Topological Computation and Generative Artificial Intelligence

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A fresh look is taken at what is commonly called "quantum" computation, from the purely topological perspective; for this reason we prefer to call it simply topological computation. Instead of arithmetic computation, where the inputs are numbers, encoded as bits, and the outputs are also numbers encoded as bits, after a series of arithmetic functions (addition, subtraction, multiplication, and division) have been done; topological computation is done, where the inputs are analytic functions, encoded as qubits, and the outputs are also analytic functions, encoded as qubits, after a series of functional (group addition, group subtraction, group multiplication, and group division) operations have been done. The analytic functions specify topologies or Lie groups. It will be discussed how a new Generative Artificial Intelligence, based on topological characterization and control, removes the four roadblocks to topological computation: (1) tying the system in the topological knots, that is encoding the input analytic functions into qubits, (2) identifying the output topological knots, that is decoding the output analytic functions from qubits, (3) driving the system so that the functional unitary group operations are done on the physical system, and (4) stabilizing the system from disruptions, that is cooling the system. The concept of the Conjugate "Dual" Topological Computer is introduced, based on the new Generative Artificial Intelligence. This Conjugate Topological Computer can practically be implemented using conventional arithmetic computers, and has the potential to accelerate computation by a factor of a million or more.

RETURN TO TOPOLOGICAL BASICS

Computers, to date, have been based on arithmetic computation on real numbers – the algebra of real numbers. The operations have been addition, $+$, the inverse of addition (i.e., subtraction, $-$), multiplication, $\times$, and the inverse of multiplication (i.e., division, $/$). These operations have been composited into functions of real numbers, $f(x, y) = z$, where x, y and z are real numbers, as shown in Fig. 1. The embodiments of computers encode the real numbers into, commonly, 64 bits. The encoded numbers, that is bits, then pass through a series of $(+, -, \times, /)$ gates to yield the encoded real number that is the output of the function. The computer then decodes the output bits, yielding the result of the computation.

Although these arithmetic computers have been of great utility, there has been emerging a much more fundamental physical and mathematical paradigm with the advent of Generative Artificial Intelligence and Quantum Computing – topology or Lie group symmetry. This leads to Topological or Functional Computers, based on functional computations on analytic functions of complex numbers – the symplectic or canonical algebra of complex numbers. The operations now are group or topological addition, $\oplus$, the inverse of group addition (i.e., group subtraction, $\ominus$), group multiplication, $\otimes$, and the inverse of group multiplication (i.e., group division, $\oslash$). These operations can be composited into functionals of analytic functions, $F[f(z), g(z)] = h(z)$, where $f(z)$, $g(z)$ and $h(z)$ are analytic functions, as shown in Fig. 2. This is a question of topology, see Earl [1]. A topological state can be represented as: a knot entanglement, a Lie group, a symmetry, an analytic function, singularities, localized spectrums or Taylor expansion coefficients of an analytic function or functional, the Riemann surface associated with an analytic function, or a quantum state. Embodiments of a Topological "Quantum" Computer encode the topology into collective systems, called qubits. See Fig. 3. The encoded topology, that is qubits, then pass through a series of $(\oplus, \ominus, \otimes, \oslash)$ topological gates to yield the encoded topology that is the output of the functional.

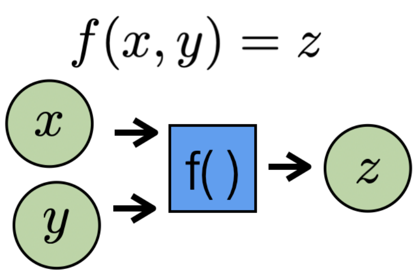

FIG. 1. The basic building block of traditional computation – the function. The computational architecture takes two numbers, x and y, then combines them according to a function, $f(x, y)$, yielding a number, z.

