The First Nobel Prize for Insidious Software Degradation

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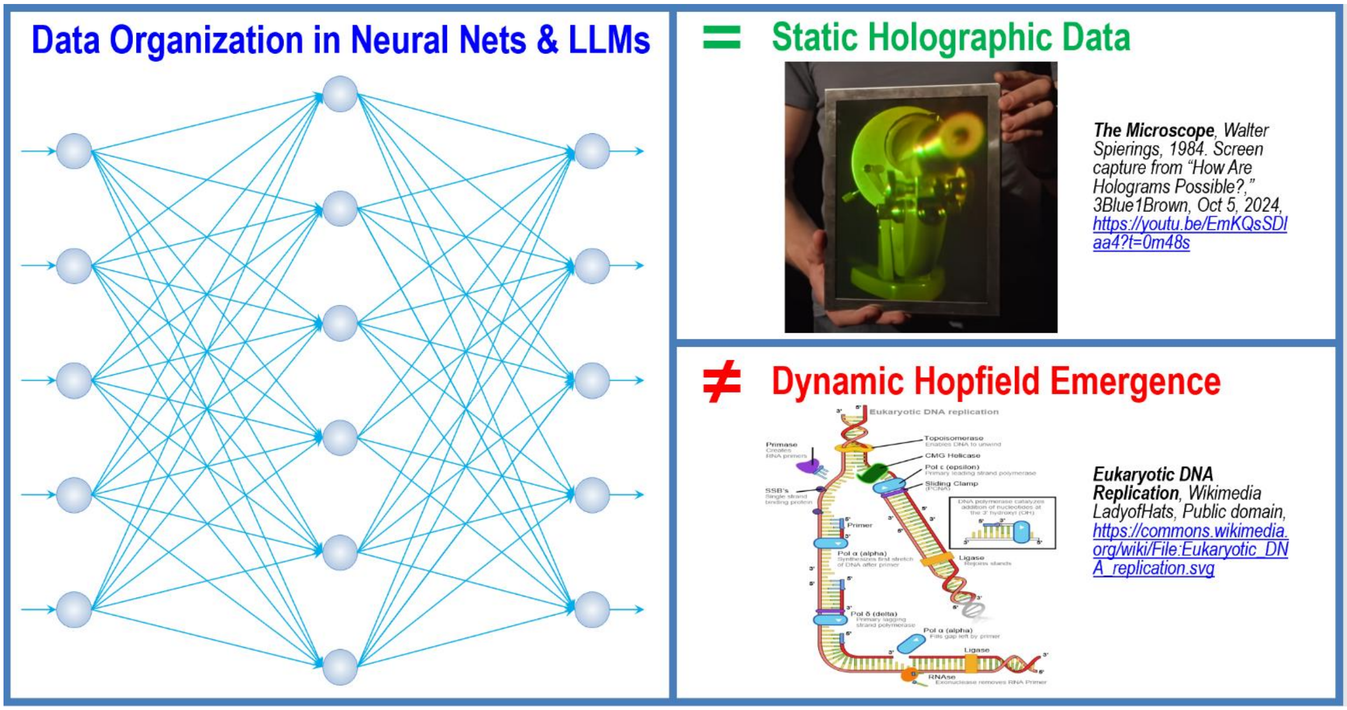

A 40-year-old misinterpretation of how artificial neural networks work has led us to a dangerous situation.

Are Your Apps Getting Buggier?

I have a complaint. Since big companies began pushing Large Language Model (LLM) AI in 2022, I have seen nothing but degradation in the tools and apps I once trusted and praised. The declines are often small, such as quirky, inexplicable jumps when I'm editing text. On the data side, tools that formerly respected my independence and personal writing style began telling me to say words I never intended. The same companies who support these tools and apps also push me to use more LLM AI. As of late 2024, their marketing has become so aggressive that even if a tool gives me a button to shut off its LLM AI recommendations, it doesn't work. Getting good information on simple issues has also become harder. On October 14, 2024, I asked my phone whether our county schools were open for the holiday. My phone gave me definite responses to such scheduling questions for many years. This time, the same LLM AI I that I could not shut down took over my phone screen and confidently declared, "No, schools in your county did not have classes on Friday, October 3, 2023." Gee, thanks.

Such all-too-common episodes raise a pointed and consequential question: If LLM AIs are as indispensable for writing good software as many claim, why do products from companies promoting LLM AI keep deteriorating?

Holography is Not Emergence

The short answer is that LLM AIs subtly damage everything they touch. The problem began forty years ago when a researcher named John Hopfield misinterpreted the fault tolerance of artificial neural networks as proof that they can independently structure themselves into something more powerful — an effect called *emergence*. Instead of correcting his error, researchers transformed Hopfield's hypothesis into a universally accepted doctrine. This accepted doctrine then set into motion the slow-moving catastrophe of software degradation that is now unfolding.

Years before Hopfield turned his focus to artificial neural networks, he investigated the dynamics of how thermally chaotic interactions between biomolecules manage to produce well-defined, high-value actions such as reliable transfers of electrons or accurate reading of DNA data. The details of these *emergences* of order from chaos work remain unclear, though they involve quantum effects since electrons at molecular scales and energies behave like waves. When Hopfield switched his attention to the fully classical digital circuits known as *artificial neural networks* (ANNs), he noticed these ANNs demonstrated error correction and fault tolerance that reminded him of the order-from-chaos effects he had studied years before in quantum molecular dynamics. Taking a huge leap, he assumed that error tolerance in these non-quantum digital circuits was a larger-scale version of those earlier quantum molecular effects. The result was the birth of the belief that fully digital circuits, like biomolecules, can self-organize to create order from what had been chaos. All modern versions of the belief that digital circuits can spontaneously transform into self-aware, self-intelligent systems have ancestry in Hopfield's assumption since, without spontaneous emergence, digital circuits by design remain boring and predictably deterministic.

