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„Might the human brain really have evolved to work at the quantum level? Are we all quantum computers in disguise? Stay tuned while the scientific community systematically works toward plausible hypotheses and validate them experimentally! It might take a while, but we shall have our answers!"

Quantum brain processes could explain why we can still outperform supercomputers when it comes to unforeseen circumstances, decision making, or learning something new

Dr. C. Kerskens

In reality we know nothing, for truth is in the depths.

Democritus

Quantum Entanglement of the Brain, Dynamics of Information, and Intelligent Finance

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If entanglement is the only possible explanation here then that would mean that brain processes must have interacted with the nuclear spins, mediating the entanglement between the nuclear spins. As a result, we can deduce that those brain functions must be quantum.

Dr. C. Kerskens

Quantum mechanics tells us that every feeling is a collapse of some wave functions due to the interference of a matrix of attention functions.

Amit Ray, Quantum Computing Algorithms for Artificial Intelligence

You can have data without information, but you cannot have information without data.

Daniel Keys Moran

I am concerned that too many people are focused too much on money and not on their greatest wealth, which is their education. If people are prepared to be flexible, keep an open mind and learn, they will grow richer and richer through the changes. If they think money will solve the problems, I am afraid those people will have a rough ride. Intelligence solves problems and produces money. Money without financial intelligence is money soon gone.

R. Kiyosa

Abstract. *Our research forms two directions, the first considers two approaches to the brain, one based on classical mechanics, the second using quantum physics, the second direction of research refers to the dynamics of0 information as an interaction between differential geometry, mathematical statistics, probability theory. and quantum mechanics which led to the construction of classical and quantum information geometry. Financial entanglement is multidimensiona in time and space, dynamic, less understood and interesting because it functions in real life, like the brain. Neuroscientists who focus on mathematical frameworks for how the brain's shape affects its activity—an area of mathematical neuroscience called neural field theory – will begin to understand the relationship between brain shape, structure, and function in yet another way. Analysis of research into the geometry of the brain's contours, that is, the way in which brain activity resonates over and through its architecture, is perhaps more significant than the connections between neurons. Research by scientists from the University of Sydney and Monash University showed that the overall shape and geometry of the human brain - its contours and curvature - has a greater influence on brain dynamics than the internal connectivity of brain cells (Our* *brain shape influences how it works, 2023) in short, Australian scientists indicate the possibility of predicting brain function directly from its shape. "We have long thought that specific thoughts or sensations elicit activity in specific parts of the brain, but this study reveals that structured patterns of activity are excited across nearly the entire brain, just like the way in which a musical note arises from vibrations occurring along the entire length of a violin string, and not just an isolated segment," (Dr J. Pang,2023)."We found that eigenmodes defined by brain geometry - its contours and curvature - represented the strongest anatomical constraint on brain function, much like the shape of a drum influences the sounds it can make" (A. Fornito, 2023). "Using mathematical models, we confirmed theoretical predictions that the close link between geometry and function is driven by wave-like activity propagating throughout the brain, just as the shape of a pond influences the wave ripples that are formed by a falling pebble" (A. Fornito, 2023).*

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Introduction

We would like to start this paper with a quote „When you change the way you look at things, the things you look at change" by Max Planck, The Father of Quantum Physics. The conducted research involved a series of questions: Is the brain quantum or classical? Does the brain follow the laws of physics? What is the classical view of the brain? and does the human brain use quantum mechanics?, We interweave physics and neuroscience, quantum geometric information and philosophy as the focal spark of intelligent finance within the framework of the development of artificial intelligence as a thought process.

Understanding physics is knowing experiments and theory. Knowing the theory cannot be reduced to the possibility of making a prediction from it, but knowing this is within the framework of knowing the theory. Consensus on theories can be difficult to achieve because the evidence is not yet strong enough to decide between them, but in principle this is a difficulty. A person has a feeling when an observed phenomenon has been successfully explained or not.

Most neuroscientists believe that the brain works in a classical way. However, if brain processes rely on quantum mechanics, this could explain why our brains are so powerful. Research may indicate that some of our brain activity, and perhaps even consciousness, operates on a quantum level.

The human brain is the most complex system of condensed matter. It contains approximately 102 billion neurons and at least as many glial cells (von Bartheld, C.S.; Bahney, J.; Herculano-Houzel, S, 2016) The brain is composed of 77 to 78% water, 10 to 12% lipids, 8% protein, 2% soluble organic matter and 1% carbohydrates and inorganic salts (McIlwain, H.; Bachelard, H.S., 1985). Our brains are powerful computers that use not only neurons, but also connections between neurons to process and interpret information. Some of the most complex brain functions are delocalized over large distances and require synchronization processes that are not easy or simple to explain by classical mechanics alone. The integrity of perception requires the integration of the activities of a huge number of brain cells. In view of this, quantum features such as entanglement (. Bengtsson, I.; Zyczkowski, K., 2006; Jaeger, G., 2009), nonlocality, contextuality and coherence (Ballentine, L. E., 2001; . Cook, D. B., 2002) may be the key to a possible microscopic understanding of brain function.

