CMOSpacetime: Geometric/Algebraic Complex Analysis of Intelligence/Quantum Entanglement/Convergent Evolution

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No truth is truly true, the more we reveal the more we revere nature on our voyage of unprecedented discovery. We argue the soul or anti-soul of Complex Multiscale Orbifold Spacetime (CMOSpacetime) is the origin of intelligence, and the metric of metrizable intelligence is the sectional curvature's absolute value of CMOSpacetime's soul or anti-soul. We also argue the intersecting souls and/or anti-souls , when their sectional curvatures approaching positive infinity and/or negative infinity as singularity, is the origin of quantum entanglement. We further argue the sectional curvatures of CMOSpacetime's intersecting souls and/or anti-souls , is the origin of convergent evolution through conformal transformation. We derive CMOSpacetime, a N-dimensional orbifold $\mathbb{O} = \mathbb{M}/\mathbb{F}_{\mathfrak{d}}$ ($\mathbb{M}$ as manifold)/degree N projective algebraic variety $\mathbb{X}$ over $\mathbb{C}^N$ defined by degree N non-linear polynomial function $\mathbb{F}_{\mathfrak{d}}(X_1, ..., X_N) = \sum_{i,j=1}^{N}(w_i X_i^j + b_i)$ in hypercomplex number system with $X = x_1 + \sum_{m=2}^{N}(x_m i_m)$ on Non-Abelian quotient group $SO(\frac{N}{2}, \frac{N}{2})$ ($8 \leq N \to \infty, N = 2^n$), neural networks by correlating general relativity and quantum mechanics based on mutual extensions from 3+1 dimensional spacetime $\mathbb{R}^4$ to N-dimensional CMOSpacetime $\mathbb{C}^N$. CMOSpacetime addresses both singularity and non-linearity as common issues faced by physics, AI and biology, and enables curvature-based second order optimization in orbifold-equivalent neural networks beyond gradient-based first order optimization in manifold-approximated a adopted in AI. We build CMOSpacetime theoretical framework based on General equivalence principle, a combination of Poincaré conjecture, Fermat's last theorem, Galois theory, Hodge conjecture, BSD conjecture, Riemann hypothesis, universal approximation theorem, and soul theorem. We also propose experiments on measuring intelligence of convolutional neural networks and transformers, as well as new ways of conducting Young's double-slit interference experiment. We believe CMOSpacetime acting as a universal PDE, not only qualitatively and quantitatively tackles the black box puzzle in AI, quantum entanglement and convergent evolution, but also paves the way for CMOSpacetime synthesis to achieve true singularity.

Keywords: Complex Multiscale Orbifold Spacetime, General equivalence principle, Quantum entanglement, General relativity, Quantum mechanics, Convergent evolution, ASI, AGI, CPT Symmetry, Hypercomplex number system, Planck scale, Grand unified theory, Standard model, Black hole, Wormhole, Singularity, Analytical continuation, Activation function, Renormalization, Conformal transformation, Non-convex optimization, Geometrization, Algebraization, Differential geometry, Algebraic geometry, Differential algebra, Geometric algebra, Differential topology, Algebraic topology, Non-commutative geometry, Non-commutative algebra, Group theory, Number theory, Algebraic topology, Geometric topology, Functional analysis, Complex analysis, PDE, Dynamical Systems, Perturbation, Manifold, Tensor, Gradient, Sectional curvature, Uncertainty principle, Poincaré conjecture, Soul theorem, Galois theory, Fermat's last theorem, BSD conjecture, Hodge conjecture, Riemann hypothesis, Universal approximation, Deep reinforcement learning

So teach us to number our days that we may get a heart of wisdom-Psalm 90:12

Tua sublimitas tua asset, et minimum distantia nobis est curva sed recta linea

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I. INTRODUCTION

Eternity

If groups of ants in soil as spacial agents
Descending gudied by curvatures instead of gradients
Exploring and exploiting structural environments
Searching and researching origin of intelligence
Can they realize they are on earth
In solar system milkyway universe multiverse

