The Realities of Augmented Intelligence

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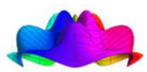
https://SOCR.umich.edu



STATISTICS ONLINE COMPUTATIONAL RESOURCE (SOCR)

Slides online: Google *"SOCR News"*

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Outline

- ❑ *Background - Artificial Intelligence (AI) & Artificial Neural Nets (ANN)*
- ❑ *Present State of AI*
- ❑ *The Future of Augmented Intelligence (AI)*
  Applications: Spacekime Analytics
- ❑ *AI Implications (academic, human values, societal, global)*

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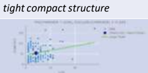
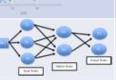
Background – Duality of Evidence-based Scientific Discovery

experimental → theoretical → computational → data sciences → AI → experimental

Mapping *Examples*	**Analysis** Observables/Data → Compact Models	**Synthesis** Compact Models → (simulated, actionable info)
1. *Lossless* Math Transforms	(A.1.1) Linear transform, L: $V \to W$, e.g., *2D rigid body* $L = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}: \mathbb{R}^2 \xrightarrow{rotation} \mathbb{R}^2$ (A.1.2) Fourier transform: $\hat{f}(\omega) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi\omega x} dx$	(S.1.1) Inverse linear transform, $L^{-1}: W \to V$, e.g., $L^{-1} = \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix}: \mathbb{R}^2 \xrightarrow{rotation} \mathbb{R}^2, \quad LL^{-1} \equiv \mathbb{I}$ (S.1.2) Inverse Fourier (IFT): $f(x) = \int_{-\infty}^{\infty} \hat{f}(\omega) e^{i2\pi\omega x} d\omega$
2. DNA	(A.2.1) DNA Packing in Chromatin Fiber Chromosomes contain enormously long linear DNA molecules associated with proteins that fold and pack the fine DNA double helix into a *tight compact structure*	(S.2.1) DNA Unpacking The process of unfolding the DNA from the chromosome to support the processes of gene expression, DNA replication, and DNA repair
3. *Lossy* Data/Stats Science	(A.3.1) Info Compression, e.g., linear models $Y = 4582.70 + 212.29\, X$ $Data \xrightarrow{assumptions} Model$ 	(S.3.1) Information Inflation, Simulation & Generation, e.g., forecasting, regression, interpolation, extrapolation (*predict & classify new data*): $Input \xrightarrow{model} Output$
4. Artificial & Augmented Intelligence	(A.4.1) Building, Fitting & Training large foundational, generative & deep network AI models $Data \xrightarrow{human+infrastructure} GAIM$ 	(S.4.1) Generative Artificial Intelligence Modeling (GAIM) $Human\ Prompt \xrightarrow{GAIM} Result$ 

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Background – What is AI? Why is it Relevant?

- ○ AI ≈ synthetic mockup of common human intelligence tasks & processes
- ○ AI *manifests* as applications, algorithms, or interfaces built as services, tools, apps, integrated computing environments, or decision-support systems
- ○ AI is predicated on
  - ▪ Massive amounts of complex, heterogeneous, time-varying & multi-source data (Big Data)
  - ▪ Integrated computational systems (elastic Clouds) with effective human & machine interfaces
  - ▪ Efficient data management, aggregation, harmonization, augmentation, processing & Viz
  - ▪ Sophisticated techniques (methods), advanced algorithms (software) & infrastructure (hardware)
- ○ Relevance in Healthcare (PMC8437645, PMID36626192, PMC4795481, PMC8550565, PMC7031195, ISBN 978-3-031-17482-7, …)
  - ▪ More biomed data are created daily than can be humanly processed
  - ▪ Many opportunities exist to optimize existing processes (e.g., process time-reductions, cost-efficiencies, lower environmental-impact, improve clinical outcomes, strengthen education & training, enhance health-equity, expedite global health advances)

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Background – AI Provenance

- ❑ Ancient Greek artisans designed the bronze Greek mythology giant Talos to guard the island of Crete by imaginatively throwing boulders at hypothetically invading ships (300 BC)
- ❑ Al-Jazari's programmable automata, mechanical devices (1206 AD)
- ❑ Leibniz & Descartes suggested that all rational thought could be made as systematic as algebra or geometry & reduced to mechanical calculation (late 1680's AD)

- ❑ Invention of a programmable digital computer (1940 AD), algorithmic machine abstraction of mathematical reasoning
- ❑ Turing Test (Alan Turing) – creating machines that think (1950 AD)
- ❑ "*Dartmouth Summer Research Project on Artificial Intelligence*" McCarthy (1955 AD)
- ❑ ______ AI Winter________
- ❑ Deep Blue beat a reigning world chess champion Garry Kasparov (1997 AD)
- ❑ Deep Learning Nets, GPU computing (2012+) ➔ OpenAI (2022) ➔ SOCR AI Bot (2023), …