However, there are still open questions whether our brains work on quantum or classical mechanics. Some scientists believe that the brain could be a quantum computer, while others think that it primarily relies on classical computations. There is evidence to support both theories, but no definitive conclusion has yet been reached. Quantum mechanics is a branch of physics that deals with the behavior of matter and energy at the atomic and subatomic level. It is responsible for many "strange" and impossible phenomena, such as quantum entanglement and superposition. On the other hand, classical mechanics is a branch of physics that describes the motion of macroscopic objects. It does not take into account the behavior of matter and energy on very small scales. One of the reasons some scientists believe the brain could be a quantum computer is that quantum computers can perform certain tasks much faster than classical computers.

Almost all quantum models of the brain depend on how long the brain can maintain quantum coherence. R. Penrose claims that microtubules - small hollow cylinders that help cells keep their shape in the brain - work like a quantum computer and can store information stored as 'quantum waves' for long periods of time. These are places of 'human consciousness'.

The decoherence time – the time a quantum wave can remain coherent before collapsing – for microtubules must be at least 1 second. However, M. Tegmark claims that R. Penrose neglected the effects of distant ions on the decoherence time. These ions are found in the material surrounding microtubules and in other neurons. According to his calculations, the decoherence time is 10-13 seconds, which is not long enough for quantum effects to affect the brain. This proves, says M. Tegmark, "that there is nothing fundamentally quantum-mechanical in cognitive processes in the brain" ("Based on the calculation of neural decoherence rates, we claim that the degrees of freedom of the human brain related to cognitive processes should be considered classical, not quantum system, there is nothing fundamentally wrong with the current classical approach to neural network simulations. We find that the decoherence time scales (approximately 10(-13)-10(-20) s) are shorter than the relevant dynamical time scales (approximately 10(-3) -10(-1) s), both for regular neuronal firing and for kink-like polarization excitations in microtubules. This conclusion disagrees with suggestions by Penrose and others that the brain behaves like a quantum computer and that quantum coherence is fundamentally linked with consciousness" - The importance of quantum decoherence in brain processes, 1999).

When we think about understanding something, we often think about being able to explain it in a relatively simple way. In science, researchers in other fields look to physics as a model of understanding, (C.Koch, 2023), the physical world is subject to abstractions that can be reduced to (relatively) simple equations. Scientists at the Allen Institute, USA, are studying the brain on a large scale, looking at many or most cells in the brain, not just a few, even parts of neuroscience that they thought the field had established. more complicated than anyone could fathom.

"Perhaps there is no simple path to understanding complex systems shaped by natural selection" (C. Koch, 2023) "Evolution does not care about elegance." The brain doesn't care if you understand it."

"If the brain uses quantum computing, then these quantum operators could be different from the operators known from atomic systems", C. Kerskens, 2022). "Quantum brain processes could explain why we can still outperform supercomputers when it comes to contingencies, making decisions or learning something new. Our experiments performed only 50 meters from the lecture hall, where Schrödinger presented his famous thoughts on life, could shed light on the mysteries of biology and consciousness that are even more difficult to fathom scientifically."

Intelligent financial management implies the use of an integrated intelligent human-computer system composed of financial experts and intelligent machines (M. Witthaut; H. Deeken, P. Sprenger; P. Gadzhanov, M. David;2017; V. Ravi, S. Kamaruddin, 2017; N. R. Mosteanu, A. Facia, G. Torrebruno, F. Torrebruno, 2019).

Quantum information geometry is a powerful formulation that makes it possible to understand the intricate relationships between many different fields. The geometric structure of the state space is consistent with the classification of topologically ordered phases, the scaling of classical, quantum and dynamical phase transition exponents, the design of sensors that overcome classical limitations, anti-de Sitter/conformal field theory (AdS/CFT) mapping and resource quantification for processing tasks information; mathematical finance, statistical mechanics, computational and systems biology (to name just a few fields of application).

From the aspect of philosophical thought, whether quantum physics had any influence on philosophy. Quantum mechanics matured in the 1920s, coming of age with books by Weyl (1931), Dirac (1931), and Neumann (1932); Jammer (1966, 1989). It became clear that quantum mechanics was more than just another physical theory. Bohr's reflections on the 'epistemological lessons taught us by quantum theory' became legendary. Most of the founders of quantum mechanics were sensitive to the philosophical implications of quantum mechanics. They thought about it, talked about it and wrote about it in letters and newspapers (Jammer 1974). Somewhat earlier, Einstein's theories of relativity were also shown to have philosophical consequences. The revolution of relativity and the quantum revolution fundamentally changed physics: modern physics was born. Classical physics had to give way.

The Importance of Philosophy in Physics?