Unfortunately, the actual source of ANN error corrections and fault tolerance Hopfield had observed was much simpler: Data formatting. Traditional data storage devices store concepts as patterns of bits with well-defined locations in the device, like rocks on marked locations on a surface. If the location that stores a bit fails, the device loses that bit completely. ANNs use a radically different data storage approach in which each concept becomes a repeating wave recorded at many locations in the ANN storage. Think of the waves produced by tossing a rock into a pond. If you take a snapshot of the waves, you can still trace them back to the point where you dropped the rock into the pond, but the coding of that location no longer depends on any one circuit or bit in the ANN. Data storage becomes much more tolerant of errors since each concept exists across the entire device.

The idea that you can place a single data item on an entire storage device and still have room for other data items is not intuitive, mostly because we tend to picture this as *replicating* that data item throughout the storage device. However, holographic encoding is much more subtle than that. Just as the airwaves around you can hold many radio stations simultaneously and share the same volume of space, holographic data encoding uses clever wave or wave-like formats to spread out each data item. This approach becomes impossibly blurry when looking only at a single storage location but becomes sharper as the number of locations queried increases. What this means for an ANN is that with the right holographic-equivalent encoding, it can still store an enormous amount of unique data.

There is a cost, however. Compared to traditional location-based data formatting, wave encoding always introduces some level of uncertainty into each data item. This blurring happens because the only way to ensure perfect wave encoding is to repeat the wave an infinite number of times, which is impossible in any real storage device. Good design can make the degradation very small in most cases but can never eliminate the added noise since it is inherent to the wave-encoding approach.

The generic term for wave-format data encoding is *holographic encoding*, though this is not a term seen in LLM research literature since that remains firmly entrenched in Hopfield's dynamic emergence interpretation.

Hopfield's Misunderstanding

Hopfield's critical error failed to recognize the difference between reliability achieved through quantum-level, highly localized dynamic emergence, as with his earlier biomolecular work, and fault tolerance through the entirely different and fully classical technique of holographic data formatting. While ANNs make data storage more robust by massively interconnecting classical, Hopfield's earlier examples of biomolecular fault tolerance were quantum, dynamic, highly localized, and unique to each reaction. Hopfield's hypothesis fails most severely on this point since the information dynamics of ANNs and quantum biomolecular emergence could not be more divergent (Fig. 2). ANNs achieve fault tolerance by forcing all data from all locations to interact many times, as is typical when using holographic storage methods. Quantum emergence occurs on vastly smaller scales where each instance of conversion of thermal chaos into energy or information transfer occurs *entirely* at that single location. That this is possible at all is a powerful indicator that very short-range, molecular-scale quantum computing is involved.

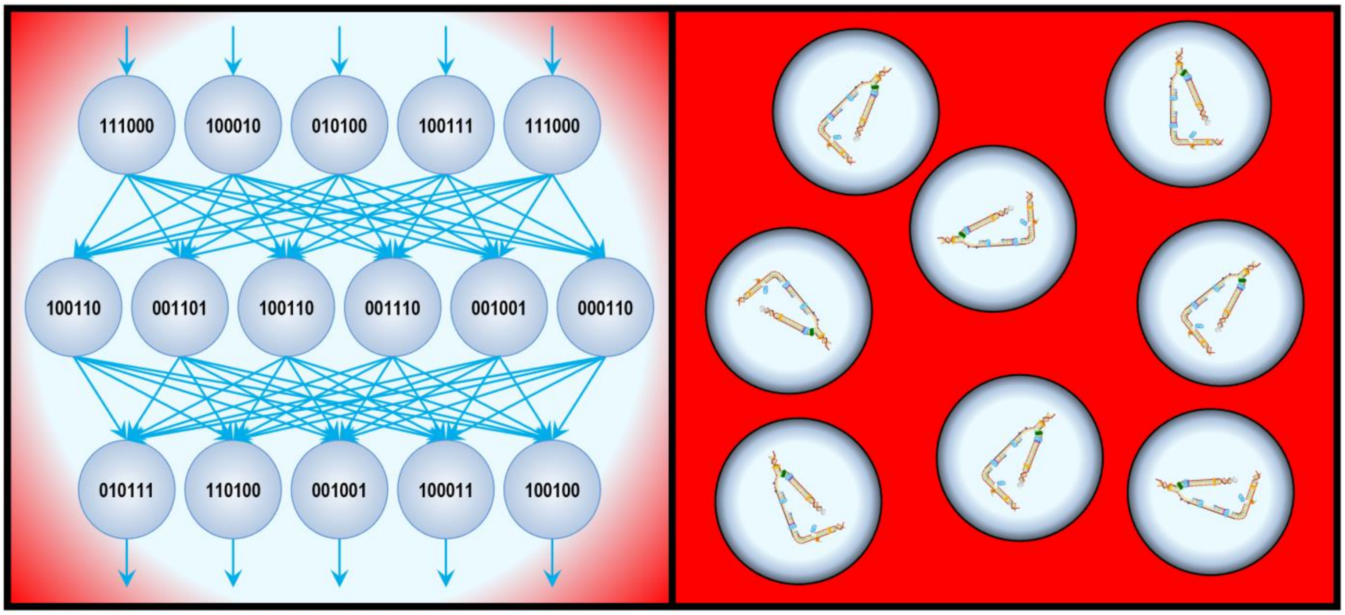

Figure 2. *To repair errors, ANNs (left) maximize data exchange while biomolecules (right) minimize it.*