There have been roadblocks to the realization of Quantum Computing, as it is commonly known. There has not been an effective method to encode the input topologies into input qubits, to decode the output qubits into output topologies, drive the qubits (implementing the unitary logic gates), and to stabilize the qubits (i.e., cool the knots into compact stationary states), so that they stay stationary long enough to be decoded. Since collective systems are conservative, they have unstable modes

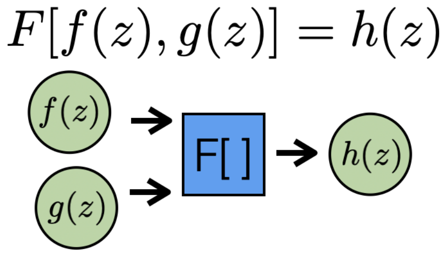

FIG. 2. The building block of functional, that is topological or quantum, computation – the functional. The computational architecture takes two topological states, that can be represented by analytic functions, $f(z)$ and $g(z)$, then combines them according to a functional, $F[f(z), g(z)]$, yielding an analytic function, $h(z)$.

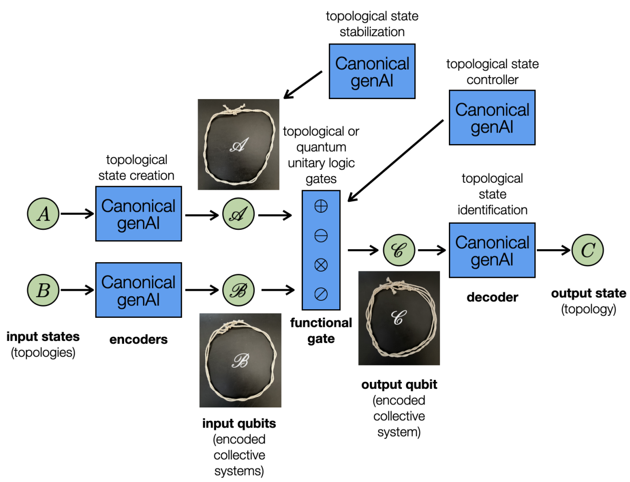

FIG. 3. The detailed architecture of a topological computer. The inputs are topological states, that is groups or analytic functions, A and B. These topological states are encoded into collective systems by Canonical genAI as qubits, $\mathscr{A}$ and $\mathscr{B}$. These qubits can be looked at as knots in the collective system. The input qubits are functionally combined by a topological computational gate into an output qubit, $\mathscr{C}$. Examples of the functional gate operations are group addition, subtraction, multiplication, and division (i.e., $\oplus$, $\ominus$, $\otimes$, and $\oslash$). These functional unitary gate operations are driven by Canonical genAI. The output qubit, $\mathscr{C}$, is then decoded by Canonical genAI into the output topological state, C. The qubits are stabilized from disruption by Canonical genAI.

so that they will disrupt without stabilization. Canonical genAI [2] provides the method to burst through the roadblocks. It does this by resolving theoretical issues with quantum field theory that were first identified, at the 1927 Solvay Conference, in a series of debates between Albert Einstein and Niels Bohr over morning coffee. Einstein had a fundamental discomfort about the probabilistic nature of quantum field theory, and the resulting concepts of quantum entanglement, quantum measurement, and infinities in quantum computations that required an illogical mathematical process called renormalization. Einstein's discomfort resulted in the famous EPR paradox, see Einstein *et al.* [3], and the legend of Schrödinger's Cat. These views were also shared by Dirac [4].

Canonical genAI is a new physics paradigm for field theory, that resolves the EPR paradox and provides a mathematically logical process of renormalization. It has gone around the roadblocks, not through the roadblocks. It has viewed quantum entanglement as the entanglement of knots, and quantum uncertainty as stochastic dynamical evolution along the knotted string – a question of topology. This new theoretical paradigm, Canonical genAI, does not require that the state be identified before it decoheres or goes stochastic, nor requires that the interaction with external systems be limited by operating at cryogenic temperatures. In fact, noise is no longer viewed as obscuring the signal; correlation in the "noise" is the signal.