Commitment to truth and certainty and the humble power of science. C.Rovelli

Those who deny the utility of philosophy, are doing philosophy. Aristotle

"Man is what we all know." Democritus

"The nature of a man is not his internal structure but the network of personal, familial and social interactions within which he exists." Democritus

"Against claims about the irrelevance of philosophy to science, I argue that philosophy has had, and still has, much more influence on physics than is commonly assumed. I argue that the current anti-philosophical ideology has had detrimental effects on the fertility of science. Empirical results, such as the detection of the Higgs particle and gravitational waves, and the failure to detect supersymmetry where many expected to find it, call into question the validity of certain philosophical assumptions common among theoretical physicists, inviting us to engage in a clearer philosophical reflection on scientific methods." C. Rovelli – Theeoretical physicist, Professor of Physics, Aix-Marseille University

Physics and philosophy are historically intertwined and each continues to contribute to the development of the other. In short, philosophy played a key role in two revolutions in 20th century physics – relativity and quantum mechanics. Philosophy contributes both to the fundamental research of theoretical physics and to the articulation and criticism of the scientific method. Whereas discoveries in physics have profound implications for philosophical inquiry, such as the nature of space and time and the behavior of matter in the quantum realm.

Inspired by Aristotle's statement about the inevitability of philosophy, C. Rovelli points out that "declaring the uselessness of philosophy, which Weinberg, Hawking and other 'anti-philosophical' scientists indicated in their discussions and reviews of philosophy, actually pay tribute to the philosophers of science they read, or whose ideas absorbed from their surroundings" (C. Rovelli, 2018), returning to their positions of neopositivism and the Vienna Circle, as well as Popper and Kuhn. Stenger, Lindsay, and Boghossian prefer to return to Platonism (which they carefully lowercase 'p' in order to distinguish it from Plato), then observe that "those who hold to the Platonic view of reality are disingenuous when they disparage philosophy. They adopt the doctrine of one of the most influential philosophers of all time. It also makes them philosophers" (.Stenger, Victor J., James A. Lindsay, and Peter Boghossian, 2015).

The Power of Theory from Physics to Neuroscience

Neuroscience is beginning to uncover the physical foundations of the brain (Abbott, 2008). Since the 1970s, the term neurophysics has been proposed as a term denoting the essential role of physics in understanding the brain (Scott, 1977). In recent times, considerable progress has been made in the study of brain connectivity and brain functions using theories of statistical physics (Lynn & Bassett, 2019).

Physics provides insights into its origin, organization and evolution. Random graphs (Betzel et al., 2016; Betzel & Bassett, 2017a), percolation (Breskin, Soriano, Moses, & Tlusty, 2006; Guo et al., 2021), and other physical theories of correlated systems (Haimovici, Tagliazucchi, Balenzuela, & Chialvo, 2013; Wolf, 2005) are applied to reveal the underlying mechanisms that explain the origin of brain network properties. Complex network theories act as a basis for characterizing organizational features of brain connectivity (e.g., community; Betzel & Bassett, 2017b; Betzel, Medaglia, & Bassett, 2018; Khambhati, Sizemore, Betzel, & Bassett, 2018), hub (Deco, Tononi, Boly, & Kringelbach, 2015; Gong et al., 2009) and small world (Bullmore & Sporns, 2012; Deco et al., 2015; structures) and embedding attributes in physical space (Bassett et al., 2010; Kaiser & Hilgetag, 2006). Network evolution driven by neural plasticity helps explain the dynamics of brain connectivity structures during information processing (Del Pozo et al., 2021; Galván, 2010; Montague, Dayan, & Sejnowski, 1996; Robert & Vignoud, 2021; Song, Miller, & Abbott, 2000) . For brain functions, physics presents possible explanations for the origin of information processing capacity from collective neural activities. From single neuron dynamics models (Gerstner, Kistler, Naud & Paninski, 2014), stochastic network models of neuronal populations and circuits (Tian, Li & Sun, 2021; Tian & Sun, 2021), mean field models of neuronal mass of a brain region (David & Friston, 2003; Touboul, Wendling, Chauvel, & Faugeras, 2011), finally in models of whole brain networks (Hopfield, 1982; Schneidman, Berry, Segev, & Bialek, 2006), important efforts have been made to characterize the neural dynamics associated with information processing at different levels. Networks with memory capacities (e.g., Hopfield networks; Tyulmankov, Fang, Vadaparty, & Yang, 2021), which are equivalent to Ising models under certain conditions (Lynn & Bassett, 2019), have been applied to study neural information storage and recall (Haldeman & Beggs, 2005; Krotov & Hopfield, 2020), adaptation to environmental changes (Shew et al., 2015), optimization of information transfer (Beggs & Plenz, 2003), maximization of dynamic range (Kinouchi & Copelli, 2006; Shew, Yang, Petermann , Roy and Plenz, 2009) and neural computing power (Bertschinger and Natschläger, 2004). These models are further related to maximum entropy models (eg, specific fine-tuned Ising models) that predict the long-range correlations observed among neurons (Ganmor, Segev, & Schneidman, 2011; Schneidman et al., 2006). Moreover, the general theories of the free energy principle (Friston, 2009, 2010; Guevara, 2021) and informational thermodynamics (Capolupo, Freeman, & Vitiello, 2013; Collell & Fauquet, 2015; Sartori, Granger, Lee, & Horowitz, 2014; Tian & Sun, 2014). 2022) are proposed as the unified foundations of perception, action and learning in the brain.

