response

Designed for communication channels. Nearly 80 years later, describes what ChatGPT does with striking precision.

KEY TAKEAWAYS

Information Theory

- Cross-entropy = minimize surprise — the LLM training objective
- Shannon’s communication model maps remarkably onto the LLM pipeline
- A 1948 formula designed for communication channels trains every modern AI

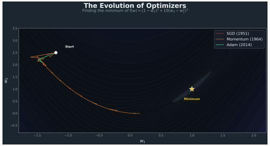
PILLAR 5

Numerical Optimization

Training at Scale

P5

The Evolution of Optimizers



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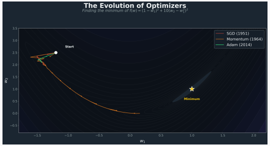

1951 Robbins & Monro invent SGD ORIGIN

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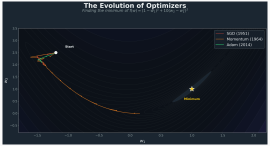

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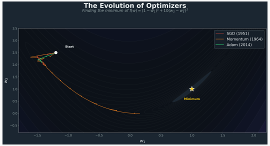

xkcd.com/1838 (CC BY-NC 2.5)

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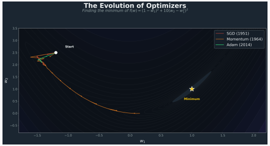

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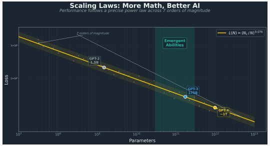
2014 Kingma & Ba create Adam — 200,000+ citations BREAKTHROUGH

More Math, Better AI: Scaling Laws



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

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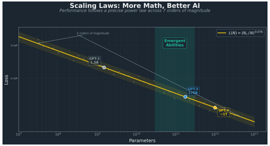

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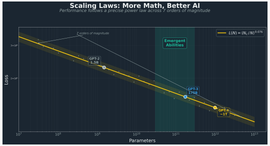

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$$L(N) = \left(\frac{N_c}{N}\right)^{0.076}$$

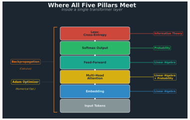
Kaplan et al., 2020: LLM performance follows a power law. Double the parameters → ~5% lower loss. Halving the loss requires ~10,000x more parameters. This equation is why companies spend billions on bigger models.

KEY TAKEAWAYS

Numerical Optimization

- Adam is the workhorse of modern AI training
- Scaling laws reveal a power law — more parameters, predictably better
- The optimization frontier turns mathematical insight into economic force

Where All Five Pillars Meet



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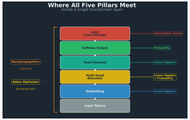

Linear Algebra Embeddings & attention matrices

Calculus Backprop via chain rule

Probability Soft-max distributions

Info Theory Cross-entropy loss

Optimization Adam updates weights

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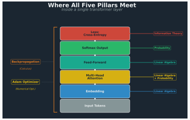

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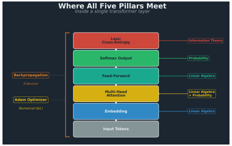
Five branches of pure mathematics, developed over **2000 years**, all running simultaneously in a single forward-backward pass. This is the code of the universe.

What AI Can Actually Do

35/42

IMO Gold Medal — Gemini Deep Think (2025)



Five pillars powering AI capabilities

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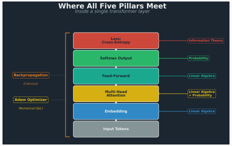

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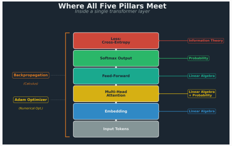

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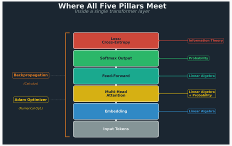

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1M+ tokens

Context window — Gemini processes entire codebases at once

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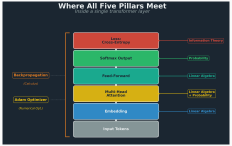

Five pillars powering AI capabilities

1M+ tokens

Context window — Gemini processes entire codebases at once

∼90%

MMLU — frontier models match expert human level (89.8%)

The Numbers Are Staggering

∼1.7T

ESTIMATED PARAMETERS IN GPT-4 (OPENAI HAS NOT CONFIRMED)

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Plot twist: DeepSeek R1 matched GPT-4 for $6 million. Open source. Nvidia lost nearly $600 billion in one day.

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Strawberry: Ask an LLM to count the R's in "strawberry." It says 2. There are 3. The same system that earns an IMO gold medal cannot count letters.

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Why? LLMs are statistical pattern completers, not fact databases. They predict the most likely next token. They have no internal fact-checker and no concept of truth.

The Race: Zero to Gold in 8 Years

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2017 *"Attention Is All You Need"* — the transformer is born ORIGIN

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

The Math Behind the Headlines

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Dubai Smart City & Abu Dhabi AI Strategy — From autonomous transport to AI-powered government services. The UAE is building its future on mathematical foundations.

The five pillars you just learned are the foundation of all of this.

What YOU Can Do Right Now

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1. **GitHub Student Pack** — free Copilot, free cloud credits
2. **Kaggle Intro to ML** — free course, one weekend
3. **Google Colab** — free GPU in your browser
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The tools are free. The courses are free. The barrier has never been lower. What are you doing *this weekend*?

Mathematics Competition Pathways

IMO / EGMO / Math Competitions $\rightarrow$ AI Research

The proof techniques you practice — induction, estimation, combinatorial arguments — train the same mathematical thinking that builds AI. Linear algebra, probability, and optimization *are* competition mathematics.

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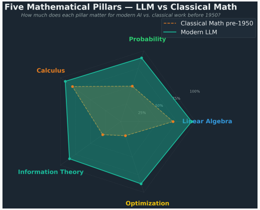
The math you study for competitions **IS** the math inside AI. The same inequalities that win medals are the same bounds that prove convergence of gradient descent. Your preparation already has a destination.

Five Pillars: The Complete Picture



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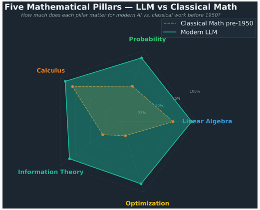

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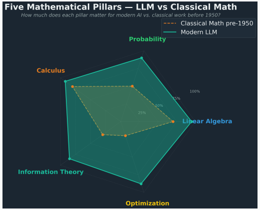

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> *"The mathematicians who built these tools never imagined AI. The AI researchers who use them stand on 2000 years of shoulders."*

The Code Is Still Being Written

Active frontiers: Sparse attention (linear algebra), calibration (probability), second-order methods (calculus), mechanistic interpretability (information theory), distributed optimization at scale.

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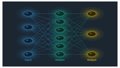
The code of the universe is still being written. The next chapter may be written by someone in this room.



Thank You

Questions?

UAE Mathematics Conference 2026 · Prof. Jörg Osterrieder

The Five Pillars of AI Mathematics

Appendix: Formula Reference