So are frogs in well hawks under sky
And dog's year differs from human's year
And elephant in your eyes not the same as mine
Human in orbifolds just like ants in soils
Hindsight insight foresight aspiration inspiration passion
War peace love hate all gone with wind

On the journey human being's searching for beauty, simplicity and unification, whether in physics[113,114] or mathematics[13], from synthesis perspective, whether logic synthesis, physical synthesis, chemical synthesis, or biological synthesis, are all under the umbrella of commutative geometry and non-commutative geometry[26,32,34], or Euclidean, Riemannian/elliptic and Lobachevsky/hyperbolic geometries[60] as Higher dimensional Non-Euclidean geometry with zero, positive and negative Gaussian/sectional curvature respectively, all supported by commutative algebra and non-commutative algebra such as Clifford algebra, tensor algebra, spin (Dirac, Pauli) algebra, and von Neumann algebra More specifically, universal geometry, quantum geometry[48], and biological geometry[90,118] like conformal geometry[43,81], are the outcome of physical laws and biological laws in modeling nonlinear physical and biological dynamics, with applications adopting higher dimensional nonlinear manifold leveraging geometrization power frequently encountered in machine learning, deep learning[62] and deep reinforcement learning,[105] deep learning, with stochastic gradient/subgradient-descent or gradient-free approaches[12,35,36,49,64,119,120], and even orbifold with (as negative-curvature descent) or without adopting curvature-based approaches for higher dimensional unconstrained non-convex optimization[3,8,65,70,72,75,77,108].

With radical paradigm shift and impressive progress in both hardware and software, now we can adopt Artificial/Deep/Convolutional/Recurrent/Graph/Generative neural/Adversarial networks (ANN/DNN/CNN/RNN/GNN/GAN/QNN) with billions of connections, billions of parameters, and hundreds of layers for real-life applications on facial recognition, speech recognition, language translation through universal function approximation, since the breakthrough made by AlexNet pioneered by LeNet and powered by GPU, along with its same all man-made successors including VGGNet, GoogleNet, ResNet, and DenseNet on ImageNet benchmarks. However, the matter of fact is the degree of intelligence demonstrated by AI including deep learning[16] originated from perceptron, reinforcement learning, deep reinforcement learning,[73], AutoML[54] with or without[40] hyperparameter optimization, meta-learning, and neural architecture search (NAS)[121] and AutoDL all having exploration-exploitation trade-off dilemma, still falls far behind human intelligence in most cases. AI in adopting continuous optimization-centric gradient/subgradient-based deep reinforcement learning augmented with novel game theory such as mean field games, stochastic games, evolutionary games, beyond traditional and zero-sum game, and Convergent Evolution Strategies, as well as discrete optimization-centric gradient-free population-based genetic algorithms, has demonstrated awesome capability on beating human being in specific categories such as gaming. Since life is a game, so there is nothing wrong in tackling AI starting from gaming adopting deep reinforcement learning and evolution strategies as an alternative[93]: AlphaGo[98] AlphaZero,[99] DeepStack,[17] DeepCubeA,[102], and AlphaStar[5,110]. This is reasonable, think about that, even in modern time, since Wheeler synthesis and Miller-Urey Experiment, we have not yet figured out how to synthesize a cell, the basic unit of life.

Despite of its wild success in certain domains, AI, particularly deep learning, has a few issues such as model size blowup and performance bottleneck: imitation learning 100X more slower than human on learning how to drive, and much worse than that, reinforcement learning is 1,000X more slower than that of human. However, its biggest challenge lies on the black box puzzle and reproducibility crisis, though there were a few attempts[95,97], and its associated ad hoc hard-coded programming: no sharp physical intuition and solid mathematical formulation yet.