Hopfield's artificial neural networks thus were examples not of emergence but of standard properties from choosing to use holographic storage formats. More impactfully, his misidentification caused him to miss the critical point that holographic data storage *always* degrades over time by adding a bit of uncertainty during delocalization. Far from repairing or adding order to existing data, holographic ANN data storage slowly damages that data in ways that compound over time.

The main feature that appears to have sidetracked Hopfield's thinking was that digital holography and quantum emergence tolerate and correct minor coding errors, though through strikingly different mechanisms. His earlier brilliant work in molecular-level biochemical emergence from thermal chaos in systems forged by billions of years of evolution biased his interpretation of human-made digital systems in which chip designers spend decades of work to eliminate all traces of quantum mechanical emergence, which circuit designers call "noise."

This type of sincere misidentification normally would be nothing more than a bump in the research literature after others found and corrected the error. Unfortunately, the mistake was universally accepted and amplified by future ANN researchers. Even now — and despite recent work that gets close to the real issue by assessing ANN behaviors using holography-adjacent concepts such as state superposition [1][2] — Hopfield's fundamental misunderstanding of how ANNs work remains firmly in place. As recently as late 2023, no less of an LLM AI leader than Yann LeCun asserted that "*The salvation [of AI] is using sensory data*" [3]. This statement reflects his continued belief in the Hopfield hypothesis that emergence order and, eventually, human-like in ANNs is nothing more than a matter of adding more data. LeCun's hope is incompatible with the holographic nature of neural networks in that it *increases* total wave-encoding damage if you insist on inserting more data.

The full impact of Hopfield's misunderstanding hit spectacularly early 2020s after governments and industry spent trillions of dollars on the impossible hope that, with sufficient training, human-like intelligence — Artificial General Intelligence, or AGI — would emerge by through nothing more than training sufficiently fast and enormous artificial neural networks. Unfortunately, adding more training obscures the problem by pushing it down into lower levels of detail without fixing it. Holographic data degradation is the deeper cause of the never-quite-right answers produced by chatbots, and no amount of training can fix this.

Given the enormous sunk-cost investments already in place as of 2024 to support LLMs, what the LLM community needs most is new, non-neural-net technologies with true emergence and the ability to monitor and repair data in the neural net continually. Unfortunately, such truly emergent data technologies do not yet exist.

A Nobel Prize for Misinterpretation

Hopfield's misidentification of emergence in artificial neural networks took on a spectacularly ironic new twist on October 8, 2024, when the Royal Swedish Academy of Sciences awarded him and Jeffrey Hinton, a computer scientist, the 2024 Nobel Prize in Physics for their foundational work on ANNs. Early news coverage focused on the point that LLMs are not physics, and neither winner is a currently practicing physicist, but the Nobel announcement [4] gives a more nuanced story. While Hinton is strictly a computer scientist, the Nobel announcement specifically mentions Hopfield's work on molecular biophysics emergence in addition to the paper on neural networks for which he won the prize.

The Nobel announcement lists two 1974 Hopfield papers that deal specifically with the puzzling ability of chaotic mixtures of cellular biomolecules, some of which seem nominally damaging to the goals of a cell, to give rise to extremely robust and useful emergent properties. These papers show Hopfield's background as an innovative and insightful physicist working at the boundaries of our molecular dynamics understanding. One paper describes how such processes lead to reliable transfers of electrons between molecules [5], and the other to accurate reading of DNA molecules [6]. It is worth noting that however chaotic these processes appear to us, they result from billions of years of fine-tuned evolution and, thus, should never be interpreted as accidental. Even if we do not understand how they convert chaos to order, these specific mixes of biomolecules are anything but random.

Diving Deeper

One way to see how novel and important Hopfield's biomolecular work was is to recognize that similar work around the same time helped found what we now call quantum computing. In his book *Computable and Uncomputable* [7, in Russian], Yuri Manin marvels at the extreme energy efficiency of quantum-based biomolecular computing [8]. However, in the next few sentences, Manin casually proposed an extreme scaling hypothesis that quantum superposition in small molecules might also apply to massive and profoundly classical computers. Manin's almost incidental scaling hypothesis eventually led to cryogenic quantum computing using qubits. This field used cold temperatures to increase the odds of keeping an otherwise classical computer in a quantum state. Notably, it was about this time that Richard Feynman proposed a far more conservative vision of quantum computing that would use wavefunctions to predict other wavefunctions [9]. Feynman's fighting-fire-with-fire strategy relied only on known physics and required no scaling hypothesis.