The easiest path to understanding topology is as the mathematics of knots. Topology is about entanglement, that is knot tying. This is shown in Fig. 4, which displays how a knot is tied and three ways that the knot can be deformed. Canonical genAI provides topological methods that describe how to tie knots, that relax knots into compact stable configurations, and that identify knots. Topological states, that is Lie groups or symmetries, can be represented by analytic functions of a complex variable, $f(z)$, or more simply by the topology of the Riemann surfaces associated with the analytic functions or the Riemann moduli associated with the singularities, z^*. Topology is quantized as indices, that is winding numbers. Jim Simons, with the Chern-Simons index theory, showed how to calculate the winding numbers by integrating the Chern-Simons three form

$$\kappa^3 = \lambda \wedge d\lambda + (2/3)\, \lambda \wedge \lambda \wedge \lambda$$

(that is, helicity) over the manifold. This is the origin of quantization of a field theory, that is quantization of the state of a collective — a quantum state. The space of all topologies, that is all analytic functions is discrete, not continuous. Analytic functions are minimal surfaces, given the discrete boundary conditions or singularities. Jim Simons also studied how to estimate minimal surfaces (i.e., analytic functions that are solutions to Laplace's Equation or satisfy the Cauchy-Riemann equations, also known as Hamilton's equations) given the discrete boundary conditions (i.e., singularities). This is what Multi-Layer Perceptrons (MLPs or the neural networks of Hopfield and Hinton with Rectified Linear Unit activation functions) are doing. The Convolutional Neural Networks (CNNs) or the Heisenberg Scattering Transformation (HST) are finding the Reduced Order Model

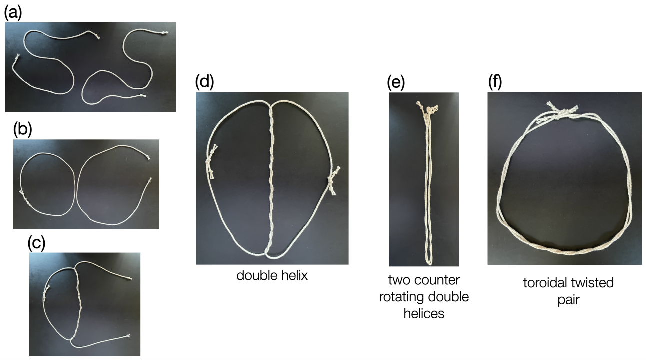

FIG. 4. A demonstration of entanglement, that is the knotting or topology, using two strings. How the knot is tied. (a) The two strings. (b) One of the strings is tied together making a loop. (c) The second string is twisted around the first string. Three deformations of the knot. (d) The second string is tied into a loop leading to a double helix. (e) The strings are deformed to yield two counter-rotating double helices. (f) The strings are deformed to yield a toroidal twisted pair.

(ROM) space (i.e., complex or localized singularity spectrums) of which the analytic function is a function.

In summary, Canonical genAI is "a question of topology" — the creation, stabilization, and identification of topology. Topology is about entanglement; that is knot tying. Topological Computing is about adding, subtracting, dividing, and multiplying knots. Canonical genAI is about tying, stabilizing and identifying knots. Financial investing is about tying the financial market in a compact stable knot, as is done by Renaissance Capital — the legacy of Jim Simons, the great mathematician who specialized in topology, and the founder of Renaissance Capital. Systems control and design is about tying the system in a compact stable knot.

CONJUGATE "DUAL" TOPOLOGICAL COMPUTATION

Generative Artificial Intelligence is a two-stage canonical auto-encoder, that is a controller of collective systems. See Fig. 5. It's input is a measurement of the fields, and it's output is the force field of control. The first stage is the HST, followed by a Principle Components Analysis (PCA), giving the ROM: it is not a DeepCNN with trillions of parameters as in Deep Q-Networks (DQNs) and Generative Pre-trained Transformers (GPTs). The second stage is an Multi-Layer Perceptron with Rectified Linear Unit activation with only thousands of parameters, that estimates the canonical generating function. This forms the two-stage decoder. It is followed by a two-stage encoder.