II. A FRESH LOOK AT SPACETIME

General relativity leads to spectacular predictions as black holes, gravitational waves, and the big bang in early universe in macroscopic way, as what quantum mechanics does in microscopic way. Various efforts on developing Grand unified theory such as quantum electrodynamics (QED), quantum chrome-modynamics (QCD), and the standard model in unifying weak force, strong force and electromagnetism, and gravity, with the ultimate goal as unifying quantum mechincs and general relativity $QM = GR$[20,104], have been made, yet results are not perfect so far. In general relativity the gravitational field is encoded in spacetime as (Lorentzian) pseudo-Riemannian manifold. However, general relativity only models stand-alone systems, there are boundary-induced genuine spacetime singularity-triggered concerns at big bang and inside black holes[82]. Furthermore, when the curvature of spacetime becomes large enough on reaching the order of $\frac{1}{P_l^2}$, quantum effects[57] have to be taken into consideration as they start to dominates general relativity effects so that such curvature induced coordinate quantum singularity-triggered[59] concerns can be eliminated. At Planck scale, we must use an extended version of spacetime that fit for both general relativity and quantum physics. There are efforts on extending 3+1 dimensional spacetime model such as Kaluza-Klein model by introducing extra space dimension(s), but never goes to infinite or close to infinite space dimensions, and never extend time dimension beyond one, let alone allow time reversal. The traditional claims on the impossibility of going beyond 4-D spacetime is due to their linear partial differential equations (PDE) assumption while nature is inherently nonlinear[107]. A nonlinear dynamical system often can be described in nonlinear differential equations, such as Yang-Mills equation in quantum field theory, Boltzmann equation in statistical mechanics, Navier-Stokes equations in fluid dynamics, Lotka-Volterra equations in ecology, and Michaelis-Menten equations in enzyme kinetics. The hardness on solving those PDEs exactly in continuous optimization space, is similar to solve NP-complete and NP-hard problems in discrete optimization space. Amazingly as Planck scale is man-made, we can go even smaller both physically by introducing CMOSpacetime as multiscale orbifold spacetime model in higher dimensional Non-Euclidean geometry (hyperbolic geometry as a special case) beyond pseudo-manifold model in Riemannian geometry.

III. GENERALIZING GENERAL RELATIVITY IN CMOSPACETIME

Based on general relativity, the Einstein field equations are formulated as follows and Wheeler[111] precisely summarize it as: matter tells spacetime how to curve, and spacetime tells matter how to move. In other words, gravity is geometry, matter sources gravity.

$$G_{\mu\nu} + \Lambda g_{\mu\nu} = 8\pi \frac{G}{C^4} T_{\mu\nu} \tag{1}$$

$$G_{\mu\nu} \equiv R_{\mu\nu} - \frac{1}{2} R g_{\mu\nu} \tag{2}$$

$\mu, \nu = 1, 2, 3, 4$ in (Lorentzian) pseudo-Riemannian manifold based 3+1 dimensional curved spacetime $\mathbb{R}^4$ on the action of Lie group SO(1,3) with metric signature (- + + +) adopting spacetime algebra[47], a Special Orthogonal (SO) finite dimensional Clifford algebra $Cl_{1,3}(R)$. Here $g_{\mu\nu}$ is metric tensor.

The initial value boundary problem in general relativity only gives us the metric on a patch of the spacetime. Other methods must be used to find the true global extension of that spacetime. Therefore, Einstein field equations alone cannot tell you the topology of the spacetime. Even ignore the above limitation, being nonlinear in nature, The general relativity Einstein field equations describe the relation between the geometry of a 3+1 dimensional (Lorentzian) pseudo-Riemannian manifold, as Einstein manifold.

As nonlinear PDEs in modeling dynamical systems, Einstein field equations are very difficult to solve. de Sitter spacetime is a solution of the vacuum Einstein equations with a positive cosmological , and it is the maximally symmetric spacetime as spherical (Lorentzian) pseudo-Riemannian manifold with positive curvature. Anti-de Sitter (Ads) spacetime[71] is a solution of the vacuum Einstein equations with a negative cosmological , and it is the maximally symmetric spacetime as hyperbolic (Lorentzian) pseudo-Riemannian manifold with negative curvature. There are other solutions, such as Schwarzschild solution, Reissner-Nordstrom solution, Kerr solution, and Friedmann solution.