The past 25 years have seen a strong increase in the number of publications related to criticality in different areas of neuroscience. The potential of criticality to explain various brain properties, including optimal information processing, has made it an increasingly exciting area of investigation for neuroscientists. Thus, the hypothesis that gained importance, serving as a possible mechanism behind various intriguing, but elusive phenomena in the brain. In light of our limited understanding of the complex nature of collective neural dynamics, these phenomena include efficient transitions between cortical states (Fontenele et al., 2019), maximal dynamic ranges of neural responses (Antonopoulos, 2016; Gautam, Hoang, McClanahan, Grady, & Shew, 2015; Kinouchi and Copelli, 2006; Shew et al., 2009), optimized transfer and representation of information (Antonopoulos, 2016; X. Li and Small, 2012; Shew, Yang, Yu, Roy, & Plenz, 2011) and numerous other issues which concern the functions of the brain that we mentioned above. Beggs (2007), Chialvo (2010), Cocchi, Gollo, Zalesky, and Breakspear (2017), Hesse and Gross (2014), and Shew and Plenz (2013) can be seen for systematic reviews of the benefits of various functions that implies brain criticality and their experimental demonstrations.

Generic features of the critical brain with characteristics such as divergent correlation length, neuronal avalanches with power-law behavior and long-term correlations on a microscopic scale (neural populations), extensively observed in mathematical models in combination with experimental data can be seen in scientific papers (Beggs and Plenz, 2003 ; Dalla Porta and Copelli, 2019; Fosque, Williams-García, Beggs and Ortiz, 2021; Gireesh and Plenz, 2008; Hardstone, Mansvelder and Linkenkaer-Hansen, 2014; Petermann et al., 2009; Poil, Hardstone, Mansvelder and Linkenkaer, 2014. -Hansen, 2012; Poil, van Ooyen, & Linkenkaer-Hansen, 2008; Ponce-Alvarez, Jouary, Privat, Deco, & Sumbre, 2018; G .Scott et al., 2014; Shew et al., 2009; Shriki et al. , 2013; Tagliazucchi, Balenzuela, Fraiman and Chialvo, 2012; Tkačik et al., 2015).

However, brain criticality is an established area of neuroscience research, yet remains controversial in several views (Wilting and Priesemann, 2019).

Current intellectual activities lead us to the synthesis of machine learning, theoretical physics and neuroscience. Bringing these fields together allows us to potentially use complex systems analysis, developed in theoretical physics and applied mathematics, to elucidate and understand the design principles that govern neural systems, both biological and artificial, and apply these principles to develop better algorithms. Directions include: (1) determining the best optimization problem to solve in order to perform regression in high dimensions; (2) finding exact solutions for generalization error dynamics in deep linear networks; (3) developing interpretable machine learning to perform and understand state-of-the-art retinal models; (4) analyzing and explaining the origin of hexagonal firing patterns in recurrent neural networks trained for path integration; and (5) understanding the geometry and dynamics of high-dimensional optimization in the classical limit of dissipative quantum many-body optimizers.

Brain Source of Quantum Geometric Information

The Quantum Computer in the Brain

The brain consists of electrically excitable neural networks regulated by the activity of voltage-gated ion channels (it is natural to try to understand the computational properties of neural systems through the network dynamical systems paradigm, where a series of dynamically simple units interact to yield computation as an emergent property of the system. This is for biological models of processing information, pattern generation and decision making as well as for artificial neural networks inspired by these models. Various specific models have been developed to describe the dynamics and training of recurrent networks consisting of connected neurons in biological and artificial environments. invariant objects of the autonomous system (such as balances , periodic orbits and chaotic attractors) form only part of the picture. Few technologies are more widespread in modern biological laboratories than imaging. Recent advances in optical technologies and instrumentation are providing hitherto unimagined capabilities. Almost all these advances have required the development of software to enable the acquisition, management, analysis and visualization of the imaging data (B S Manjunath, at al., 2012) Further rendering of the molecular composition of the brain, however, will not reveal anything remotely resembling feeling, sensation or conscious experience. In classical physics, solving the mind-brain problem is a difficult task because no physical mechanism is able to explain how the brain creates an imperceptible, internal psychological world of conscious experiences and how these conscious experiences direct underlying brain processes toward desired behavior. Modern quantum physics asserts an interplay between two types of physical entities in Hilbert space: unobservable quantum states, which are vectors that describe what exists in the physical world, and quantum observables, which are operators that describe what can be observed in quantum measurements. The quantum no-go theorems provide a framework for studying the quantum dynamics of the brain, which must be governed by a physically acceptable Hamiltonian. Encompassing consciousness from imperceptible quantum information integrated into quantum states of the brain explains the origin of the inner privacy of conscious experiences and reexamines the dynamic time scale of conscious processes to picosecond conformational transitions of neural biomolecules. The observable brain is an objective construction created from classical bits of information, which are bound by Holevo's theorem, and obtained by measuring quantum brain observables (In physics, in the area of quantum information theory, Holevo's theorem (sometimes called Holevo's bound, since it establishes an upper bound) is an important limiting theorem in quantum computing which was published by Alexander Holevo in 1973. According to the theorem, the amount of information accessible given a quantum state ρ is limited by its Holevo information9. of the perceptive brain and supports a solid physical foundation for the exploration of consciousness.