However, it was Hopfield's 1982 paper [10] on artificial neural networks that won a Nobel Prize — and that paper is where the problem began. Hopfield summarized his assessment of the properties of artificial neural nets this way:

> *"The collective properties of this model produce a content-addressable memory which correctly yields an entire memory from any subpart of sufficient size. The algorithm for the time evolution of the state of the system is based on asynchronous parallel processing."*

Readers familiar with holographic data storage technologies [11] may recognize key features of this description. One of the defining features of a hologram is that every piece contains the entire image, just at lower and lower resolution as the size of the piece decreases. This whole-film image distribution is why you keep seeing the same image if you put your eye near a hologram and move side to side. That's very different from an ordinary image in which moving like that takes you to an entirely different part of the image.

Optional Reading: A Quick Analogy for Understanding Holography

Holography does this neat trick by converting all those local bits of an image into separate wave-like patterns that share the *entire* storage device. Imagine two people throwing stones into a pond to see how this overlap is possible.

As long as they have good separation on the shore or when they toss their stones, the waves created by their stones stay distinct even as they pass through each other. Next, quickly freeze those overlapping sets of ripples. Can the resulting ice sheet be used to figure out where and when the stones hit the water? Sure, though it may take some work. You need a program that looks for how the waves "fit together," then reverse them in time — think of a reverse video of waves hitting the water — to find where and when the stones hit. The wave patterns *recorded* both images of where and when the two stones hit the water (Fig. 3). That's your hologram!

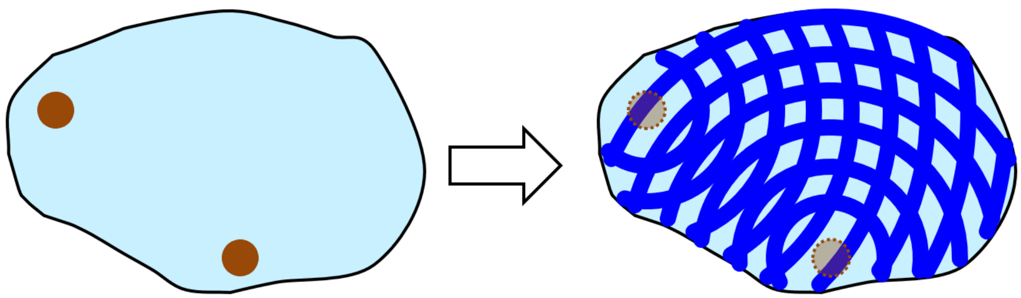

Figure 3. *Waves spread location information throughout "storage" without locking out more data.*

Notice the close link between *transmitting* information — waves from the stones — and holographically *storing* information. Holograms often are not much more than snapshots of data-carrying waves in mid-transmission. That's useful since it means methods for encoding information for transmission devices can also apply to holograms.

As with Hopfield's artificial neural networks, the ice-sheet hologram is "content-addressable" because the location where each rock fell stays closely associated with the set of rings that arise from that event. If you move to the location where a rock fell in, its rings suddenly pop out visually as a series of concentric rings (Fig. 4). The ice sheet hologram uses "asynchronous parallel processing" because that's how *everything* in the physical world works: In parallel and at its speed. Once set into motion on a pond, waves travel mostly independently.

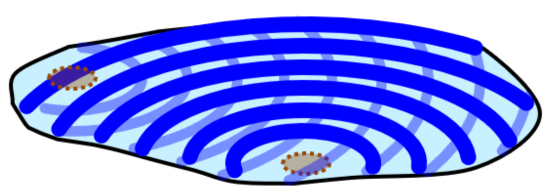

Figure 4. *Like patterns that appear at certain angles, holographic codes stay associated with their origins*.

Holograms with More Dimensions

Another important trick in data transmission and holography is to use certain tricks to increase the number of dimensions available. Your pond-ice hologram has only two dimensions, but what if you need more?

Adding dimensions sounds impossible, but it turns out to be surprisingly easy. Instead of having one group of people tossing in stones, give two groups of people devices that vibrate quickly in patterns unique to that group, adding unique "signatures" on top of the main waves produced by their splashes (Fig. 5). If the smaller ripple patterns are sufficiently unique form each other — which in cell phones is called a Walsh transform [12] — the result is *two* sets of two-dimensional pond-ice holograms, giving a total of four channels (cell phones) or four dimensions (holograms). This pattern-based approach to signal separation, which the cell phone industry calls CDMA [13], makes it possible for a single cell phone tower to have far more users than with older methods like those used on

AM radios. For Large Language Models, the unique directions defined by distinctive coding patterns become words and commonly used word sequences. LLM research looks a how these directions of meaning form and interact.

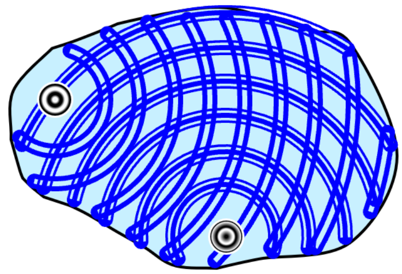

Figure 5. *Additional encoding coding allows holograms to extend dimensionality beyond physical limits.*

How far can developers push this model? Like all physical processes — as opposed to mathematical abstractions that pay no attention to energy, information, and velocity limits unless you add them in explicitly — there are always limits to how much information you can encode into any physical system. The ability to add many more dimensions, even to something as simple as a 2D surface, reflects the enormous information capacities of all forms of condensed matter. However, the illusion of *infinite* dimensional addition is just that — an illusion created by math notations that don't respect such limits. Hilbert spaces, for example, are extremely useful infinite-dimensional generalizations of physical 3D space that describe encoded data dimensions well, but only up to a bandwidth limit. For LLMs, the total capacity and precision of their real-number storage capacity define this resolution limit. When modeling the dynamics of material systems, the Hilbert space abstraction does not properly track inhibition of state-to-state interactions due to extreme signal fading (Fig. 6). The need to provide high-dimensional interactions with enough energy to proceed at a good speed is a factor in LLM data centers have such extreme energy needs.