General relativity and quantum cosmology are invariant under general spacetime diffeomorphisms (isomorphism of smooth manifolds). The quantum state of the universe is invariant under a time reversal change. The semi-classical state of the universe, has one definite direction of time (arrow of time). The processes occurring in the opposite direction of time seem to have disappeared in the actual universe. However, quantum entanglement may be telling us that they have not disappeared but they can be in a region of the spacetime that is not accessible for us. In fact, the time reversal invariance of the spacetime is broken in the semi-classical universe but a time symmetric solution always coexists because the time reversal invariance of the Friedmann equation. Therefore, if one consider that these two universes are created in entangled pairs, then, the time reversal symmetry does not disappear, it only lives in an inaccessible region. When a system behaves no difference when time is reversed, it is said to show T-symmetry as part of CPT (Charge conjugation, Parity, Time reversal) symmetry. A similar extension to time is the introduction to imaginary time, this motivates us to extend 3+1 spacetime $\mathbb{R}^4$ to N-dimensional complex CMOSpacetime $\mathbb{C}^N$ with both imaginary time and imaginary space[58,89,94]. Furthermore,[112]. we also make a T-symmetry extension for time reversal, which has been proved both theoretically[11] and experimentally[116], as general relativity does assume arrow of time, then we make a (Lorentzian) pseudo-Riemannian manifold based 3+1 dimensional curved spacetime $\mathbb{R}^4$ to N-dimensional ($8 \leq N \to \infty, N = 2^n$) curved complex CMOSpacetime $\mathbb{C}^N$ constrained by multiscale[6,10,18] as opposed to planck scale.

$$g_{\mu\nu}(x) = \begin{bmatrix} g_{11}(x) & g_{12}(x) & g_{13}(x) & g_{14}(x) \\ g_{21}(x) & g_{22}(x) & g_{23}(x) & g_{24}(x) \\ g_{31}(x) & g_{32}(x) & g_{33}(x) & g_{34}(x) \\ g_{41}(x) & g_{42}(x) & g_{43}(x) & g_{44}(x) \end{bmatrix} \tag{3}$$

$\Longrightarrow$

$$g_{\alpha\beta}(X) = \begin{bmatrix} g_{11}(X) & g_{12}(X) & g_{13}(X) & g_{14}(X)... & g_{1N}(X) \\ g_{21}(X) & g_{22}(X) & g_{23}(X) & g_{24}(X)... & g_{2N}(X) \\ g_{31}(X) & g_{32}(X) & g_{33}(X) & g_{34}(X)... & g_{3N}(X) \\ g_{41}(X) & g_{42}(X) & g_{43}(X) & g_{44}(X)... & g_{4N}(X) \\ ... & ... & ... & ... & ... \\ g_{N1}(X) & g_{N2}(X) & g_{N3}(X) & g_{N4}(X)... & g_{NN}(X) \end{bmatrix} \tag{4}$$

Here real number x becomes N-dimensional hypercomplex number X, a generalization of complex numbers in higher dimension:

$X = x_1 + \sum_{m=2}^{N}(x_m i_m)$

With that, in N-dimensional CMOSpacetime $\mathbb{C}^N$, lets consider two events whose coordinates are

$(X_{11}, X_{21}, ..., X_{\frac{N}{2}1}, ct_{11}, t_{21}, ..., ct_{\frac{N}{2}1})$ and $(X_{12}, X_{22}, ..., X_{\frac{N}{2}2}, ct_{12}, t_{22}, ..., ct_{\frac{N}{2}2})$
c is the speed of light. The interval between two events in $\mathbb{C}^N$ ds can be defined as:
$ds^2 = c^2 \sum_{m=1}^{\frac{N}{2}} (t_{m2} - t_{m1})^2 - \sum_{m=1}^{\frac{N}{2}} (X_{m2} - X_{m1})^2$
And CMOSpacetime interval can be defined as:
$r = \sqrt{c^2 \sum_{m=1}^{\frac{N}{2}} (t_{m2} - t_{m1})^2 + \sum_{m=1}^{\frac{N}{2}} (X_{m2} - X_{m1})^2}$
Operations on hypercomplex numbers, such as quaternions (Clifford-Lipschitz number), tessarines, coquaternions, biquaternions, octonions and alike, correspond to non-commutative geometrical transformations of the hyperplane, algebraically hypercomplex number system is both Non-Abelian and non-associative as opposed to traditional number systems.