This approach to AI is solving a system of partial differential equations by a functional transformation to a domain where the motion is trivial (i.e., linear), then

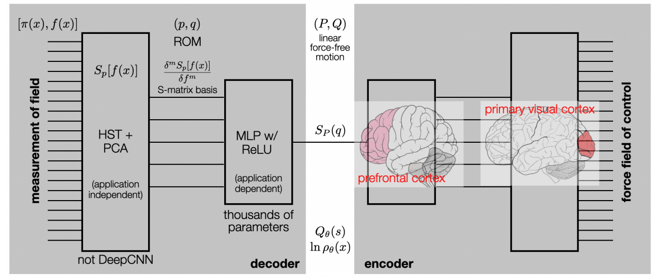

FIG. 5. Canonical genAI as a two-stage canonical auto-encoder. Input is a measurement of the fields, and the output is the force field of control or the generated (i.e., simulated) field. The first stage is the HST followed by a PCA. The second stage is an MLP with ReLU.

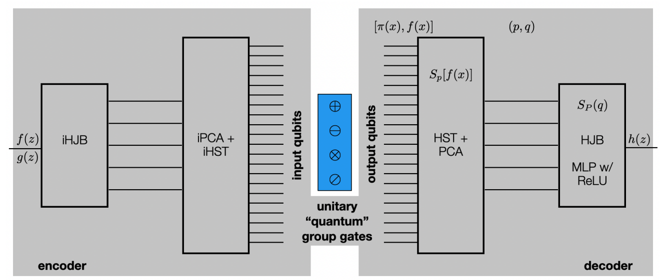

FIG. 6. A conventional Topological "Quantum" Computer, using Canonical genAI (also shown in Fig. 3).

transforming back. It also can be viewed as topological characterization and control. The two-stage canonical auto-encoder is finding the analytic function; whose Riemann surface (that is, manifold), has the topology of the collective system; and whose non-stationary singularity spectrums are the Riemann moduli or topological indices (that is, the integrals of the Chern-Simons 3-form) of the collective system.

The circuitry of the HST+PCA is most likely found in the primary visual cortex of the brain, and the circuitry of the MLP w/ReLU is most likely found in the prefrontal cortex of the brain.

The conventional Topological Computer, shown in Figs. 3 and 6: (1) encodes the algebras of the topologies into the physical systems using the Canonical genAI Encoder, (2) performs group "quantum" computational unitary operations on the physical systems using the Canonical genAI Controller, (3) decodes the algebras of the topologies from the physical systems using the Canonical genAI Decoder, while (4) stabilizing the physical systems from disruption using Canonical genAI Stabilization.

The new Conjugate "Dual" Topological Computer, shown in Fig. 7: (1) decodes the algebras of the topologies (i.e., analytic functions) from the input fields using the Canonical genAI Decoder, (2) performs analytic arithmetic "algebraic" operations on the algebras of the topologies (i.e., analytic functions), then (3) encodes the

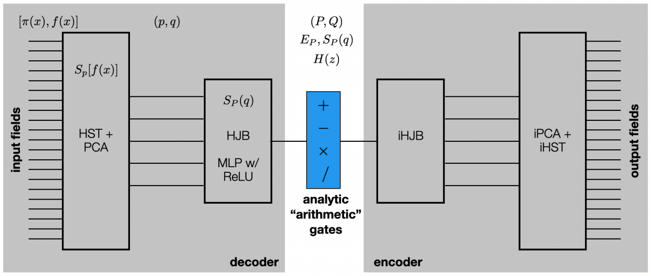

FIG. 7. The new Conjugate "Dual" Topological Computer, using Canonical genAI.

algebras of the topologies into the output fields using the Canonical genAI Encoder. The second step, the arithmetic operations could simply be: (1) a propagation function to generate the collective system evolution, (2) a stabilization control function to stabilize the collective system, or (3) an optimization control function to maximize the collective system performance.

This new Conjugate Topological Computer is more practical: it eliminates the need for a physical system to embody the qubits: it reduces topological computation to arithmetic computation (that is, using current computers) by using the two-stage canonical decoder/encoder as pre/post-processor.