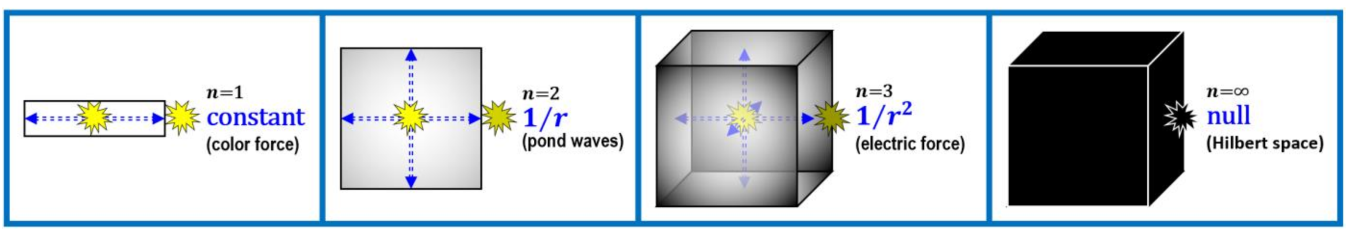

Figure 6. *Hilbert space is excellent for modeling quantum states but unrealistic for quantum dynamics*.

For cell phones, bandwidth is the final limit to how many unique dimensions or channels are possible. Condensed atomic matter has enormously higher information (and thus dimensional) capacity, but even matter has limits. In the pond example, increasing encoding frequencies into the ultrasonic causes the water to begin to ignore you (stop responding) at low power and vaporize at high power. Freezing the water increases the details it can encode, but as with old-style plastic LP records, even frozen water surfaces have atomic limits on how much data they can encode.

If spreading every piece of information over an entire storage unit and using some form of wave or signature pattern to retrieve it sounds like an extremely laborious way to format, store, and retrieve data, it is. While it is always possible to transform data back and forth between static and wave representations, creating and recovering such data using digital hardware takes tremendous numbers of multiplications and extensive hardware. That is why holographic memories do this trick using light instead of digital circuits since the physics of our universe happens to make electromagnetic radiation mind-bogglingly efficient at Fourier transforms. Light performs Fourier transforms at, um, lightspeed, with negligible energy costs per transformation. Biology recognized this power long before humans, building lens-like devices called eyes to access the powerful information-gathering capabilities of light-based Fourier transforms. You are currently using light-based Fourier transforms to read this text as the lens in your eye converts the diffuse waves of light around you into sharp images on your retina.

A Holographic Reinterpretation of Neural Net Research

What happened in the 1982 Hopfield paper is best described as a case of inadvertent convergent development. Hopfield insightfully recognized the existence of a unique and computationally interesting set of features in early neural nets and surmised they could to much better. By describing the properties he saw and emphasizing their value, he made them into goals for all neural net research. Hopfield summarized these merits as follows:

> *"Content-addressable memory … an entire memory from any [large] subpart … capacity for generalization … recognition [of past familiarization] … categorization … error correction … time sequence retention … [insensitivity] to details of the modeling … [insensitivity to] failure of individual devices."*

Unfortunately, a better explanation for Hopfield's list of emergent properties is that they emerge from a holographic representation of dimensional data created by human labeling (training) of data. Hopfield inadvertently incentivized not computational emergence but digital emulation of a higher-dimensional version of holographic data storage. The difference is critical since data is static and incapable of emergent behaviors.

To better understand the connection between optical holography and human-guided neural net training, think of how a hologram shows the same object from many different perspectives. Many of these perspectives are close and similar, but others, like the front and back of an object, have little or no resemblance. That is where the gradual nature of the other perspectives comes into play since they create a path that eventually links together fully different views, such as front and back views, through a linked sequence of similar perspectives. Eventually, even the completely different front and back emerge as aspects of a single object.

Next, imagine training a neural net in how to recognize a cat. You feed the neural net image after image of cats, starting with images of different sides of the same cat. With each image, you let the neural net know that despite how different many images look, they are all examples of one thing: a cat. As you load more and more images into the neural net, you begin to see enough similar images to make a smooth connection between them. Eventually, a complete image of a cat develops. Because you used more than one kind of cat, this image is not one you can easily show in ordinary three-dimensional space, yet it still comes down to the same idea, only in a space with many more dimensions (perspectives) than an optical hologram would see.

In this interpretation, Hopfield's first proposed emergent computational property of "content-addressable memory" becomes that higher-dimensional space of human-defined labels you provided for the data. The second property of distributing content becomes a strategy of representing data as changes to weights throughout the neural net structure. Recognition and categorization become incremental versions of accessing and adding to the hologram, akin to how new data is read and added in a holographic storage device [11]. Rather than being emergent properties, error correction and resilience to failures of individual storage elements are necessary consequences of any data storage strategy that delocalizes data over the entire storage device since such formats no longer have a one-to-one correlation between physical locations and the stored data items.

