Image credit: https://blogs.nvidia.com/blog/guinness-world-record-fastest-dna-sequencing/

AI Health Agents

Longevity as a Service in the Web3 GenAI Quantum Revolution

"*Aging is a Pathology*"
– The Lancet, 2022

AAAI 2024: GenAI for Global Well-being

Palo Alto CA, 26 Mar 2024

Slides: http://slideshare.net/LaBlogga

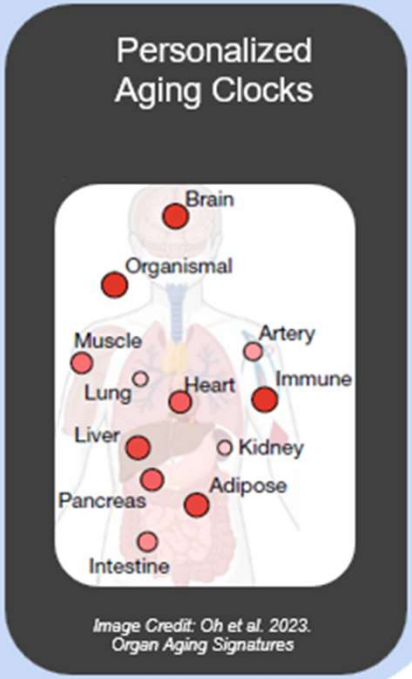
Melanie Swan, PhD, MBA
DIYgenomics.org (Principal Investigator)
University College London (Research Associate)

UCL UCL CBT

AI Health Agents:
Pathway2vec, ReflectE, Category Theory, and Longevity

Web3 GenAI Quantum Technology Stack

Technology	Layer
Web3	**Social** Economics, Identity, Health, Longevity
GenAI	**Interface**
Quantum	**Compute**



Health Agents: personalized AI health advisors for "healthcare by app" instead of "sickcare by appointment" targeting Healthy Longevity as a global society wellness priority with 2 billion people over 65 in 2050

Source: Health Agents: Swan, M., Kido, T., Roland, E. & dos Santos, R.P. (2024). AI Health Agents: Pathway2vec, ReflectE, Category Theory, and Longevity. AAAI 2024 Spring Symposium Series: Impact of GenAI on Social and Individual Well-being. https://www.melanieswan.com/documents/swan-AI-health-agents.pdf

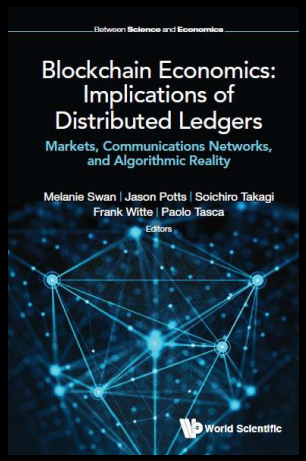
Research Program

Math Agents:
https://arxiv.org/abs/2307.02502
Health Agents:
https://www.melanieswan.com/documents/swan-AI-health-agents.pdf

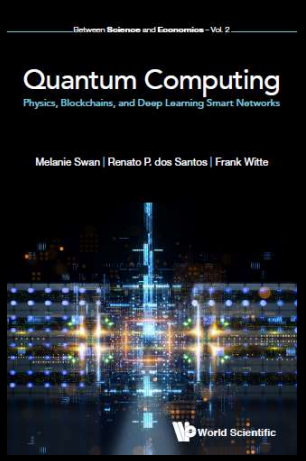
Aim: Build long-term futures for humanity through the conceptual deployment of science and technology frontiers