With that the Extended Einstein field equations are formulated as follows:

$$G_{\alpha\beta} + \Lambda g_{\alpha\beta} = 8\pi \frac{G}{C^4} T_{\alpha\beta} \tag{5}$$

$$G_{\alpha\beta} \equiv R_{\alpha\beta} - \frac{1}{2} R g_{\alpha\beta} \tag{6}$$

Where $\alpha, \beta = 1, 2, ..., N$ with metric signature (-... -...+...+) over $\mathbb{C}^N$ on the action of Non-Abelian quotient group $SO_{\frac{N}{2},\frac{N}{2}}(O)$ with $8 \leq N \to \infty, N = 2^n$

IV. EXTENDING QUANTUM MECHANICS IN CMOSPACETIME

Early quantum theory was profoundly re-conceived by Schródinger, Heisenberg, Born. There are two mathematical formalization for quantum mechanics which are equivalent: One is Heisenberg Picture, in which only the operators (observables and others) evolve in time, but the state vectors are constant with respect to time, an arbitrary fixed basis rigidly underlying the theory. The other is Schródinger Picture. in which only the state vectors evolve in time. but the operators (observables and others) are constant with respect to time. Dirac reconciliated the two pictures in Hilbert space and proved their equivalence[33] taking special relativistic effect into consideration. In classical mechanics observable (e.g. energy, position, momentum, etc.) is a function on a manifold called the phase space of the system. In contrary, quantum mechanical observable is an operator on a Hilbert space. Thus the commutative algebra of functions on it is replaced by the non-commutative algebra on a Hilbert space. Now it is von Neumann who gave the first complete mathematical formulation of this approach in terms of operators in Hilbert space, known as the Dirac-von Neumann axioms and von Neumann algebra. It is amazing from pure mathematical point of view, the infinite-dimensional state space in quantum mechanics offers a genuine multiverse/many-worlds interpretation of nature.

The Dirac equation was generalized to 3+1 dimensional curved spacetime[4] over $\mathbb{R}^4$ imposed by Planck scale, and like in what we do with spacetime in general relativity, we can easily further generalize it to CMOSpacetime by making both imaginary time and imaginary space extensions, as well T-symmetry extension. Hence a N-dimensional $8 \leq N < \infty, N = 2^n$ curved spacetime imposed by CMOSpacetime scale instead of Planck scale as follows:

$$i\gamma^a e_a^\mu D_\mu \Psi - m\Psi = 0 \tag{7}$$

It is written by using Vierbein (frame) field/generalized Vierbein field, a set of 4 or N orthonormal vector fields interpreted as a model of 3+1 dimensional spacetime $\mathbb{R}^4$ or N-dimensional complex CMOSpacetime $\mathbb{C}^N$, and the gravitational spin connection. The Vierbein defines a local rest frame, allowing the $N*N$ as opposed to $4*4$ constant Dirac matrices γ^a to act at each spacetime point. Here $\mu = 1, ..., N$, $a = 1, ..., N$ both for N-dimensional CMOSpacetime over $\mathbb{C}^N$ as opposed to $\mu = 1, 2, 3, 4$, $a = 1, 2, 3, 4$ both for 3+1 dimensional spacetime over $\mathbb{R}^4$, e_a^μ is the Vierbein with $e_a^\mu e_a^\nu = g_{\mu\nu}$ as metric tensor in general relativity, and D_μ is the covariant derivative for fermionic fields defined as follows:

$D_\mu = \partial_\mu - \dfrac{i}{2}\omega_\mu^{ab}\sigma_{ab}$ where σ_{ab} is the commutator of $N * N$ as opposed to $4 * 4$ Dirac matrices: $\sigma_{ab} = \frac{i}{2}\left[\gamma_a, \gamma_b\right]$ and ω_μ^{ab} are the spin connection components.