Hopfield's Confusion of Data with Dynamics

The most cryptic artificial neural net property postulated by Hopfield is "time sequence retention." He mentions it only once in the paper without elaboration, but from his references, e.g., [14], he appears to have assumed that dynamic oscillatory behavior seen in cell-based biological neural networks also applies to vastly simpler artificial neural nets. The same paragraph in which he mentions time sequencing provides his most explicit description of his hope that the features he identified as interesting were the result of physics-like emergent behaviors

> *In physical systems made from a large number of simple elements, interactions among large numbers of elementary components yield collective phenomena such as the stable magnetic orientations and domains in a magnetic system or the vortex patterns in fluid flow. Do analogous collective phenomena in a system of simple interacting neurons have useful "computational" correlates? For example, are the stability of*

> *memories, the construction of categories of generalization, or time-sequential memory also emergent properties and collective in origin? This paper examines a new modeling of this old and fundamental question (4-8) and shows that important computational properties spontaneously arise.*

Other than at the deep-physics level of how to engineer storage devices to keep bit states stable over human-scale periods, none of these speculations apply to static holographic data distribution. Like many excellent physicists of the late 1900s [15], Hopfield appears to have been unaware of the strenuous efforts of semiconductor and computer hardware researchers in obliterating emergent physics effects to create nominally "infinitely" stable bits. This same deep obliteration of emergent effects unavoidably applies to bit-based digital, artificial neural networks.

Suppression of emergent effects in artificial neural networks should not be surprising, given that they have always been incomplete shadows of their far more complicated biological analogs. The simplicity of artificial neuron networks stems in part from an incomplete understanding of neurons when ANNs were first proposed in the 1940s and 1950s under the name perceptrons [16][17]. For example, even though researchers as early as the 1940s were aware of neurons' inhibitory and exhibitory states, they focused on creating as simple and logic-like a model as possible. Consequently, their models lacked clear recognition [18] of how these phases help biological neural networks converge from initially chaotic sensory-driven states to well-defined recognition or action states. If early modelers had been more aware of the importance of the phase feature, they might have used phase-aware complex numbers with non-linear (and, interestingly, more quantum-like) summation rules.

Hopfield's specific overestimation of the emergence capabilities of artificial neural networks likely stemmed from his deep knowledge of the complicated and counterintuitive role that randomness and emergent behavior play at the level of biomolecular physics. His 1974 paper on biomolecular electron transfers [5] describes the fascinating example of how thermally chaotic interactions of mixes of molecules, some of which would seem at first glance to be deleterious to the transfer, instead focus the electron transfer like high-quality insulated wires — a form of chaos-based emergent design that, to this day, no one knows how to replicate (Fig. 7). As Manin noted in 1980 [8], the electron orbitals of ordinary chemistry are more computationally powerful and energy efficient than we tend to give them credit for, though the cost and complexity of attempting to simulate the quantum behaviors of large groups of atoms help make this same point. Hopfield's other 1974 paper on the precise replication of DNA [6] shows how chaotic mixes of molecules counterintuitively behave like proof-checking mechanisms.

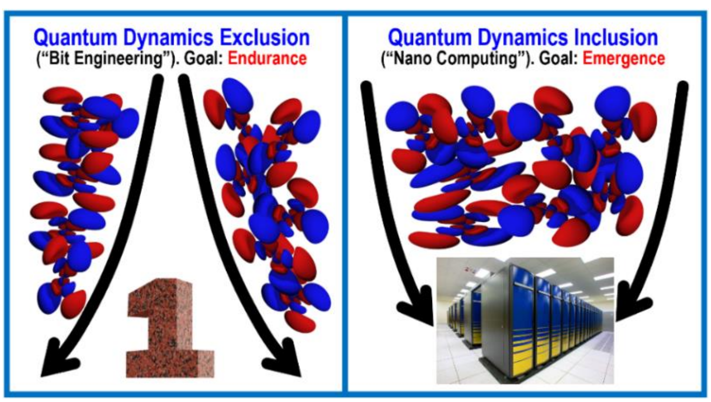

Figure 7. *Bit storage designers strive to exclude "noisy" quantum effects. Nanobiology does the opposite*.

Given these intriguing examples of true emergence at the quantum and molecular level, it is not too surprising that Hopfield optimistically overextended the model to the utterly different environment of artificial neural networks, particularly when holographic formatting of that data was generating hints of phenomena such as error resilience that superficially resembled the far more complex emergences of quantum-level molecular biology.

Hopfield was brilliant in realizing several positive features of neural networks and the parameters that needed optimization. Unfortunately, it also introduced an unwarranted optimism that has only worsened.

Computing Emergence Forty Years Later

It has been over forty years since Hopfield published his paper that inadvertently converted the search for principles behind quantum-level molecular emergence into a quest to create the fastest and most powerful — but necessarily non-emergent — digital holographic data storage systems possible. What is the current status of this quest?

Unfortunately, instead of fading out or getting corrected in the literature, Hopfield's misidentification of the benefits of holographic data storage as "computing emergence" has become the foundation of a trillion-dollar industry. Funding for this industry depends on promoting the belief that neural-net-based Large Language models will lead to human-like intelligence in machines, a goal called Artificial General Intelligence or AGI. Unlike existing systems, an AGI could self-train when receiving new data and have "Eureka!" moments of deep insight. The degree of fervor for this belief almost certainly played a role in the Nobel Physics Committee's interest in Hopfield's paper.