Although quantum physics replaced classical physics a century ago, current neuroscience is still based on classical principles. This conservative approach denies any essential role for quantum effects in relation to consciousness and assumes that brain processes associated with input, processing, storage and output of classical information are sufficient to explain consciousness. Restricting quantum theory to the narrow region where quantum physical systems exhibit classical behavior, however, leads again to classical functionalism, epiphenomenalism, and the notorious hard problem of consciousness (Chalmers, 1995). The characteristic features of classical behavior are the observability and communicability of classical information, and the deterministic temporal evolution of physical states (Susskind & Hrabovsky, 2013). Classic information encoded on a physical carrier can be read and copied to a new carrier. If the old copy is preserved intact in the copying process, classical information can be duplicated. Changing the nature of the physical carriers (eg from massive electrons to massless photons) allows classical information to be broadcast to a distant receiver where it is recorded and stored.

Functionally, neurons encode and transmit classical information in terms of electrical spikes. Neuronalelectrical activity is a consequence of ion flows through excitatory or inhibitory ion channels embedded in the excitable plasma membrane. Sodium (Nav), potassium (Kv) and calcium (Cav) voltage-gated ion channels are instrumental for most neurophysiological processes, which selectively conduct Na+, K+ or Ca2+ ions down ion concentration gradients (Georgiev & Glazebrook, 2014). The voltage sensor derives an electrically charged α-helix within each domain of the α-subunit of ion channels. Macroscopic electrical currents flow through a rich repertoire of neuronal voltage-gated ion channels, the opening of which is regulated by the local voltage across the plasma membrane (Georgiev, 2015). As a result, the transmembrane voltage of the neuron undergoes dynamic changes in time. Pyramidal neurons are quiescent if the transmembrane voltage in the soma and initial segment of the axon does not exceed a threshold value of about −55 mV (Gasparini et al., 2004). When a threshold voltage is reached, the neuron fires a short electrical spike that propagates down the axon to activate synapses that innervate other target neurons. Glial cells, including astrocytes and oligodendrocytes, maintain the homeostasis of electrolytes and other biologically active substances in the brain, thus feeding and nurturing easily vulnerable neurons (Verkhratsky & Nedergaard, 2017). Using electrical spikes that propagate within the neural network, the brain is able to perform various computational tasks. Yet the difficult problem of consciousness is to explain why neural computation in the brain creates any conscious experiences at all (Chalmers, 1995).

Quantum information is a new type of information that is stored in the quantum states of quantum physical systems. Quantum information cannot be converted into classical information, which means that it is not contained in the mathematical description of the quantum physical state Ψ, but is found in the physically existing substrate denoted by Ψ. That is, just as a map is not a territory, the quantum physical state Ψ of, say, an electron written as a mathematical symbol on a sheet of paper is not the same as the quantum state of an electron in quantum physical reality. This needs to be understood if one wants to overcome the possible discomfort arising from being fixed in quantum mechanical expressions for Ψ while mathematically deriving, for example, that Ψ is not observable (Georgiev, 2017). Quantum information is a new type of information that is stored in the quantum states of quantum physical systems. 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The two main laws of quantum physics are the Schrödinger equation (Hayashi et al., 2015), which governs what physically exists and how it changes in time, and the Born law (Busch et al., 2016), which governs what it can be observed or measured by physical devices. Our conscious minds exist in a physical universe where causally powerful agents are able to control our behavior and transform the world around us (Yablo, 1992; Crane & Brewer, 1995; Jackson, 1996). Therefore, if we want to have a scientific theory of consciousness, conscious experiences should be represented in physical equations and must be governed by physical laws (Georgiev, 2013, 2017). In the classical world, all physical quantities are visible and communicable. This severely limits the scope of classical physical theories because unobservable and incommunicable consciousness cannot be reduced to anything that is already present in the physical equations. Instead, consciousness must somehow appear as a functional product of the observed brain, which will turn the resulting consciousness into a useless, causally ineffective epiphenomenon overcome by the deterministic laws of classical physics (Georgiev, 2019). However, in a quantum universe consisting of unobservable and non-transmissible quantum information, epiphenomenal consciousness can be avoided by quantum indeterminism, and the puzzling inner privacy of consciousness can be seen to originate from the physical properties of quantum information integrated into the quantum states of the cerebral cortex (Georgiev, 2017, 2020). ; Melkikh & Khrennikov, 2015; Melkikh, 2019). In a quantum reductive approach to consciousness, conscious experiences are equated with quantum brain states, which are in some relevant sense private or non-communicable. When we introspect our quantum states of consciousness, we are able to report only a certain amount of classical information that does not exceed the Hall limits. The incommunicable qualities of conscious experiences, accessed privately through introspection, then correspond to quantum information that cannot be converted into classical information. This non-transferable quantum information is inaccessible to external observers. So introspection is not equivalent to quantum measurement. We continuously experience the contents of our conscious mind, which means that introspective access to our inner mental world, made possible through the identity relationship between consciousness and the quantum information contained in the brain's quantum state Ψ, is continuous and not discrete. The unitary quantum evolution of the brain's quantum state Ψ, which among other things also leads to the entanglement of different brain subcomponents, describes changes in imperceptible conscious experiences and their connection or composition. Quantum measurements of the brain are discrete events performed by effector organs such as muscles or glands, which respond to neuronal electrical impulses emitted by efferent axon terminals. Glia cells, which feed neurons, perform quantum measurements on brain neurons in order to maintain proper homeostasis of brain electrolytes or other chemicals. Measuring quantum brain observables using glial cells, effector organs, or physical devices leads to decoherence of the quantum brain state Ψ and extracts the available classical pieces of information from which the "observable brain" is constructed. Thus, quantum information theory addresses the mind-brain problem using the dichotomy between quantum state vectors and quantum observables. Quantum physical laws, expressed in Schrödinger's equation and Born's rule, introduce a paradigm shift in the study of consciousness by subjecting all physical statements about the mind or brain to mathematical precision. General statements that hold for all physically acceptable Hamiltonians, which govern the dynamics of a quantum system, are subject to quantum prohibition theorems. This can solve philosophical problems just by considering the physical properties of quantum information without the need to explicitly solve any equations. Specific statements valid for a concrete biomolecular Hamiltonian, however, require quantum chemical methods for numerical solving the many-body Schrödinger equation. Currently available supercomputers make it possible to perform and experimentally test quantum predictions for physical systems consisting of several thousand atoms. The future development of faster supercomputers and better techniques for solving the Schrödinger equation numerically will enable an even tighter integration of quantum physics into consciousness research.