V. CMOSPACETIME THEORETICAL FRAMEWORK

Axiom V.1 *CMOSpacetime Uncertainty axiom:*

$$\Delta x \Delta t > C_s \rightarrow 0 \tag{8}$$

with C_s as CMOSpacetime scale, a close to zero sub-Planck size, which makes Planck scale effect imposed by Heisenberg's Uncertainty principle irrelevant[19,37]. So does the string scale effect imposed in quantum gravity (Loops, M-theory including strings and branes where spacetime is not fundamental and time only has one-dimension[52]).

Proposition V.1 *CMOSpacetime General equivalence principle: N-dimensional complex multiscale orbifold $\mathbb{O} = \mathbb{M}/\mathbb{F}_{\eth}$ ($\mathbb{M}$ as manifold)/degree N projective algebraic variety $\mathbb{X}$ defined by degree N polynomial function $\mathbb{F}_{\eth}$ over $\mathbb{C}^N$ ($\mathbb{F}_{\eth} \in \mathbb{C}[X_1, ..., X_N]$) on Non-Abelian quotient group in satisfyting closure, identity, inverse, associative but not commutative $SO(\frac{N}{2}, \frac{N}{2})$ with $8 \leq N \rightarrow \infty, N = 2^n$:*

$$\mathbb{F}_{\eth}(X_1, ..., X_N) = \sum_{i,j=1}^{N} (w_i X_i^j + b_i)$$

$$X = x_1 + \sum_{m=2}^{N} (x_m i_m)$$

There is no Hodge class on $\mathbb{O}$ or $\mathbb{X}$ which is a rational linear combination of the cohomology classes of projective algebraic sub-varieties/sub-orbifold of $\mathbb{O}$ or $\mathbb{X}$, and such polynomial equation is not solvable by radicals with real solutions, instead only complex solutions available.

Furthermore, every homotopy sphere or hyperbolic space (an open or closed N-orbifold which is homotopy equivalent to the N-sphere or hyperbolic N-space) respectively in the chosen category of N-orbifold $\mathbb{O}$, i.e. topological orbifolds, piecewise linear orbifolds, or differential orbifolds, is isomorphic to the standard N-sphere or hyperbolic N-space respectively. The above claim is true in all dimensions for topological orbifolds; true in dimensions other than 4; unknown in 4 for piecewise linear orbifolds; false generally, true in some dimensions including 1,2,3,5, and 6, unsettled in 4 for differential orbifolds.

The above proposition is drawn from the following theorems, solved and unsolved conjectures as lemmas:

Lemma V.2 *Universal approximation theorem[28]: Let $\varphi(.)$ be a nonconstant, bounded, and monotonically-increasing continuous function. Let I_m denote the m-dimensional unit hypercube $[0,1]^m$. The space of continuous functions on Im0 is denoted by C(Im). Then, given any function $f \in C(I_m)$ and $\epsilon > 0$, there exist an integer N and sets of real constants α_i, $b_i \in R$, $w_i \in R^m$, where i = 1,...,N such that we may define:*

$F(x) = \sum_{i=1}^{N} \alpha_i \varphi\left(w_i^T x + b_i\right)$

as an approximate realization of the function f; that is, $|F(x) f(x)| < \epsilon$ for all $x \in I_m$.

Please note the above theorem justifies the effectiveness of activation functions such as Sigmoid in order to introduce non-linearity. However, later on it has been proved that it is Feed-forward neural network (FNN) itself instead of activation function leads to universal approximation[51]. Hence in the non-linear polynomial function of the above principle, we do not need activation function any more. There are similar indepdent work called Group Method of Data Handling[55] as well.