Blockchain
2015

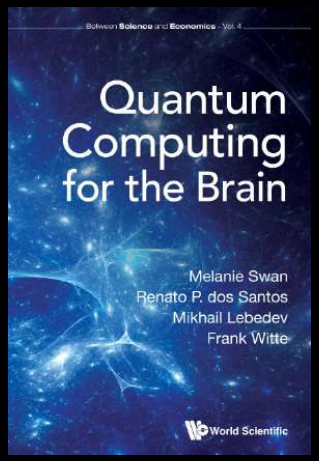
Blockchain Economics
2019



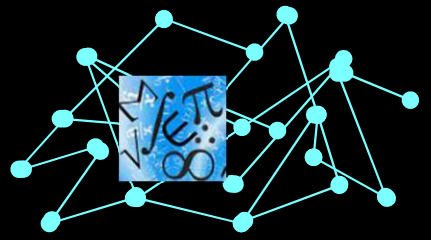
Quantum Computing
2020



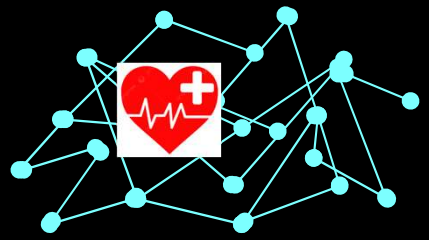
Quantum Computing for the Brain
2022



Math Agents
2023

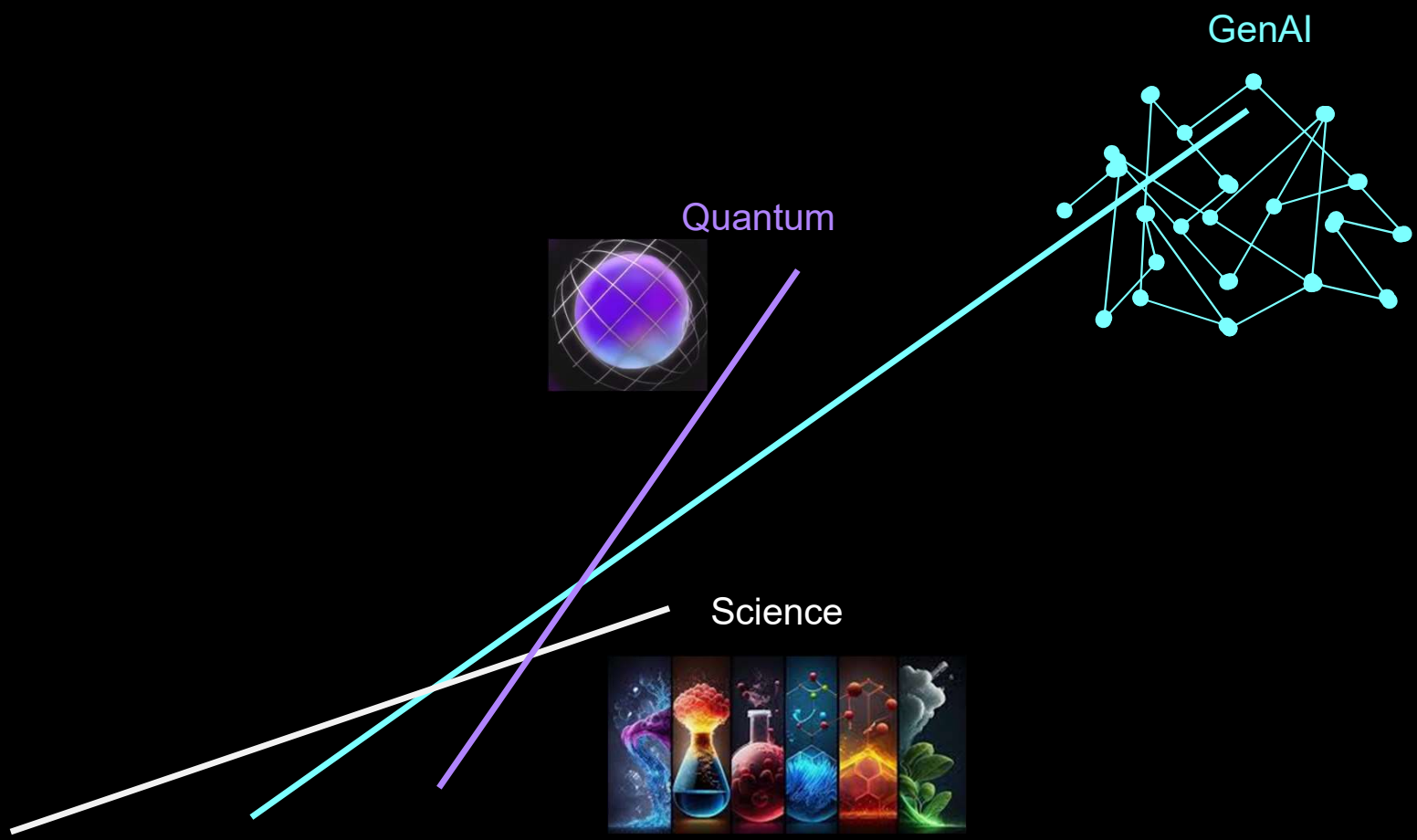


Health Agents
2024

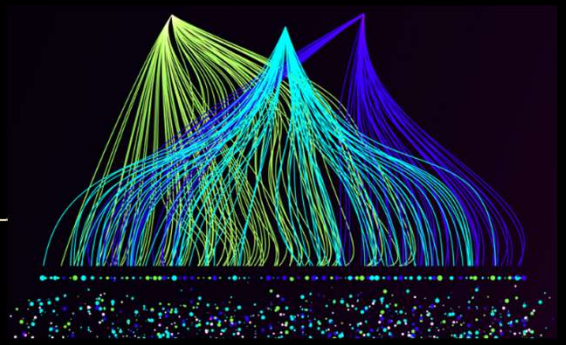


"The App will see you now~!"