- quantum computer in the brain

„Might we, ourselves, be quantum computers, rather than just clever robots who are designing and building quantum computers?“

Matthew Fisher, Physicist, 2020.

Quantum theory frames our physical reality in ways like a philosophical or psychological thought experiment rather than physics. The observer is inseparable from the observed. Everything looks and behaves as if it is interconnected even if we don't know why. You cannot determine in advance how a photon will behave; you can only observe it from one perspective and watch it change, almost in response to your observation. Things can be off and on at the same time. Being able to turn on and off, 0 and 1, at the same time makes things run exponentially faster. If these were human traits, they would point to a refusal to recognize boundaries, a willingness to live with ambiguity, and an openness to the dynamics of constant change. Recent research into the quantum attributes of our brains suggests that quantum traits are human traits - that our brains can be described as (slightly slimy and meaty) quantum computers.

Scientists at the universities of Bonn and Tübingen have linked "simple processes" to our identities as quantum computers. Researchers have found "abstract codes" for processing arithmetic - especially addition and subtraction - in the brain. They found that the neurons that fire during addition are different from those that fire for subtraction problems, and that different parts of the brain are deployed for diagnosis and problem solving. One of the researchers explained: "We found that different neurons fire during addition than during subtraction, it's like the plus key on a calculator keeps changing its position. It was the same with confiscation." conducted research shows that different neurons are activated for different cognitive functions, and the brain is able to learn the difference between these functions.

By reviewing older research, we find further connections between human brain activity and quantum mechanics. In learning tasks, recurrent neural networks "not only learn the prescribed input-output relation, but also the order in which the inputs are presented." They also learn to interpret what to do "if the order of presentation changes." Meaning in natural languages goes beyond the mere matching and computation of symbols; language entanglement is quantum entanglement.

The case is compelling and consistent that one might ask, is the brain a quantum computer, or is quantum mechanics, our systematic perception and interpretation of quantum reality, modeled after our own brains?

The goal of a quantum computer is to perform calculations that would be too intensive and impractically long for a classical computer. One such computation that a quantum computer is often said to be able to do much more efficiently than standard classical computers (a computer that is ubiquitous today) is the factorization of very large numbers. Multiplying two large numbers is easy for any computer. But calculating the factors of a very large number is not an easy task. The challenge of breaking apart large numbers after encryption is what secures the internet and protects communications, our bank accounts and other sensitive data. Will quantum processes render these encryptions useless in the future?

It is possible that quantum computers will usher in a new era for neuroscience and understanding the brain. It may even be the only true way forward. But as of now, actually building functional quantum computers with qubits stable enough to outperform classical computers at even modest tasks remains a work in progress. Although there are several commercial attempts that have shown varying degrees of success, there are still many difficult hardware and technological challenges. Some experts argue that quantum computers may ultimately never be built due to technical reasons. But there is a lot of research around the world, both in academic labs and in industry, that is trying to overcome these engineering challenges. Neuroscientists will have to wait a little longer.