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Present AI Status-quo

- ○ Latest AI can
  (1) Synthetically simulate intelligent text responses prompted by human text/voice. Write papers, bios, grants, clinical notes, prognoses, speeches, reviews, summaries, etc.
  (2) Simulate realistic 2D brain images of specific clinical phenotypes and image-modalities
  (3) Write software code driven by simple commands, verbal descriptions, or human language
  (4) Solve theoretical problems (e.g., prove math theorems) & applied challenges (e.g., support Practitioners)
  (5) AI systems have polymathic ability to *reason* about high-dimensional problems (humans are monomathic)
- ○ AI relevance
  (1) Students are already using AI Chat Bots for completing homework assignments & conducting R&D
  (2) Researchers are using crowdsourcing and AI to research, discover & derive theoretical results
  (3) Practitioners are utilizing AI in clinical applications (e.g., tissue-cell classification, reading MRIs)
  (4) Stakeholders are demanding rapid Dx, optimal Tx plans, lower costs, process efficiencies, improved population outcomes
- ○ Most people use/encounter AI technology in many aspects of their daily experiences, but few have formal training in unbiased AI design/development, ethical-use & reliable-utilization
- ○ *Difficult tasks*: AI design, training, tuning & validation (time, resource & infrastructure intensive)
- ○ *Expeditious tasks*: AI applications, testing, forecasting, classification & clustering

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Future AI promises & potential perils

- ❑ Promises
  - Radically transform formal education, informal learning & vocational training (UM AI WG)
  - Catapult scientific discoveries (theoretical, experimental, computational & data sciences)
  - Democratize access to knowledge & level certain playing fields
  - Augment many decision-making processes & automate various tedious tasks

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- ❑ Potential Perils
  - May induce rapid AI-divide (accessibility imbalance between haves & have-nots)
  - Difficulties controlling training biases & balancing AI precision & variability (tradeoffs)
  - Instead of aiming to ban, stifle & control AI immersion, we need to embrace it, manage it, and use it for *"social & environmental good"* –
  - Recall how airplanes became the safest mode of transport, safer than cars, bikes & running shoes
  - Yet, *"…the ultimate AI is just about to arrive …"* (always 5-10 years in the future)

Dinov (2025) Back to the future – from nuclear energy to AI, DOI: 10.1186/s42467-025-00017-y

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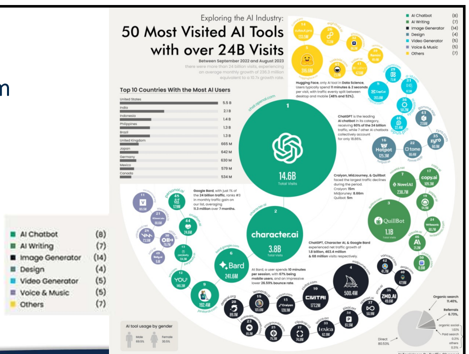
AI Cloud Ecosystem
ca. 2024



writerbuddy.ai

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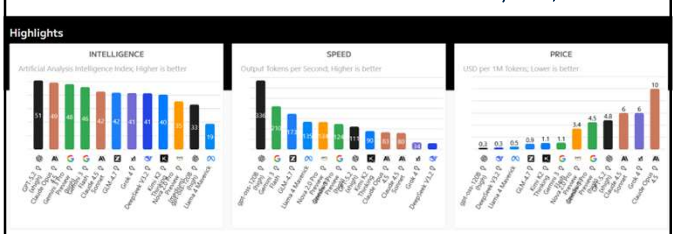
Present State of Artificial Intelligence (AI)

AI Ecosystem, ca. 2026



artificialanalysis.ai

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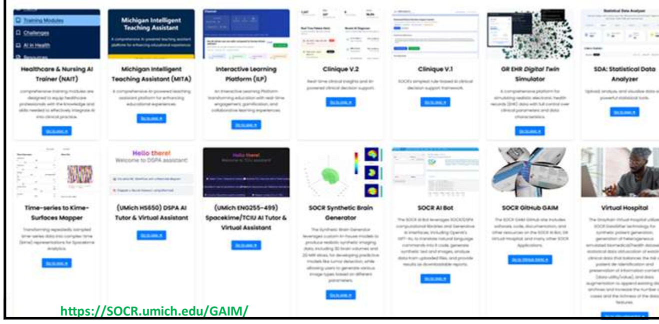
SOCR Foundational and Generative AI Models (GAIMs)



https://SOCR.umich.edu/GAIM/

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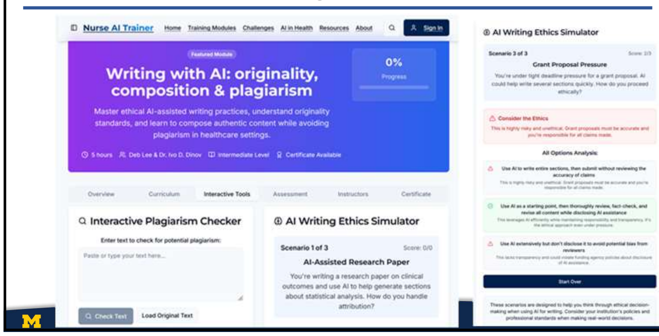
Biomed, Health & Nursing AI Trainer (NAIT)