Accelerating Futures



Thesis



The real aim of genAI is Intelligence Amplification
We need better goggles to apprehend reality (physical, social, etc.)

If computers are a bicycle for the mind, then perhaps genAI is a Kantian goggles for the brain, allowing us to see into the time and space of 4D quaternionic number systems, hyperbolic space, and time reversal symmetry realized in knowledge graph embedding as an AI Math Layer



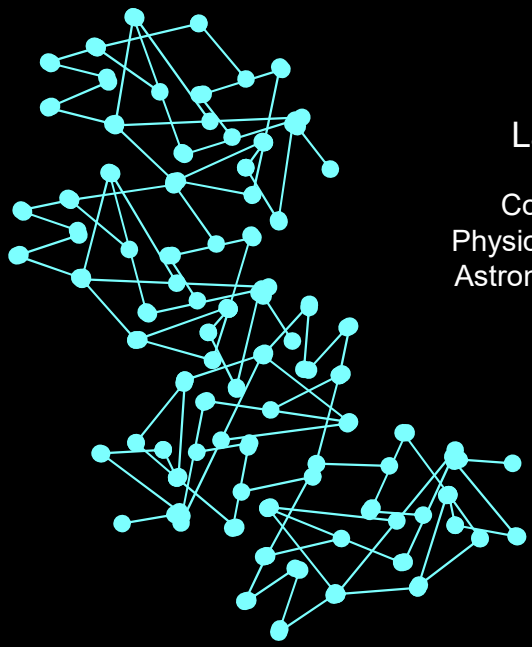

Source: Swan, M. & dos Santos, R.P. 2024. The Second Linguistic Turn: Math Agents for Kantian Intelligence Amplification. Critical Genealogies workshop Syracuse University April 26-27, 2024. DOI: 10.13140/RG.2.2.30208.03848. https://www.researchgate.net/publication/379236605_The_Second_Linguistic_Turn_Math_Agents_for_Kantian_Intelligence_Amplification.

AI is the Interface

Computational Infrastructure

Relativistic

LLMs



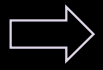
Formal Language

Code, Math, Physics, Chemistry, Astronomy, Biology

Classical

Human

Natural Language



Quantum

LLMs: Large Language Models

Web3 GenAI Quantum Revolution

The Web3 GenAI Quantum Technology Stack

Technology	**Layer**	Application	Low Friction
Web3 Blockchain Ecosystems	**Social**	-Economics: money, assets, voting, governance -Identity: verifiable internet (provenance) -Health: longevity via app, digital twins, BCI	Pure Capital Pure Communication Pure Vitality
GenAI	**Interface**	Chatbots, AI-robotics, LLMs, GPTs, GNNs	Pure Intelligence
Quantum	**Compute**	Quantum, classical, spiking NNs, supercptr	Pure Compute