If the human brain does indeed contain a quantum processor, we should not be blind to the possibility that everyone should be able to perform complex calculations (and more). A possible reason why these superhuman feats are uncommon is that the classical processor activities in the human brain are dominant in most people. When the classical processor is damaged or dysfunctional, as in autistic learners, these abilities can come to the fore. These savants might even be forced to use their 'quantum processor' in the absence of a proper classical processor.

So many of these math experts can't add or subtract (the 'classical' processors in their brains don't work), but they can factor incredibly large numbers using the quantum processors in their brains. It is likely that more successful scientists use both quantum processes in their brains, along with classical processing, to solve problems.

Many of the observations mentioned may not be so obvious in a normal brain. However, this becomes more apparent when researchers study split-brain patients or autistic scholars. The 'human computers' we have been discussing can be as easily distinguished from ordinary people as quantum computers are from classical computers, in terms of their capabilities. It is also equally likely that the normal human brain uses both classical and quantum processors, very similar to today's quantum computers. Further research is needed to unravel the complexity of brain functions.

The researchers' observations say that the left hemisphere of the human brain works analogously to a classical processor in a computer with the right hemisphere acting as a quantum processor. The brain as a whole is equipped with both a quantum processor and a classical processor, where the classical processor feeds or interprets the data that goes to or comes from the quantum processor. This is remarkably similar to the architecture of current quantum computers.

When computers are used to test whether certain numbers are prime, they use sophisticated algorithms that involve many shortcuts. The neurologist O. Sacks, who studied many of these scholars, did not say that they were human computers rapidly performing millions of calculations per second - serially, one after another, or in parallel, all at once - because he thought that the processes they used could not be achieved by an algorithmic process (Sacks, O., 1985). Perhaps such fast calculations are "non-algorithmic" based on what O. Sacks knew about computers, which were then mostly standard classical computers. But what about a computer that uses quantum algorithms that exploit quantum superposition?

Superposition is the core of quantum computing. Ordinary computers work with bits that can be on or off, coded as one or zero. Two bits can represent only 1 quantum state at any given moment in time. However, quantum computers work with qubits, which can have a value of 0, 1, or both at the same time! So two qubits can represent four states simultaneously (00, 01, 10, 11) which—when extrapolated to 100 qubits—can represent 1.3 quadrillion quadrillion states simultaneously! This means that a quantum processor in a computer would be much faster and more efficient in some types of calculations than a classical processor would be (Naughton, J., 2019).

Researchers at the University of New South Wales (UNSW) have created the first working quantum bit based on the nuclear spin of a single phosphorus atom, inside a protective layer of zero-spin non-magnetic silicon atoms. (Pla, J., Tan, K., Dehollain, J., Lim, W., Morton, J., Zwanenburg, F., Jamieson, D., Dzurak, A., & Morello, A., 2013)

Because the nucleus of a phosphorus atom has a very weak magnetic field and has the lowest spin number of ½ (meaning it is less sensitive to electric and magnetic fields), it is almost immune to magnetic noise or electrical disturbances from the environment. It is additionally 'protected' from noise by a surrounding layer of silicon atoms with zero spin. Consequently, the nuclear spin has a longer coherence time which allows information to be stored in it for longer, resulting in a much higher level of accuracy. Using essentially the same set-up, M.Fisher proposed a model in which nuclear spins in phosphorus atoms in the human brain can serve as qubits (the element phosphorus is abundant in the brain) (Fisher, M. P. A., 2015).

Fisher claims that the spins of the phosphorus atom nuclei in the human brain can be sufficiently insulated by the protective cloud of electrons around them and the protective shield of the zero-spin layer of atoms. Phosphorus in our brains is also less 'disturbed' by quantum noise due to its weak magnetic field (due to its low spin number), allowing it to preserve quantum coherence as UNSW researchers have confirmed. Thus, in an environment such as the brain where electric fields abound, the nuclei of phosphorus atoms would be in a sufficiently isolated environment to store quantum information. There is, in theory, a viable proposition that the brain could work like a quantum computer!

Thus, the brain is a vast network of densely interconnected cells consisting of about 171 trillion brain cells - 86 billion neurons, the main class of brain cells involved in information processing, and another 85 billion non-neuronal cells. There are approximately 10 quadrillion connections between neurons — that's a '1' followed by 16 zeros. And of the 85 billion other non-neuronal cells in the brain, one major type of cell called astrocytic glial cells has the ability to both listen to and modulate neuronal signaling and information processing. Astrocytes form a massive network on themselves, while also communicating with a network of neurons. The brain actually has two different networks of cells. Each of them performs different physiological and communicative functions, but at the same time they overlap and interact with each other.

On top of all that structure, there are billions and billions and billions of discrete electrical impulses, called action potentials, that act as messages between connected neurons. Astrocytes, unlike neurons, do not use electrical signals. They rely on a different form of biochemical signaling to communicate with each other and with neurons. So, a whole molecular mechanism of information signaling is at play in the brain.

Somehow, in ways that neuroscientists still don't fully understand, the interactions of all these electrical and chemical signals carry out all the calculations that produce everything the brain is capable of.