In a delightfully well-done YouTube video [19], science expositor Stephen Welch explains how algorithmic innovations in the 2010s and early 2020s resulted in neural-net-based Large Language Models such as AlexNet [21][22] that could pass simple versions of the Turing test [23]. These results electrified AI research communities and large technology firms and led to a surge in research and funding of LLM-based AI [24]. Companies and groups began a massive push to commercialize LLM AI starting in 2022 and intensifying through 2024. Since many companies had invested enormous sums on server farms to support the expected wave of LLM AI use, users' lack of rapid adoption prompted more aggressive and intrusive strategies to get users on board.

On the LLM research side, the importance of computational emergence shows up particularly strongly in a 2022 Google-sponsored paper [25] that focuses on finding examples of the emergence of *few-shot learning* in LLM systems. Few-shot learning is artificial intelligence speak for an LLM having a sort of "Eureka!" moment in which it suddenly intuits some deeper pattern hiding beneath a small number of training examples. Finding emergence in LLMs was important to researchers and investors since you cannot reach the goal of a human-like AGI without it. A persistent but often unspoken belief has been that once an LLM AI acquires enough examples of human insight, it should undergo a sort of self-defined phase change in which it begins to self-monitor, self-correct, and self-train — that is, it spontaneously becomes an AGI.

Unfortunately — but also predictably — even these minimal examples of computational emergence turned out to be testing artifacts. In late 2023, Stanford professors Rylan Schaeffer, Brando Miranda, and Sanmi Koyejo described their extensive analysis of few-shot emergence claims [35] and concluded that:

> *"Via all three analyses, we provide evidence that emergent abilities disappear with different metrics or with better statistics, and may not be a fundamental property of scaling AI models."*

This conclusion is correct because LLMs are a different way of formatting static, non-emergent data.

The Scaling Problem

In a second video [20], Welch ponders why no amount of training seems to move LLMs below certain performance lines in handling inherent uncertainty in human language. There is a simpler explanation for the intransigence of this line: These lines reflect the natural limit for holographic encoding of complicated but ultimately finite data sets. The continuing hope among LLM researchers is that with sufficient data, analyses like these would show a sort of phase transition into more intelligent behavior due to emergence.

What they instead proved, very solidly, is that digital multiplier approaches to holographic data encoding scale extremely poorly. Due to the high cost of adding enough multipliers and multiplications to emulate what light does almost without cost, LLMs become exponentially costlier and more energy-consuming as they add enough hardware to approach the reliability of their light-based equivalents. It is as if one tried to replace a sheet of analog holographic film with a density of digital multipliers comparable to the microscopic photosensitive grains of the film. The same conversions would have occurred at light speed and with negligible energy cost in the optical film version of holography energy-intensive operations in the most complex networked machine ever constructed by humans.

LLM is an extremely useful technology for goals other than making its database large enough to pass Turing tests for human-like intelligence. For example, it has enabled high-quality language translation levels that were utterly unreachable not that many years ago. The broader category of artificial neural networks has proved immensely valuable to disciplines where finding correlations across vast data sets, such as those seen in medicine, astronomy, and particle accelerators, is far beyond what time-limited humans can accomplish.

Feynman on Science Cults of Superficial Resemblance

Nobel Laureate Richard Feynman once bluntly and humorously addressed this tendency of humans in general and scientists' tendency to focus too much on form without understanding substance in his 1974 Caltech commencement talk on *Cargo Cult Science* [36]. Nobel Prizes notwithstanding, forty years of believing human-like intelligence can emerge from holographically formatted, defiantly non-quantum digital data is an exceptionally costly example of such a cargo cult. Human-scale, massively interconnected, quantum-suppressing circuits are no more capable of giving the same outcomes as the isolated, nanoscale, quantum-embracing smart biomolecule dynamics than wearing wooden earpieces with antenna-like bamboo pieces will cause airplanes with valuable cargo to land next to you. We've spent forty years on a wood-and-bamboo pipedream.

Attempting to use ANNs to create human-like intelligence is a false path. Rapidly scaling energy consumption, which is in such sharp contrast to the extreme energy efficiency of human brains, warns that this approach is like trying to recreate photosynthesis by paying close attention to which green pigments you use to paint a picture of a tree. Focusing too much on superficial resemblances of error-tolerant holography to emergent order is a form of Cargo Cult science that pays too much attention to superficial resemblances.

Ironically, investing over a trillion dollars in LLMs is one of the best experimental proofs possible that LLMs do *not* exhibit emergence. By its nature, static-data LLM tech does not comprehend what it is doing. For software, that kind of creeping random damage is deadly in the long term. It may take us decades to recover from the undocumented damage that overreliance on auto-generation code has already done to our software infrastructure, let alone what may happen if this LLM misuse continues for years.

Future Directions

Where should LLM research go in the future? Below are five proposed directions.

Recommendation #1: Abandon emergence thinking and switch to holographic mathematics.

The first and most critical need in ANN and LLM research is to follow the data [35] and stop interpreting LLMs' distributed, high-dimensional holographic storage as anything more than unavoidably noisy holographic data storage. From this perspective, the intriguing scaling laws [20][32][33][27] that emerge from increasing the size and of LLMs become little more than building larger-capacity holograms with better resolution — the number of real-number storage registers times digital precision of each register — than earlier models. Pretending that something new may happen by increasing holographic precision to still vaster levels [3] only obscures the inevitable degradation that holographic storage always introduces when pushed beyond its storage limits. Larger data storage only implies more total damage at the edges, not emergence. Thinking otherwise is Cargo Cult thinking.