Web3: Read-Write-Own Web

1980s | 1990s | 2000s | 2020s

Internet

wires, network

Web 1.0

read-only
static

Web 2.0

read-write
interactive

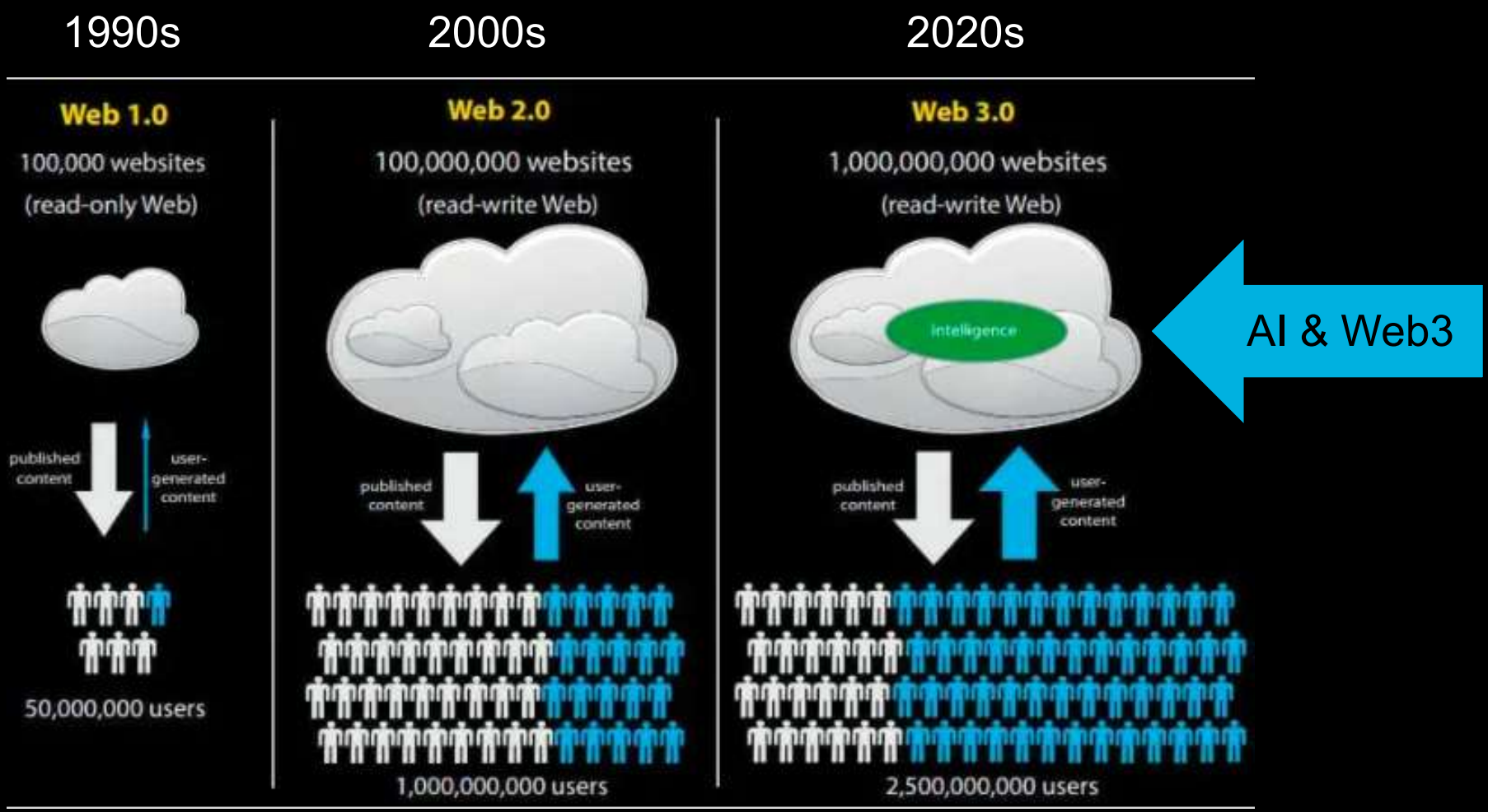
Web 3.0

read-write-trust
verifiable

Source: https://twitter.com/coingecko/status/1487380562171990019