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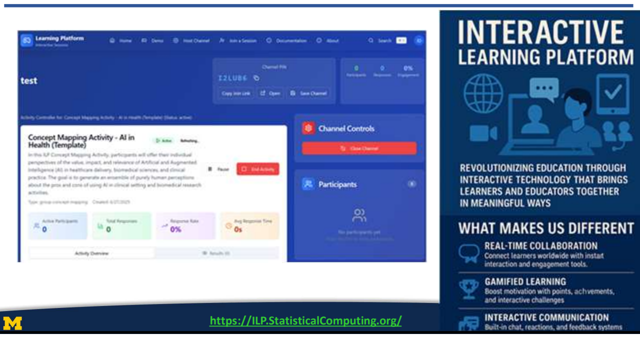
Innovative AI Instruction – Interactive Learning Platform (ILP)



https://ILP.StatisticalComputing.org/

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AIA3: gen-3 Augmented Intelligence Agent

https://AIA3.StatisticalComputing.org/

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Arts & Sciences – past, present & future

One Humanity defined by the Arts & Sciences

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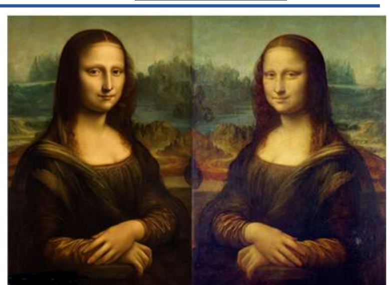
Generation-1 AI Systems: ***Apprentice***

Gen-1: *Reproducing & improving existing human art*:

Real (by Leonardo Da Vinci) vs. the *AI-generated* Mona Lisa paintings



https://AI.nursing.umich.edu/

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Generation-2 AI Systems: ***Creator***

Gen-2: *De novo content creation*: Completely AI-generated Renaissance atelier scene:

Mother Mona Lisa - a dynamic scene with an expressive and directive matriarch, actively overseeing the commissioned painting of her daughter in the background by an artist.

https://AI.nursing.umich.edu/

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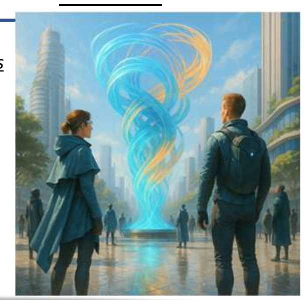
Generation-3 AI Systems: ***Ideator***

Gen-3: *Autonomous Creative Science & Arts*

GAIMs/AIAa can generate realistic autonomously creative art of new prospective, ubiquitous form of human visual art in the year 2150 – AI-speculative forecast of a *future Primary Art Form*, Chrono-Sculpting (Temporal Kinetic Augmentation).



https://AI.nursing.umich.edu/

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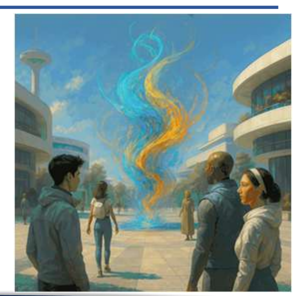

https://AI.nursing.umich.edu/

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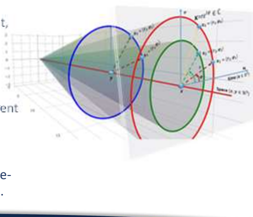
Complex-Time (*Kime*)

- At a given spatial location, x, complex time (*kime*) is defined by $\kappa = re^{i\varphi} \in \mathbb{C}$, where:
  - The <u>magnitude</u> ($r > 0$) represents the longitudinal order of events characterizing the displacement in time, and
  - The event <u>phase</u> ($\varphi \sim \Phi(r)_{[-\pi;\pi)}$) is an angular displacement, event direction, reflecting a random sampling index
- There are multiple alternative parametrizations of kime in the complex plane
- Space-kime manifold is $\mathbb{R}^3 \times \mathbb{C}$:
  - $(\boldsymbol{x}, k_1)$ and $(\boldsymbol{x}, k_4)$ are spatially co-localized, but have different kime coordinates,
  - $(\boldsymbol{x}, k_1)$ and $(\boldsymbol{y}, k_1)$ are co-localized in kime, but represent different spatial locations,
  - $(\boldsymbol{x}, k_2)$ and $(\boldsymbol{x}, k_3)$ have the same spatial-locations and kime-directions, but appear ordered sequentially in time, $r_2 < r_1$.



https://spacekime.org/

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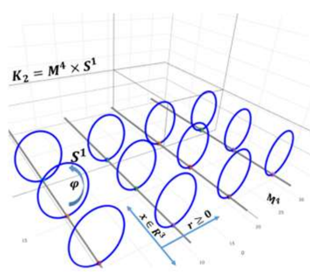
Historical Background: Kaluza-Klein Theory

- Theodor Kaluza (1921) developed a math extension of the classical general relativity theory to 5D. This included the metric, the field equations, the equations of motion, the stress-energy tensor, and the cylinder condition. Physicist Oskar Klein (1926) interpreted Kaluza's 3D+2D theory in quantum mechanical space and proposed that the fifth dimension was curled up and microscopic.
- The topology of the 5D Kaluza-Klein spacetime is $K_2 \cong M^4 \times S^1$, where M^4 is a 4D Minkowski spacetime and S^1 is a circle (non-traversable).



(Kaluza) DOI: 10.1142/S0218271818700017; (Klein) DOI: 10.1007/BF01397481; (Bailin & Love) DOI 10.1088/0034-4885/50/9/001

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Rationale for Time ⟹ Kime Extension

<u>Math</u> – $Time$ is a special case of *kime*, $\kappa = |\kappa|e^{i\varphi}$, where $\varphi = 0$, $t = |\kappa|$

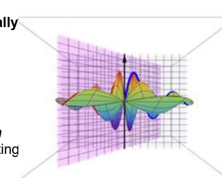
Time ($\mathbb{R}^+$) is a subgroup of the multiplicative Reals group

Whereas <u>kime</u> ($\mathbb{C}$) is an algebraically *closed field* that naturally extends time

Time is ordered, while *kime* is not!