Now pause for a moment and consider the countless number of dynamic and ever-changing combinations that the state of the brain can assume given this complexity. Yet it is this combinatorial space, the computations that produce trillions of signals and billions of cells in a hierarchy of networks, that result in everything your brain is capable of doing, learning, experiencing, and perceiving.

Therefore, any computer simulation of the brain will ultimately be very limited. At least on a classic computer.

How large and complete are the largest brain simulations made to date? And how much have they influenced the scientific understanding of the brain?

The answer depends largely on what is being simulated. At what scale - or scales - and with how much detail given the multitude of combinatorial processes. There are impressive attempts by various research groups around the world, but the amount of cells and brains that can be simulated, the level of detail and the amount of time that can be simulated remain quite limited. This is why headlines and claims about revolutionary large-scale brain simulations can be misleading, sometimes resulting in controversy and backlash.

Why could large-scale brain simulations be a real challenge for quantum computers?

First, by their very nature, given a sufficient number of qubits, quantum computers will excel at solving and optimizing very large combinatorial problems. This is an inherent consequence of the physics of quantum mechanics and computer design.

Second, given the sheer size and computational complexity of the human brain, any attempt at a large-scale, multi-scale simulation with sufficient detail will have to contend with the combinatorial problem space.

Third, the way a potential quantum computational neural simulation is set up could take advantage of the physics the brain is subject to. Despite its computational power, the brain is still a physical object, so physical constraints could be used to design and guide simulation rules (quantum computing algorithms) that are inherently combinatorial and parallel, exploiting what quantum computers do best.

Thus, local rules, such as the computational rules of individual neurons, can be used to compute aspects of the emergent dynamics of networks of neurons in a decentralized manner. Each neuron does its own thing and contributes to the larger whole, in this case the functions of the whole brain, all acting at the same time without being aware of what they are contributing to.

Ultimately, the goal will be to understand emergent brain functions that lead to cognitive properties. Large-scale quantum computer simulations can reveal latent (hidden) properties and states that are only visible at the level of the whole brain, but cannot be calculated without a sufficient level of detail and simulation at scales below it.

If these simulations and research are successful, one can only speculate about what the as-yet-unknown brain algorithms still need to discover and understand. It is possible that such future discoveries will have a significant impact on related topics such as artificial quantum neural networks or on specially designed hardware that could one day challenge the limits of existing computing systems. An international team of scientists and engineers has announced a computing 'hardware' device composed of molecular-chemical networks capable of energy-efficient fast reconfigurable) states, somewhat similar to the reconfigurable nature of biological neurons.

Perhaps neurons themselves could be tiny quantum computers in some future?

Conclusion

„To know that we know what we know, and to know that we do not know what we do not know, that is true knowledge“ Nicolaus Copernicus

“Build a strong base. The journey to peaks of excellence requires a strong base camp.” CNR Rao

We intertwine physics and neuroscience, quantum geometric information and philosophy as the focal spark of intelligent finance within the framework of the development of artificial intelligence as a thought process, as the basis of knowledge for the development of intelligent finance.

Why is interdisciplinary knowledge needed to develop and understand finance?

How to unite neuroscience and physics? (Van den Noort M, Lim S, Bosch P. 2016) Difficulties are not only fundamental, theoretical perspectives, but also of utmost importance for the development of more optimal treatments in clinical neuroscience.

Neuroscience is a relatively new research field, many discoveries are yet to come. Further technical progress is needed because the temporal resolution of currently available neuroimaging techniques is too slow (Meyer-Lindenberg A., 2010) to detect any kind of quantum processing in the human brain. To this day, we do not fully understand the basic physics of the brain; consequently, we are influencing processes (when using brain stimulation for clinical purposes in neuroscience) that we do not fully understand. An understanding of the processes underlying the brain is necessary before these brain stimulation treatment techniques can be applied without any risks. (Van den Noort M, Lim S, Bosch P. 2014) Is it time to rethink physics, (Penrose R. 2016) and although classical and quantum mechanics helped us to describe nature; in fact, what is really needed to take the next step is to consider the whole universe/nature as simple information (Verlinde E., 2016) in which the human brain/organism is just a tiny information processing system embedded in and interacting with that universe/nature . (Raichle ME. , 2006).

In intelligent finance, we need the application of refined physics methods to the busy world of the market, this implies theories of neuroscience and information, which is the basis of artificial intelligence tools in the knowledge of new algorithms, because finance is one of the most complex activities of human action.

And finally, we should briefly refer to: entanglement is a fundamental property of any quantum theory. In fact, Einstein was one of the first pioneers of quantum theory to notice entanglement (his scientific work on the subject is also known). Einstein thought that entanglement was a property that could be used to prove that quantum theory was incomplete. Unfortunately, he was wrong. The irony is all the greater because the same kind of mathematical prediction led to the theory of relativity: the theory of electromagnetism predicts that the speed of light is constant in all reference frames, just as quantum theory predicts the existence of entanglement. The reason Einstein was able to come up with relativity is because he was the first to take seriously the mathematical prediction of a constant speed of light. If Einstein had done the same with entanglement, he might have invented quantum computing 50 years before it was actually done.

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