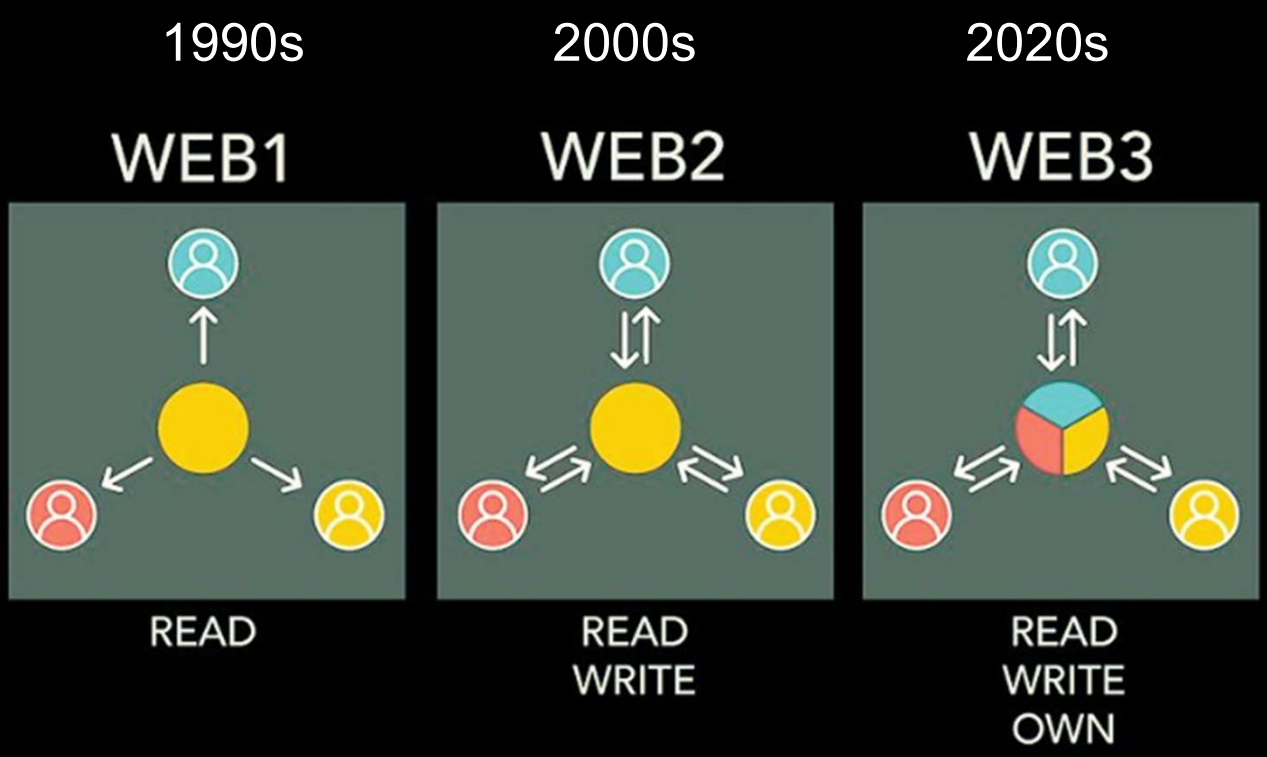
Web3: Read-Write-Own Web

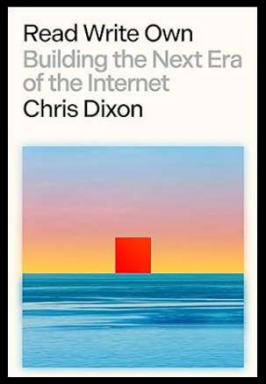
- The secure transaction layer the web never had



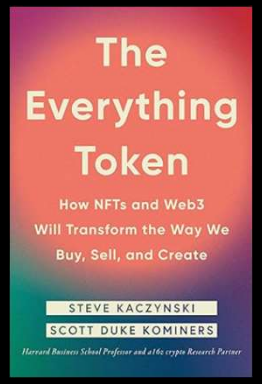
Source: https://www.eatmy.news/2022/03/what-is-web-30-how-is-web3-different.html