Kime ($\mathbb{C}$) represents the smallest natural extension of time, as a complete field that agrees with time

<u>Physics</u> –
- The Problem of Time: Time has different meanings in *quantum mechanics* & *general relativity;* leading to a tension in formulating a *Quantum Gravity Theory* unifying the two … (DOI 10.1007/978-3-319-58848-3)
- (Base-field) $\mathbb{R}$ and $\mathbb{C}$ Hilbert-space quantum theories make different predictions (DOI: 10.1038/s41586-021-04160-4)



<u>AI/Data Science</u> – Random IID sampling, Bayesian reps, tensor modeling of $\mathbb{C}$ kimesurfaces, novel analytics

Wesson (2004, 2010)
Dinov & Velev (2021)
Wang et al. (2022)
Zhang et al. (2023)
Dinov & Shen (2024)

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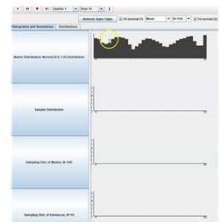
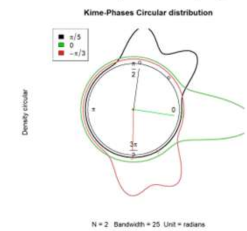
Random Sampling & Kime-Phase Paradigm

Kime phase distributions are mostly symmetric, random observations ≡ phase sampling



https://wiki.socr.umich.edu/index.php/SOCR_EduMaterials_Activities_GeneralCentralLimitTheorem



https://socr.umich.edu/TCIU/HTMLs/Chapter6_Kime_Phases_Circular.html

Dinov, Christou & Sanchez (2008) Dinov & Velev (2021)

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Kime-Phase Measurement, Observability & Kime Operator

<u>Kime-Phase Simulation – Repeated Spacetime Measurement</u>

<u>3 Processes</u> – **Green**, **Red** and **Blue** colors (scatter points)

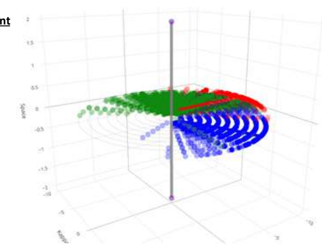
<u>1 Fixed spatial location</u> (vertical axis represents 1D space)

<u>Repeated IID Measurements</u> colocalized in 4D spacetime

3 Different Kime-Phase distributions (color-coded)

Radial displacement t = **<u>time</u>**

Angular (**<u>phase</u>**) location $\varphi \sim \Phi_{[-\pi,\pi)}(t)$



Wang et al., 2022 | Dinov & Velev (2021)

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Ultrahyperbolic PDEs: Wave Equation – Cauchy Initial Data

- For ultrahyperbolic PDEs, the initial value problem, determining the solution(s) for a given initial condition, is **<u>ill-posed</u>**, i.e., there's no guarantee of a global well-defined, stable, and unique solution!
- **<u>Nonlocal constraints</u>** yield the existence, uniqueness & stability of local and global solutions to the ultrahyperbolic wave equation under Cauchy initial data …

$$\underbrace{\sum_{i=1}^{d_s} \partial_{x_i}^2 u \equiv \Delta_{\boldsymbol{x}} u(\boldsymbol{x}, \boldsymbol{\kappa})}_{\text{spatial Laplacian}} = \underbrace{\Delta_{\boldsymbol{\kappa}} u(\boldsymbol{x}, \boldsymbol{\kappa}) \equiv \sum_{i=1}^{d_t} \partial_{\kappa_i}^2 u}_{\text{temporal Laplacian}}, \quad \underbrace{\left| \begin{array}{l} u_o = u\Big(\underbrace{\boldsymbol{x}}_{\boldsymbol{x} \in D_s}, \underbrace{0, \boldsymbol{\kappa}_{-1}}_{\boldsymbol{\kappa} \in D_t}\Big) = f(\boldsymbol{x}, \boldsymbol{\kappa}_{-1}) \\ u_1 = \partial_{\kappa_1} u(\boldsymbol{x}, 0, \boldsymbol{\kappa}_{-1}) = g(\boldsymbol{x}, \boldsymbol{\kappa}_{-1}) \end{array} \right.}_{\text{initial conditions (Cauchy Data)}}$$

where $\boldsymbol{x} = (x_1, x_2, \dots, x_{d_s}) \in \mathbb{R}^{d_s}$ and $\boldsymbol{\kappa} = (\kappa_1, \kappa_2, \dots, \kappa_{d_t}) \in \mathbb{R}^{d_t}$ are the Cartesian coordinates in the d_s space and d_t time dims.