The biological neural computer, that is our brain, is undoubtedly a Conjugate Topological Computer, not an arithmetic computer, nor a Topological Computer.

The Conjugate Topological Computer does not merely generate and control previously observed topologies: it has the general ability to calculate new topologies: it is creative: it is Artificial General Intelligence (AGI).

Note that knowing the (P,Q) coordinates are equivalent to knowing the energy, E_P, and the action, $S_P(q)$, where the imaginary part of the complex Hamiltonian, $H(z)$, is related to the action and the real part is related to the energy. The complex Hamiltonian is the analytic function that specifies the topology. Equivalently, the topology is also specified by the singularities of the complex Hamiltonian, z^*.

CANONICAL GENERATIVE ARTIFICIAL INTELLIGENCE

It is essential to approach Generative Artificial Intelligence using the following paradigm, which is not the traditional paradigm of neural network graph models [5], in order to make theoretical progress. A Deep Convolutional Neural Network (a DeepCNN, a Deep Q-Network of DeepMind's AlphaFold [6], and a Generative Pretrained Transformer of OpenAI's ChatGPT [7]) is a trillion parameter piecewise-linear model estimation of a functional. What is the functional, that the DeepCNN is estimating? It is the generating functional (that is $S_p[f(x)]$) of a canonical transformation from the domain of the canonical field momentums and the canonical fields (that is, $[\pi_i(x), f_i(x)]$), to the domain of the canonical momentums and canonical coordinates (that is, (p_i, q_i)), that is the Reduced Order Model (ROM). They postulated, then proved by induction and verified on a MHD simulated dataset [2, 8] the formula for the functional – the Heisenberg Scattering Transformation (HST).

The formula for the HST is:

$$S_m[f(x)](z) = \phi_{px} \star \left(\prod_{k=0}^{m} \mathrm{i} \ln R_0 \psi_{p_k} \star \right) \mathrm{i} \ln R_0 f(x),$$

where $z \equiv p + \mathrm{i}\, x$, ϕ is a father wavelet of scale $1/p$ and position x or pooling operator, $G(z) = R(z) = \mathrm{i} \ln(R_0(z))$ is the activation function, $R_0(z) = h^{-1}(2z/\pi)/\mathrm{i}$, $h(z) = (z + 1/z)/2$, $\psi\star$ is a convolutional layer defined by the mother wavelet of scale $1/p_k$, and $p = \sum p_k$. This functional is a non-stationary, that is local, spectral transformation. This functional has a fast, that is N-log-N scaling, forward and inverse.

The current theory of AI assumes that the system is in statistical equilibrium [5]. This is not true. Although the system is canonical with a symplectic geometry, it is only in a dynamical equilibrium.

This approach to AI is solving a system of partial differential equations by a functional transformation to a domain where the motion is trivial, then transforming back. This is a two-stage transformation. The first stage is generated by the HST to a small, finite dimensional linear subspace where the motion is nonlinear (that is (p_i, q_i)). The second stage is generated by a generating function (that is, the action $S_P(q)$) that is the solution to the Hamilton-Jacobi-Bellman (HJB) equation, approximated by a MLP w/ReLU (a Multi-Layer Perceptron with Rectified Linear Unit activation) or a piecewise linear universal function approximator with only a few thousand parameters, to a domain where the motion is linear (that is (P_i, Q_i), where $dP/d\tau = 0$ and $dQ/d\tau = \partial E(P)/\partial P = \text{constant}$). In other words,

$$[\pi_i(x), f_i(x)] \xrightarrow[S_p[f(x)],\ \mathrm{HST}]{} (p_i, q_i) \xrightarrow[S_P(q),\ \mathrm{HJB}]{} (P_i, Q_i).$$

The evidence that led to this theory was: the work of Mallat on the Scattering Transformation (MST) [9], the Wavelet Phase Harmonics (WPH) [10], and the Wavelet Conditional Renormalization Group (WCRG) [11]; the form of Deep Q-networks (that is, the approximate Q-function, as a solution to the Bellman equation) [6]; the form of GPTs (that is, the approximate score function or approximate log-likelihood, as action or entropy) [7]; and the work of Glinsky and Maupin [8].