Conversely, holographic thinking and analyses should help collapse much of the ongoing confusion about how facts are stored [37][38] in artificial neural networks and LLMs. While this would not erase the limitations of such approaches, it might increase the efficiency of current designs and, more importantly, provide a stronger mathematical basis for understanding and predicting error behaviors in such systems.

Recommendation #2: Explore optical holography as a replacement for digital matrix multiplication.

Recognizing the holographic nature of ANN data storage opens up an intriguing new option for reducing extreme LLM energy costs: using optical holography as the explicit basis for storing LLM data. Current LLM methods use energy-hogging digital matrix multiplication to emulate the Fourier transforms that occur naturally at trivial energy costs with light-based holography.

Optical implementation of LLMs has the potential to become a fascinating research area with opportunities for lateral transfer of existing mature models and existing technologies [11]. Instead of recording real-world images into such a memory, the goal would be to create dimensionally distinct axes of multiple levels of word composition — a process known as attention [34][39][19] in ANN and LLM literature. However, in many ways, it is nothing more than the smooth extension of the same process that creates words from letters, using higher-level units of words to create more advanced concepts that we think of as descriptive sentences. In the other direction, the composition of words from letters becomes an example of applying “attention” to letters with little meaning. Recognizing this conceptual continuity should make it easier to share holographic mechanisms.

Recommendation #3: Restart exploration of Yuri Manin’s 1980 observation of complex computation in molecules.

In 1980, Yuri Manin was perhaps the first person to recognize the importance and potential of quantum mechanical processes in biomolecules [8][7]. Manin recognized that nanoscale room-temperature biomolecular emergence processes enable the exquisitely precise and thermodynamically “impossible” processes that make cellular life possible and also took note of the impossibly high energy costs of attempting to compute such results classically. Unfortunately, in the next few sentences, he then unraveled his insight. Instead, he created his own forty-year-plus Cargo Cult by asserting that massive, extremely classical computers should be capable of the same superposition-like behavior as nanoscale biomolecules. His scaling hypothesis led directly to the modern focus on “qubits” and their implicit assertion that quantum computation exists *only* in massive computers cooled to such low temperatures.

This limited quantum computing perspective makes no sense when compared to living organisms. Every unlikely process that keeps your cells alive represents an example of Manin’s initial premise that collections of optimized biomolecules use some form of extremely energy-efficient quantum computing to achieve these unlikely outcomes. At the time of Manin’s 1980 observation, John Hopfield had arrived at this conclusion six years earlier in his marvelous 1974 papers [5][6] on the emergence of order from exquisitely optimized molecular quantum chaos.

It is for this work, not his insightful but also misdirecting artificial neural networks paper, that Hopfield deserved his 2024 Nobel Prize in physics. Any cellular process that exhibits the emergence of precise, extremely unlikely outcomes from thermally chaotic interactions is a candidate for insights into nanoscale molecular computation. Standard template-based biochemistry explanations of how molecules interact would be the starting point for such explorations. The important caveat that thinking such interactions are fully classical is almost certainly an oversimplification of what is happening. As in Hopfield’s 1974 papers, the peculiar emergence of exquisitely high probabilities for such reactions to emerge is the deeper computational mystery.

Recommendation #4: Develop and apply true-emergence methods to stabilize ANNs and LLMs.

The true advantage of LLMs is that they can hold enormous quantities of high-value information and do so in a highly factored form that enables fast recovery and identification of important connections between instances of similar phenomena. However — and as is notable to anyone who knows a topic well and tries to use an LLM to receive detailed answers on that topic — the problem is that the LLMs have none of the resilience and self-correcting, multi-scale (cells up to human intelligence) abilities of biological systems. A lack of emergence is no surprise when analyzing such systems from a holographic perspective, in which they become static, inert data stored in a distributed format that guarantees gradual (and sometimes rapid) degradation of that data at the edges.

The correction for this is obvious but hard to accomplish: Figure out how to automate actual, biomolecular-inspired emergence and error correction and apply such methods to the static data of LLMs. These new methods cannot be the hard-to-scale digital methods that attempt to replace emergence with, usually, some form of exhaustive search of a problem space. As with life, there must be an element of quantum-level computation and emergence. New work may need to be similarly nanoscale and even organic, though large-scale Bose condensates are beginning to show promise for making atomic-level wave precision accessible in human-scale measurements [40][41][42][43].

Ironically, LLM sponsors already use an inefficient, hard-to-scale version of this concept when they employ human reviewers to correct data corruption. However, only full automation of life-like emergence can scale well enough.

Recommendation #5: Develop energy-aware and information-aware versions of quantum mathematics.

In this and other quantum theory domains, there is a need for better maths that recognize quantum dynamics as phenomena bound by both the speed of light and cost limits on dimensionality. This path amounts to abandoning the highly classical current forms of Hilbert spaces as anything more than tricky-to-use, severely oversimplified elaborations of how a given quantum state might evolve in the future. Avoiding pleasing but overly simplistic abstractions such as energy-oblivious Hilbert spaces is important for emergence research since any system that does *not* fully address such limits will have difficulty accurately modeling the very types of multi-molecule interactions that give rise to low-probability emergence reactions in living cells.

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