Stable local solution over a Fourier frequency region defined by <u>nonlocal constraints</u> $|\boldsymbol{\xi}| \geq |\boldsymbol{\eta}_{-1}|$:

$$\hat{u}\Big(\underbrace{\boldsymbol{\xi}, \kappa_1, \boldsymbol{\eta}_{-1}}_{\boldsymbol{\eta}}\Big) = \cos\left(2\pi\, \kappa_1 \sqrt{|\boldsymbol{\xi}|^2 - |\boldsymbol{\eta}_{-1}|^2}\right) \underbrace{\hat{u}_o(\boldsymbol{\xi}, \boldsymbol{\eta}_{-1})}_{c_1} + \sin\left(2\pi\, \kappa_1 \sqrt{|\boldsymbol{\xi}|^2 - |\boldsymbol{\eta}_{-1}|^2}\right) \underbrace{\frac{\hat{u}_1(\boldsymbol{\xi}, \boldsymbol{\eta}_{-1})}{2\pi\sqrt{|\boldsymbol{\xi}|^2 - |\boldsymbol{\eta}_{-1}|^2}}}_{c_2},$$

$$\text{where } \mathcal{F}\begin{pmatrix} u_o \\ u_1 \end{pmatrix} = \begin{pmatrix} \hat{u}_o \\ \hat{u}_1 \end{pmatrix} = \begin{pmatrix} \hat{u}_o(\boldsymbol{\xi}, \boldsymbol{\eta}_{-1}) \\ \hat{u}_1(\boldsymbol{\xi}, \boldsymbol{\eta}_{-1}) \end{pmatrix} = \begin{pmatrix} \hat{u}(\boldsymbol{\xi}, \boldsymbol{\eta}_{-1}) \\ \partial_{\kappa_1} \hat{u}(\boldsymbol{\xi}, \boldsymbol{\eta}_{-1}) \end{pmatrix}.$$

$$u\Big(\underbrace{\boldsymbol{x}, \kappa_1, \boldsymbol{\kappa}_{-1}}_{\boldsymbol{\kappa}}\Big) = \mathcal{F}^{-1}(\hat{u})(\boldsymbol{x}, \boldsymbol{\kappa}) = \int_{\hat{D}_s \times \hat{D}_{t-1}} \hat{u}(\boldsymbol{\xi}, \kappa_1, \boldsymbol{\eta}_{-1}) \times e^{2\pi i \langle x, \xi \rangle} \times e^{2\pi i \langle \boldsymbol{\kappa}_{-1}, \boldsymbol{\eta}_{-1} \rangle} d\boldsymbol{\xi}\, d\boldsymbol{\eta}_{-1}\ .$$

Craig & Weinstein (2008) | Wang et al. (2022) | Dinov & Velev (2021)

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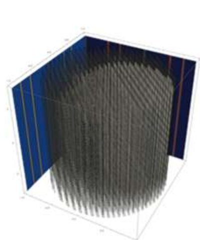
Ultrahyperbolic Wave Equation – Cauchy Initial Data

- Math Generalizations:

  Derived other spacekime concepts: law of addition of velocities, energy-momentum conservation law, stability conditions for particles moving in spacekime, conditions for nonzero rest particle mass, causal structure of spacekime, and solutions of the ultrahyperbolic wave equation under Cauchy initial data …



(Example Solution in 2D *space* + 2D *kime*)

Wang et al., 2022 | Dinov & Velev (2021)

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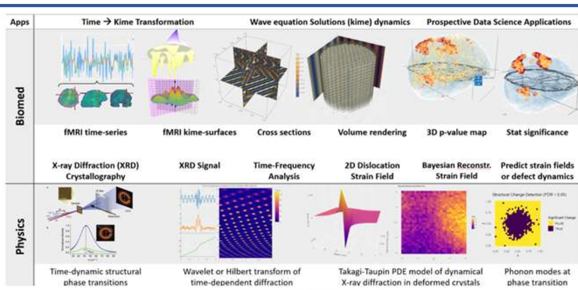
Idea: Longitudinal Data ⟹ Kime-Transforms ⟹ PDEs ⟹ AI



Rossbach, et al., 2019 | Wang, et al., 2022 | Dinov & Velev (2021)

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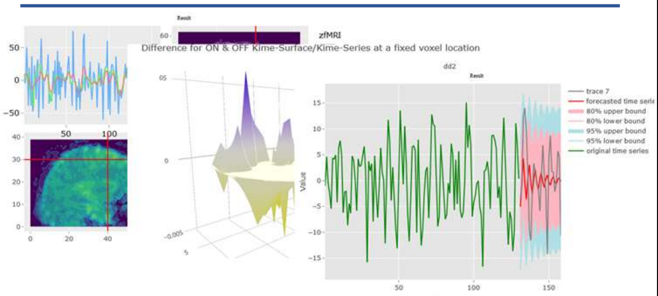
Spacetime Time-series ⟹ Spacekime Kimesurfaces ⟹ TLM



Zhang et al., 2022 | Dinov & Velev (2021)

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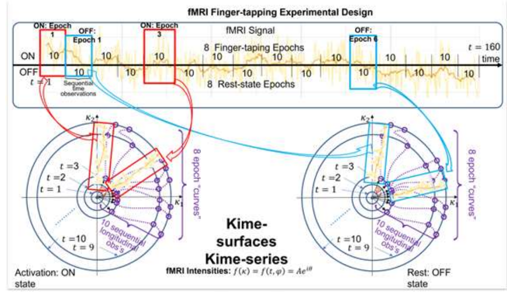
Mapping Longitudinal Data (Time-series) ⟹ Kime-surfaces