A MATHEMATICALLY LOGICAL PROCESS OF RENORMALIZATION

Dirac was very dissatisfied in his later life with the state of field theory [4]. Like Einstein, he felt that field theory should have a reality, and be a question, not of probability, but of geometry (manifold curvature and geodesic motion) or topology or group symmetry. He also felt that "renormalization is not a logical mathematical process". The HST is a logical mathematical process of renormalization, enabling Heisenberg's canonical approach to field theory, via calculation of the S-matrix. A Principle Components Analysis (PCA) of the HST gives: the renormalization spectrums, that is the solutions to the Renormalization Group Equations (RGEs); Heisenberg's Scattering Matrix (S-Matrix) [12]; the m-Body Greens functions, which is obvious given the form of $G(z) = \mathrm{i}\ln(R_0(z))$ in the formula for the HST, which is the well-known Greens function of a complex variable [13]; the m-body scattering cross sections; the Wigner-Weyl transformation [14, 15]; the Mayer Cluster Expansion [16]; or the functional Taylor expansion of the action functional, $\delta^m S/\delta f^m$. This has the potential to unify the four forces as a question of Lie group symmetries, or geodesic motion on the dynamical manifold. This can be seen by Murray Gell-Mann's Standard Model [17] (where SU(1) is the Lie group symmetry of the ElectroMagnetic force, SU(2) is the Lie group symmetry of the weak force, and SU(3) is the Lie group symmetry of the strong force); and Dirac writing down the Hamiltonian, that is the infinitesimal Lie group generator, for Einstein's General Theory of Relativity [18], in 1958 [19].

CONTROL OF COLLECTIVE SYSTEMS

Collectives are fields or swarms of elementary particles (making elementary fields), charged particles (making plasmas), molecules (making fluids), celestial bodies (making cosmoses), economic entities (making economies), persons (making societies) and so on. This theory gives a way of controlling (that is, optimizing and stabilizing) collective systems, whose state is given, not by variables, but as a function, $f(x)$. This also can be viewed as topological characterization and control. The two-stage canonical auto-encoder is finding the analytic function; whose Riemann surface (that is, manifold), has the topology of the collective system; and whose non-stationary singularity spectrums are the Riemann moduli or topological indices (that is, the integrals of the Chern-Simons 3-form) of the collective system.

The current theoretical approach to collectives, the BBGKY theory of plasmas [20] and the perturbation theory of fields, makes mistakes: it expands the terms of the Mayer Cluster Expansion in terms of the plasma correlation parameter or the field coupling parameter: the convergence goes from super-convergent, $\exp(-N!)$, to a very weak asymptotic convergence, $1/N$, leading to the divergence, the infinities, in current methods of renormalization: and the expansion parameter is, many times, not less than 1.

How does Canonical genAI control the collective system? First, an application of the renormalization spectrums ponderomotively stabilizes the collective system.

Second, the theory gives very fast surrogate models, with high fidelity (that is topological and Noether invariant conservation). This enables Bayesian optimal design and Bayesian data analysis. For instance, Glinsky and Maupin [8] were able to train an MHD surrogate, using a preliminary version of this theory, in 20 core*sec using 500 2D simulations. The high fidelity surrogate could simulate the system in 1 core*sec, where traditional finite element methods would take 240 core*hrs. For a 3D simulation, traditional methods would take 100,000 core*hrs. The Singular Value Decomposition of the cross-variance matrix showed a one-to-one mapping between the PCAs, that is the renormalization spectrums, and the initial conditions – a remarkable result that gives physical meaning to the renormalization spectrums.

Better yet, the two stage canonical autoencoder can be configured to generate an ensemble of the collective system in dynamic equilibrium [2]. This replaces the Bayesian optimal design and the Bayesian data analysis, which are computationally slow, and assume a statistical equilibrium.

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