Web3: Read-Write-Own Web

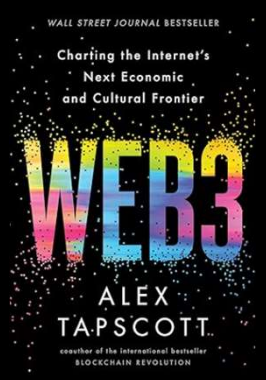




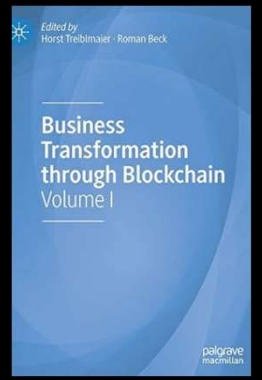
2024



2024



2023

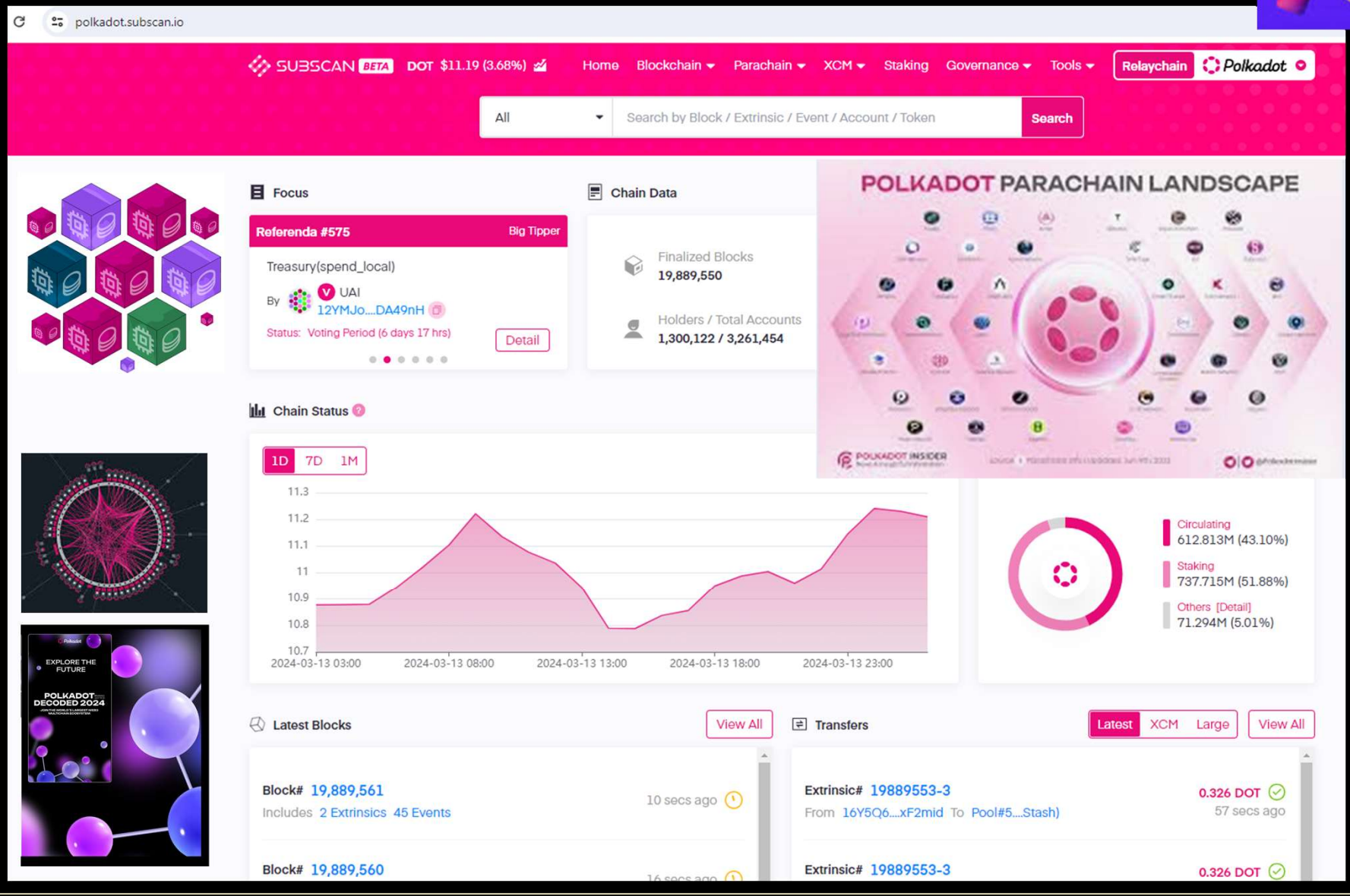


2018

Source: https://twitter.com/FrRonconi/status/1498301677581045760

Relay Chain (core infrastructure) +
49 connected projects (parachains)

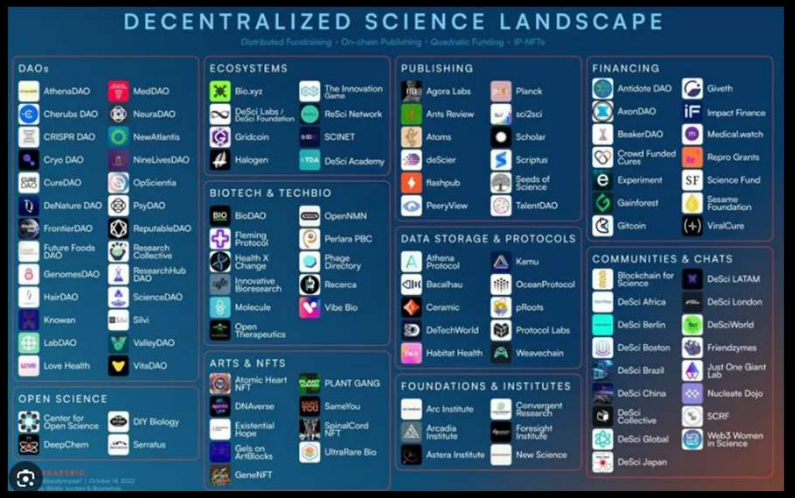
Polkadot Blockchain Ecosystem



Source: https://polkadot.network/

DeSci (Decentralized Science)

- Open Science: Data access, replicability, discovery
- Scale of contemporary science requires secure operating system for networked scientific organizations
- VitaDAO longevity platform
- LabDAO: open, community-governed platforms with democratized access to scientific tools and data
- Drug discovery paper
  - A dual MTOR/NAD+ acting gerotherapy (Jan 2023)



Source: https://www.biorxiv.org/content/10.1101/2023.01.16.523975v1

The AI Stack

Gemini (Google DeepMind Dec 2023): AlphaGo RL + LLM Backprop; reward-based action-taking + prediction