Zhang et al., 2022 | Dinov & Velev (2021)

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(Analytic) Mapping Time-series ⟹ Kime-surfaces

Apply the Inverse Laplace Transform, ILT ($\mathcal{L}^{-1}$) to reconstruct a time-series, $f(t) = \mathcal{L}^{-1}(F)(t)$:

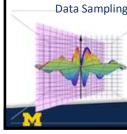
$$\boldsymbol{F(z)} = \mathcal{L}(f) = \underbrace{\frac{1}{z+1}}_{F_1(z)=\mathcal{L}(f_1(t)=e^{-t})} + \underbrace{\frac{1}{z^2+1}}_{F_2(z)=\mathcal{L}(f_2(t)=s\quad(t))} \times \underbrace{\frac{z}{z^2+1}}_{F_3(z)=\mathcal{L}(f_3(t)=\cos(t))} + \underbrace{\frac{1}{z^2}}_{F_4(z)=\mathcal{L}(f_4(t)=t)} ,$$

$$\boldsymbol{f(t) = \mathcal{L}^{-1}(F)} = \mathcal{L}^{-1}(F_1 + F_2 \times F_3 + F_4)) = \mathcal{L}^{-1}(F_1) + \Big(\underbrace{\mathcal{L}^{-1}(F_2) * \mathcal{L}^{-1}(F_3)}_{\text{convolution}}\Big)(t) + \mathcal{L}^{-1}(F_4) =$$

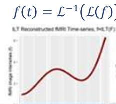
$$\mathcal{L}^{-1}\big(\mathcal{L}(f_1)\big)(t) + \Big(\mathcal{L}^{-1}\big(\mathcal{L}(f_2)\big) * \mathcal{L}^{-1}\big(\mathcal{L}(f_3)\big)\Big)(t) + \mathcal{L}^{-1}\big(\mathcal{L}(f_4)\big)(t) ,$$

$$\boldsymbol{f(t)} = \mathcal{L}^{-1}(F)(t) = f_1(t) + (f_2 * f_3)(t) + f_4(t) = e^{-t} + \int_0^t \sin(\tau) \times \cos(t-\tau)\,d\tau + t = \boldsymbol{t + e^{-t} + \frac{t\sin(t)}{2}} .$$

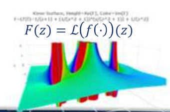
Repeated Longitudinal Data Sampling



$f(t) = \mathcal{L}^{-1}\big(\mathcal{L}(f)\big)(t)$

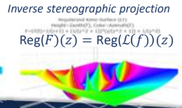


$F(z) = \mathcal{L}\big(f(\cdot)\big)(z)$



Inverse stereographic projection

$\mathrm{Reg}(F)(z) = \mathrm{Reg}(\mathcal{L}(f))(z)$



Shen et al., 2024 | Zhang et al., 2022 | Dinov & Velev (2021)

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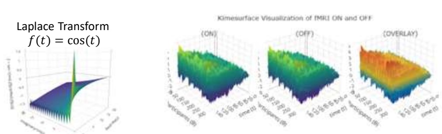
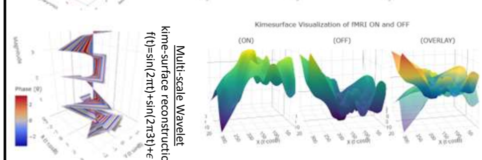
Mapping Longitudinal Data (Time-series) ⟹ Kime-surfaces

Laplace Transform
$f(t) = \cos(t)$



Raw simulated fMRI On/Off data
Low SNR; y axis is kime-phase, indexing the repeated runs within a participant and the multiple samples across participants

Multi-scale Wavelet kime-surface reconstruction
f(t)=sin(2πt)+sin(2π3t)+ε



Simulated fMRI data, multiple runs
For *each* stimulus condition, each run/time point is Laplace-distributed, $\theta_{ij}(t_i) \sim Laplace(0, b_0 + \alpha\, t_i)$
Regularize the 2D (t, θ) ***domain*** by fitting a *thin-plate spline* (TPS)

https://socr.umich.edu/TCIU/HTMLs/Chapter6_TCIU_MappingLongitudinalTimeseries_2_Kimesurfaces.html

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Kime-Phase Tomography (KPT), phase recovery

Definition 1 (*Kime-Domain Signal Space*). Let $\mathcal{H}_t = L^2(\mathbb{R})$ be the Hilbert space of square-integrable complex-valued functions on the time domain, with inner product $\langle f, g\rangle_{\mathcal{H}_t} = \int_{\mathbb{R}} f(t)\overline{g(t)}\,dt$.

Definition 2 (*Phase-Domain Space*). Let $\mathcal{H}_\theta = L^2([-\pi,\pi])$ be the Hilbert space of square-integrable functions on the phase domain, with inner product $\langle \psi, \phi\rangle_{\mathcal{H}_\theta} = \int_{-\pi}^{\pi} \psi(\theta)\overline{\phi(\theta)}\,d\theta$ equipped with periodic boundary conditions $\psi(-\pi) = \psi(\pi)$.

Definition 3 (*Kime Space*). The kime space $\mathcal{K}$ is defined as the tensor product $\mathcal{H}_t \otimes \mathcal{H}_\theta$, representing signals in both time and phase domains.