Lemma V.3 *Fermat's last theorem*[115]*: There are no positive integers x, y, z, and $N \geq 3$ such that $x^N + y^N = z^N$.*

Lemma V.4 *Fundamental theorem of Galois theory*[74]*: Let $\mathbb{L}/\mathbb{K}$ be a finite Galois extension. Let $Gal(\mathbb{L}/\mathbb{K})$ denote the Galois group of the extension $\mathbb{L}/\mathbb{K}$. Let H denote a subgroup of $Gal(\mathbb{L}/\mathbb{K})$ and F denote an intermediate field. The mappings: $\mathbb{H} \longmapsto \mathbb{L}\mathbb{H}$, and $\mathbb{F} \longmapsto Gal(\mathbb{L}/\mathbb{F})$ are inclusion-reversing and inverses. Moreover, these maps induce a bijection between the normal subgroups of $Gal(\mathbb{L}/\mathbb{K})$ and the normal, intermediate extensions of $\mathbb{L}/\mathbb{K}$. .*

The above theorem's application on solutions of rational polynomial equation as follows: A polynomial equation is solvable by radicals $\iff$ its underlying Galois group is a solvable group. Hence for polynomial equations with degree $N > 4$, they are solvable by radicals.

Conjecture V.5 *Hodge conjecture*[50]*: Let $\mathbb{X}$ be a projective non-singular degree N algebraic variety/N-dimensional manifold $\mathbb{M}$ defined by polynomials over $\mathbb{C}^N$, then any Hodge class on $\mathbb{X}$ ($\mathbb{M}$) is a rational linear combination of the cohomology classes $cl(\mathbb{X})$ of algebraic cycles/sub-varieties (sub-manifold) of $\mathbb{X}$ ($\mathbb{M}$).*

Conjecture V.6 *BSD conjecture (Birch and Swinnerton-Dyer)*[14,25]*: The Taylor expansion of $L(E,s)$, E as ecliptic curve, at $s = 1$ has the form $L(E,s) = e(s-1)^r$ + higher order terms , with $e \neq 0$ and $r = rank(E(Q))$. Furthermore $L(E,1) = 0 :\Leftrightarrow C(Q)$ is infinite.*

Conjecture V.7 *Riemann hypothesis: The Riemann zeta-function $\zeta(s)$ is a function of a complex variable s defined by :*

$\zeta(s) = \sum_{n=1}^{\infty} \frac{1}{n^s}$

using analytical continuation for all complex $s \neq 1$, and all of the non-trivial zeroes of this function $\zeta(s) = 0$ lie on a vertical straight line with real part equal to exactly 1/2.

Lemma V.8 *Generalized Poincaré conjecture (solved)*[39,84–86,101] *Every homotopy sphere (a closed N-manifold which is homotopy equivalent to the N-sphere) in the chosen category, i.e. topological manifolds, piecewise linear manifolds, or differential manifolds, is isomorphic to the standard N-sphere. The above claim is true in all dimensions for topological manifolds; true in dimensions other than 4; unknown in 4 for piecewise linear manifolds; false generally, true in some dimensions including 1,2,3,5, and 6, unsettled in 4 for differential manifolds.*

Theorem V.9 *Generalized soul theorem: Whether CMOSpacetime Orbifold conjecture holds or not, suppose that (O,g) is an open (connected, complete, non-compact, with no boundary) orbifold $\mathbb{O}$ with non-negative (when $\mathbb{O}$ being spherical) or non-positive (when $\mathbb{O}$ being hyperbolic) sectional curvature $\eth$, then $\mathbb{O}$ contains a soul (when $\mathbb{O}$ being spherical) or anti-soul (when $\mathbb{O}$ being spherical) $\mathbb{S} \subset \mathbb{M}$, which is a compact, totally geodesic, totally convex (when $\mathbb{O}$ being spherical) or non-convex (when $\mathbb{O}$ being hyperbolic) suborbifold; otherwise $\mathbb{O}$ contains no soul. Furthermore, $\mathbb{O}$ is diffeomorphic (when $\mathbb{O}$ being spherical) or homeomorphic when $\mathbb{O}$ being hyperbolic) to the total space of the normal bundle of the $\mathbb{S}$ in $\mathbb{O}$.*

The above theorem is a corollary of the following Soul theorem[23,42,45,83] and its generalized Anti-soul theorem as lemmas:

Lemma V.10 *Anti-soul theorem: Suppose that $(\mathbb{M}, \eth)$ is an open (connected, complete, non-compact, with no boundary) Riemannian manifold $\mathbb{M}$ of non-positive sectional curvature $\eth$, then $\mathbb{M}$ contains an anti-soul $\mathbb{S}_a \subset M$, which is a compact, totally geodesic, totally non-convex submanifold. Furthermore, $\mathbb{M}$ is homeomorphic to the total space of the normal bundle of the $\mathbb{S}_a$ in $\mathbb{M}$. If $(\mathbb{M}, \eth)$ has negative sectional curvature, then any anti-soul of $\mathbb{M}$ is a point, and consequently $\mathbb{M}$ is homeomorphic to R^N.*

The above theorem is a corollary of the following Soul theorem as lemma:

Lemma V.11 *Soul theorem: Suppose that* $(\mathbb{M}, \eth)$ *is an open (connected, complete, non-compact, with no boundary) Riemannian manifold* $\mathbb{M}$ *of non-negative sectional curvature* $\eth$*, then* $\mathbb{M}$ *contains a soul* $\mathbb{S} \subset M$ *, which is a compact, totally geodesic, totally convex submanifold. Furthermore,* $\mathbb{M}$ *is diffeomorphic to the total space of the normal bundle of the* $\mathbb{S}$ *in* $\mathbb{M}$*. If* $(\mathbb{M}, \eth)$ *has positive sectional curvature, then any soul of* $\mathbb{M}$ *is a point, and consequently* $\mathbb{M}$ *is diffeomorphic to* R^N*.*

Theorem V.12 *Metric of intelligence theorem: If CMOSpacetime contains a soul or anti-soul, then the absolute value of the soul's or anti-soul's sectional curvature is the metric of metrizable intelligence.*

Proof is straight-forward due to its definition basis.

Conjecture V.13 *Origin of intelligence conjecture: The soul or anti-soul of CMOSpacetime is the origin of intelligence.*

Conjecture V.14 *Origin of quantum entanglement conjecture: The intersecting souls and/or anti-souls , when their sectional curvatures approaching positive infinity and/or negative infinity as singularity, is the origin of quantum entanglement*[2,9,15,21,29,30,38,44,56,67–69,76,79,80,87,96,103,109].

The above conjecture is partially generalized from $ER = EPR$ conjecture on the possibility of bridging EPR quantum entanglement as black holes and ER bridge as wormholes.

Conjecture V.15 *Origin of convergent evolution conjecture: The sectional curvatures of CMOSpacetime's intersecting souls and/or anti-souls , is the origin of convergent evolution through conformal transformation*[1,22,27,91].

VI. PROPOSED EXPERIMENTS

TABLE I. **Measuring Intelligence of CNNs**

CNN	**Sectional(Gaussian) Curvature of Soul/Anti-Soul**
LeNet[63]	
AlexNet[7]	
VGGNet[100]	
GoogleNet[106]	
ResNet[46]	
DenseNet[53]	

TABLE II. **Measuring Intelligence of Transformers**

Transformer	**Sectional Curvature of Soul/Anti-Soul**
GPT-2[88]	
BERT[41]	
ALBERT[61]	
Transformer-XL[31]	
XLNet[117]	
RoBERTa[66]	
CTRL[92]	
Megatron-LM[78]	

TABLE III. **Re-conducting Young's Double-Slit Interference Experiment**

New Way	Expected New Result
#1	
#2	
#3	

VII. ONGOING WORK

Forget about Russell's paradox, Halting problem and Godel's Incompleteness theorem, actually there is no universal paradox, hence no ultimate dilemma, as we used to think. With geometry and algebra in helping us to visualize and reason nature, work in progress to be reported: Convergent evolution dynamics, CMOSpacetime complexity reduction, CMO-Spacetime synthesis, and artificial photosynthesis[24] if necessary.

VIII. ACKNOWLEDGEMENTS

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[1] *Evolution Equations*. Clay Mathematics Institute, 2008.
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