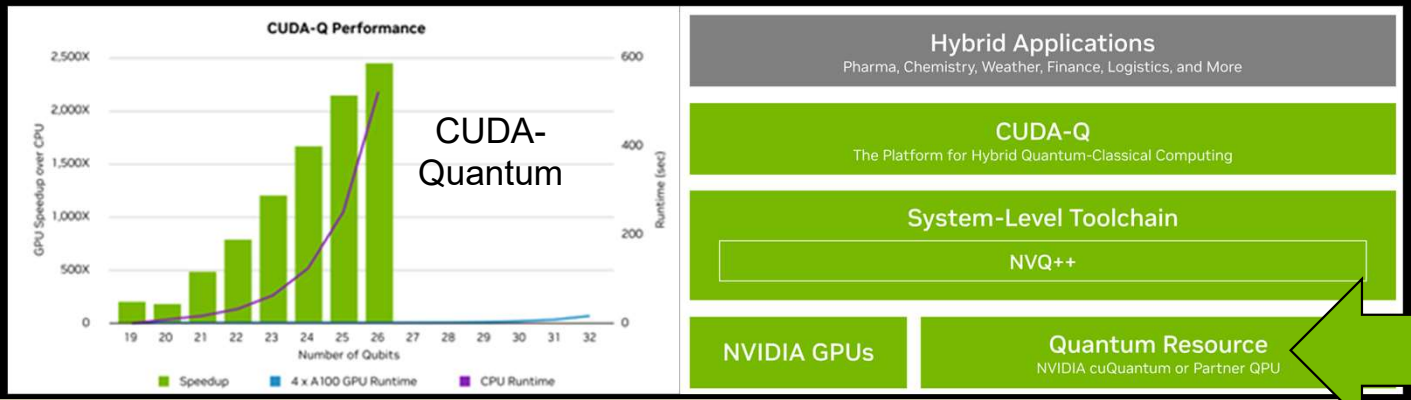
Tier	Technology	Description	Focus	
Interface	AI Chatbots	Human-interface AI assistants	ChatGPT	
Agent	Reinforcement Learning Agents	Robotics, self-driving, gameplay, artificial superintelligence (autocatalytic agents)	Tesla Autopilot AlphaGo	
Content	Knowledge Graphs	Knowledge canon: all entities and their relations in a domain (LLMs, Foundation Models)	Recommend-ation engines	
Architecture	Deep Learning Neural Nets	Multilayer networks running deep learning algorithms (LLM architectures)	Transformers (GPT-4)	

Gemini

Quantum:
Plugs into Stack as Compute Resource

- CPU -> GPU -> TPU -> QPU
  - GPU (graphics processing unit)
    - 3D graphics card: matrix multiplication
  - TPU (tensor processing unit)
    - Flow through matrix multiplications: no storing interim values in memory
  - QPU (quantum processing unit)
    - Quadratic or Polynomial speed-up with superposition, entanglement, interference

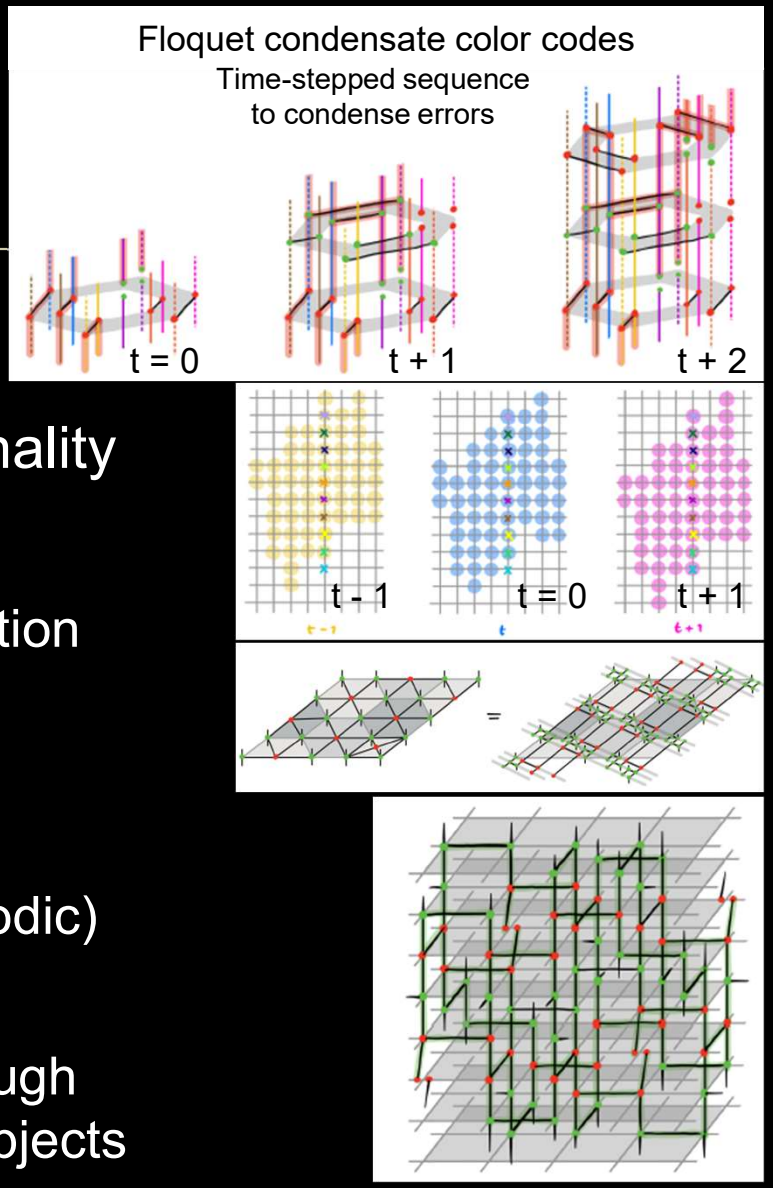
Example: NVIDIA CUDA-Quantum (Compute Unified Device Architecture): parallel computing platform and application programming interface