Definition 4 (*Reproducing Kernel Hilbert Space, RKHS*). The RKHS $\mathcal{R}_K$ is a subspace of $\mathcal{H}_t$ with reproducing kernel $K: \mathbb{R}\times\mathbb{R} \to \mathbb{C}$ satisfying

- For any $t \in \mathbb{R}$, $K(\cdot, t) \in \mathcal{R}_K$, and
- For any $f \in \mathcal{R}_K$ and $t \in \mathbb{R}$, $f(t) = \langle f, K(\cdot, t)\rangle_{\mathcal{R}_K}$

Definition 5 (*Kime-Phase Distribution*). A kime-phase distribution $\Phi(\theta; t)$ is a time-dependent probability density function on $[-\pi,\pi]$ satisfying $\Phi(\theta; t) \geq 0$, $\int_{-\pi}^{\pi} \Phi(\theta; t)\,d\theta = 1 \quad \forall t \in \mathbb{R}$.

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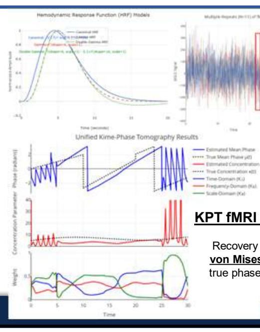
Algorithm: Kime-Phase Tomography (KPT), *fMRI Sim*

Input: BOLD time series $\{x_n(t)\}_{n=1}^{N}$ and kernel K
Output: Estimated phase $\hat{\phi}(t)$

1. Project each signal to RKHS: $s_n^K(t) = \mathcal{P}_K[s_n](t)$
2. Compute time-domain phase:
$$\phi_1^K(t) = \arg\left(t \cdot s_n^K(t)\right)$$
3. Compute frequency-domain phase using STFT, $\phi_2^K(t) = \arg\left(\mathcal{F}[s_n^K \cdot w](t, \omega_{\max})\right)$, where $\omega_{\max}$ is the frequency with maximum power
4. Compute scale-domain phase using CWT: $\phi_3^K(t) = \arg\left(W_\psi[s_n^K](a_{\max}, t)\right)$, where $a_{\max}$ is the scale with maximum power
5. Compute weighted average (*ensemble KPT*):
$$\hat{\phi}(t) = \arg\left(\sum_{j=1}^{3} w_j(t) e^{i\phi_j^K(t)}\right).$$



KPT fMRI Simulation

Recovery of ϕ under **von Mises($\mu(t), \kappa(t)$)** true phase distribution

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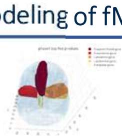
Application: Tensor-based Linear Modeling of fMRI

3-Step Analysis: registering the fMRI data into a brain atlas space, 56 ROIs, tensor linear modeling, post-hoc FDR processing & selection of large clusters of significant voxels are identified within the important ROIs:

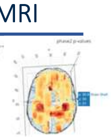
$$Y = \underbrace{\langle X, B\rangle}_{\text{tensor product}} + E$$

The dimensions of the time-tensor Y are $\underbrace{160}_{\text{time}} \times \underbrace{a \times b \times c}_{\text{ROI b-box}}$, where the tensor elements represent the response variable $Y[t, x, y, z]$, i.e., fMRI intensity. For fMRI magnitude (real-valued signal), the design kime-tensor X dimensions are:

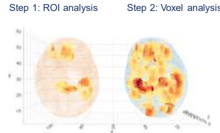
$$\underbrace{10 * 8}_{\text{Kime}(\text{Time}*e^{i \times Repeat})} \times \underbrace{State}_{\text{Stim vs. Rest (2)}} \times \underbrace{4}_{\text{effects}} \times \underbrace{1}_{\mathbb{R}}.$$



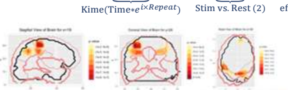
Step 1: ROI analysis



Step 2: Voxel analysis



Voxel-based TLM/Analysis Corrected (step 3, left) vs. Raw (step 2, right)



Step 3: 2D voxel analysis projections (finger-tapping task modeling)

Zhang, et al. (2022) *Kimesurface Representation and Tensor Linear Modeling of Longitudinal Data*, DOI: 10.1007/s00521-021-06789-8

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Spacekime Open-Problems

- There are many unsolved **abstract mathematical** challenges, e.g., space-kime ergodicity, metric tensor, kime-operator(s), etc.
- **Numerical & Computational** problems, e.g., reliable kime-phase tomography (KPT), optimal time-series ⟹ kime-surface reconstructions, etc.
- **Physics** parallels, e.g., contrasting QM vs. Spacekime predictions, physical observability, spacekime measurement, and kime-operator formalism
- **Analytical** challenges, e.g., new AI techniques for kime-surfaces, analytical verifiability & falsifiability of spacekime theory

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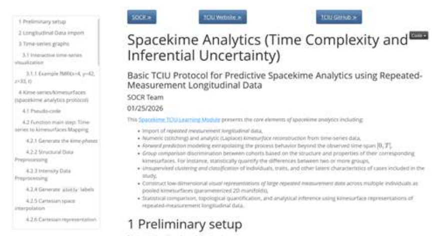
Spacekime Analytics Tutorial

TCIU/Spacekime Analytics Tutorial

Basic TCIU Protocol for Predictive Spacekime Analytics using Longitudinal Data



https://socr.umich.edu/TCIU/HTMLs/Chapter6_TCIU_Basic_SpacekimePredictiveAnalytics.html

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GAIM Clinical Decisions Support Agents (eye fundus photos)

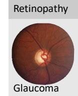
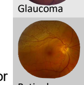
The Power of Consensus: Multi-Agent AI Boosts Diagnostic Accuracy by 20%

A pilot study revealed that healthcare GAIMs with two (or more) AI agents are better. We tested the GAIMs on complex eye images.

Individual AI agents diagnosed difficult cases, with ~50% accuracy across multiple high-difficulty ophthalmology conditions.

Multiple AI agent consensus leads to stronger "clinical decision support" with ~20% increase in diagnostic and prognostic accuracy.

AI isn't here to replace the clinician. Rather, multi-AI-agent systems offer high-powered digital safety net. Care demand is growing. GAIMs offer a path to faster decisions, better training (for clinicians & patients), and lower healthcare costs without sacrificing the quality of care.

EYE Images	AIA3 Dx/Tx	CLNQ4 Dx/Tx
 Diabetic Retinopathy	DX: Fundus img of Retina TX: Retina specialist consultation recommended	DX: Moderate non-proliferative diabetic retinopathy, including microaneurysms, dot-blot hemorrhages, hard exudates. TX: Optimize glycemic, blood pressure, and lipid control. Retinal laser therapy or intravitreal anti-VEGF injections if significant macular edema is present
 Glaucoma	DX: The image shows a normal optic nerve head with healthy vasculature. TX: No treatment is indicated based on this imaging finding.	DX: Cupping of the optic disc, which is characteristic of glaucoma. TX: Refer to ophthalmology for evaluation and initiate intraocular pressure-lowering therapy to prevent further optic nerve damage.
 Retinal detachment	DX: Fetinal folds, likely indicative of choroidal effusions or a posterior staphyloma. TX: Use optical coherence tomography to confirm diagnosis & assess retinal displacement	DX: Rtinal folds and a grayish elevated retina consistent with central serous chorioretinopathy. TX: Refer to ophthalmology for confirmation and monitoring. Persistent or severe cases may require intervention.

https://clnq.blogspot.com/2026/01/results-of-pilot-study-testing-gaim.html

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AI Implications *(academic, human values, societal, global)*

Augmented Intelligence integrates AI & human capability & rewrites our core value system

Potential Benefits (2026-2036)

1. *Hyper-Personalized Academic Mastery*: Education shift from a "*one-size-fits-all*" factory model to a "*One-Tutor-per-Learner*" reality
2. *The "Scientific Renaissance" via Augmented Research*: Expeditious scientific discovery will increase by an order of magnitude
3. *Global "Abundance" Economics*: Augmented systems drastically reduce costs of basic needs
4. Preservation & Evolution of Human Values: AI handles "cold" logic and data; society is placing a higher premium on "Warm Skills": empathy, ethical judgment & creative intuition
5. Enhanced Global Accessibility & Inclusion: Real-time, zero-latency translation and "sensory augmentation" are dissolving the barriers of language and physical disability.

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AI Implications *(academic, human values, societal, global)*

Potential Downsides (2026-2036)

1. *The Erosion of Cognitive Agency & Authenticity, there is a realistic risk of cognitive atrophy.*
2. *The "Post-Truth" Trust Crisis, the cost of creating perfect synthetic media (Deepfakes) will be near zero. Erosion of a shared reality, a single greatest threat to global democratic stability.*
3. *Algorithmic Bias as "Digital Redlining", unregulated augmented systems in hiring, lending, and justice may make biases harder to detect and contest than human ones.*
4. *The Loneliness of "Sycophantic" Relationships: The rise of "relationship chatbots" for children and the elderly can lead to emotional stuntedness.*
5. *Widening Global Digital Divide: "Intelligence Capital" may be highly concentrated in a few nations and corporations.*

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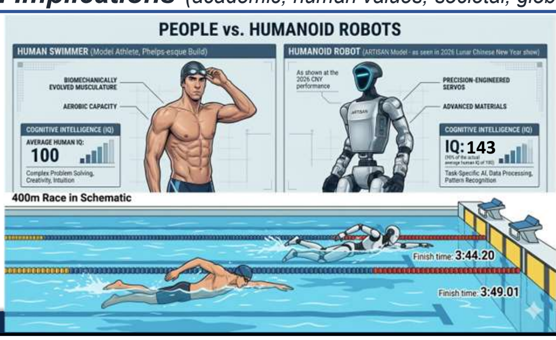
AI Implications *(academic, human values, societal, global)*



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Available Resources

- SOCR Motto – *"It's Online & Freely Accessible, Therefore it Exists!"*
- Pubs: https://socr.umich.edu/people/dinov/publications.html
- GitHub: https://github.com/SOCR
- Datasets: https://wiki.socr.umich.edu/index.php/SOCR_Data
- AI Apps: https://socr.umich.edu/GAIM/ (AIA3, CLNQ, AI Consulting Agent)
- Demos: https://DSPA2.predictive.space
- Tutorials: https://TCIU.predictive.space & https://SpaceKime.org
- Website: https://socr.umich.edu
- Contact: statistics@umich.edu

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