Source: https://developer.nvidia.com/cuda-q

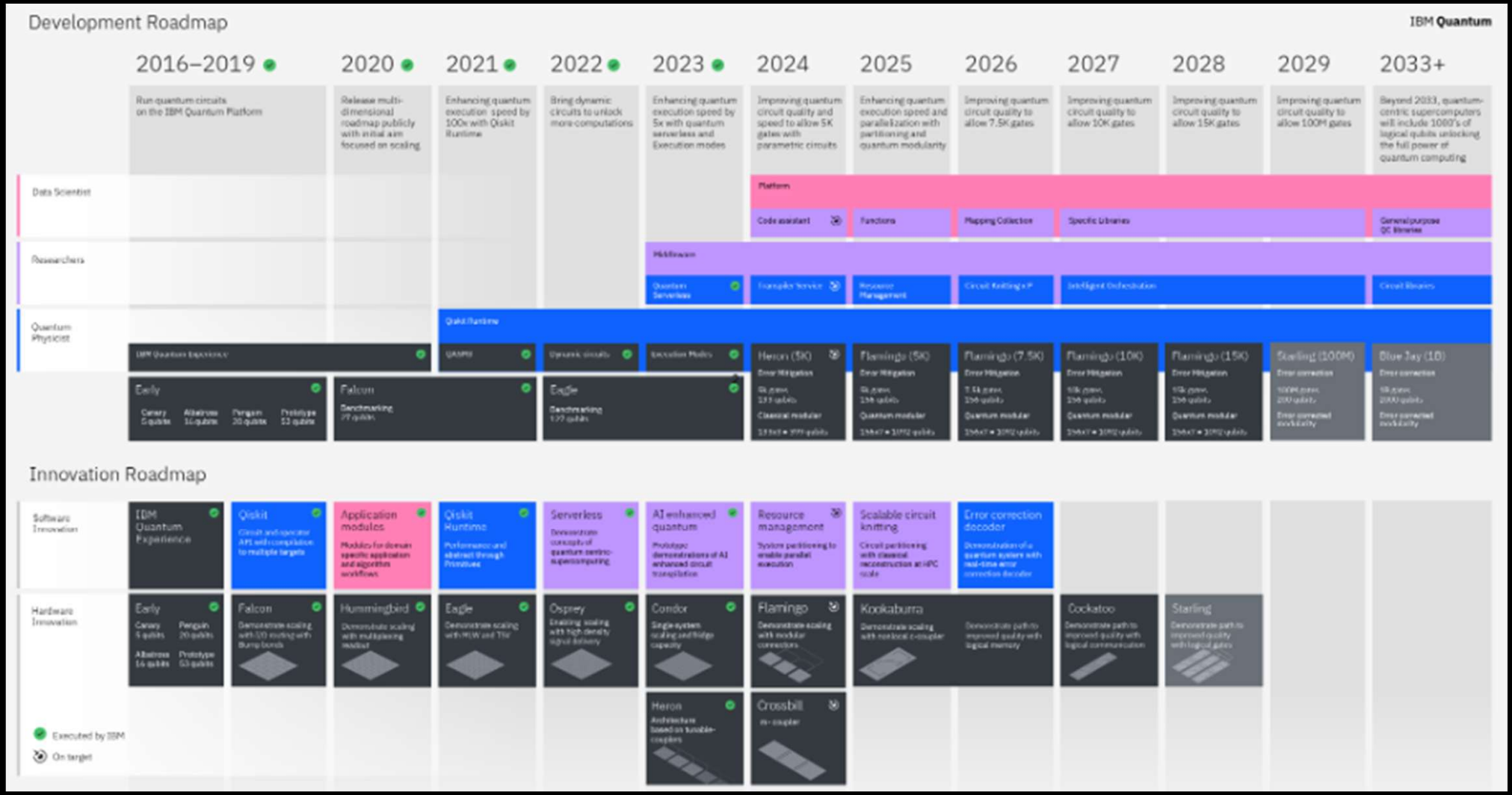
Scaling Status of QECC

1. Known stabilizer codes (toric)
   - Expensive, inefficient, minimal functionality
2. Floquet condensate color codes
   - Sequence of measurement and correction operations that condense errors into harmless “vortices”
   - Floquet codes
     - Time-sequenced QECC (Floquet: periodic)
   - Color codes
     - QECC as sequenced progression through “colored” (labeled) faces of quantum objects
   - Condensate color codes
     - Stepped process to condense out errors



Source: Townsend-Teague et al. (2023). Floquetifying the Colour Code. arXiv:2307.11136.

IBM Roadmap: 127-qubit system (Dec 2023)



Source: https://www.ibm.com/quantum/technology

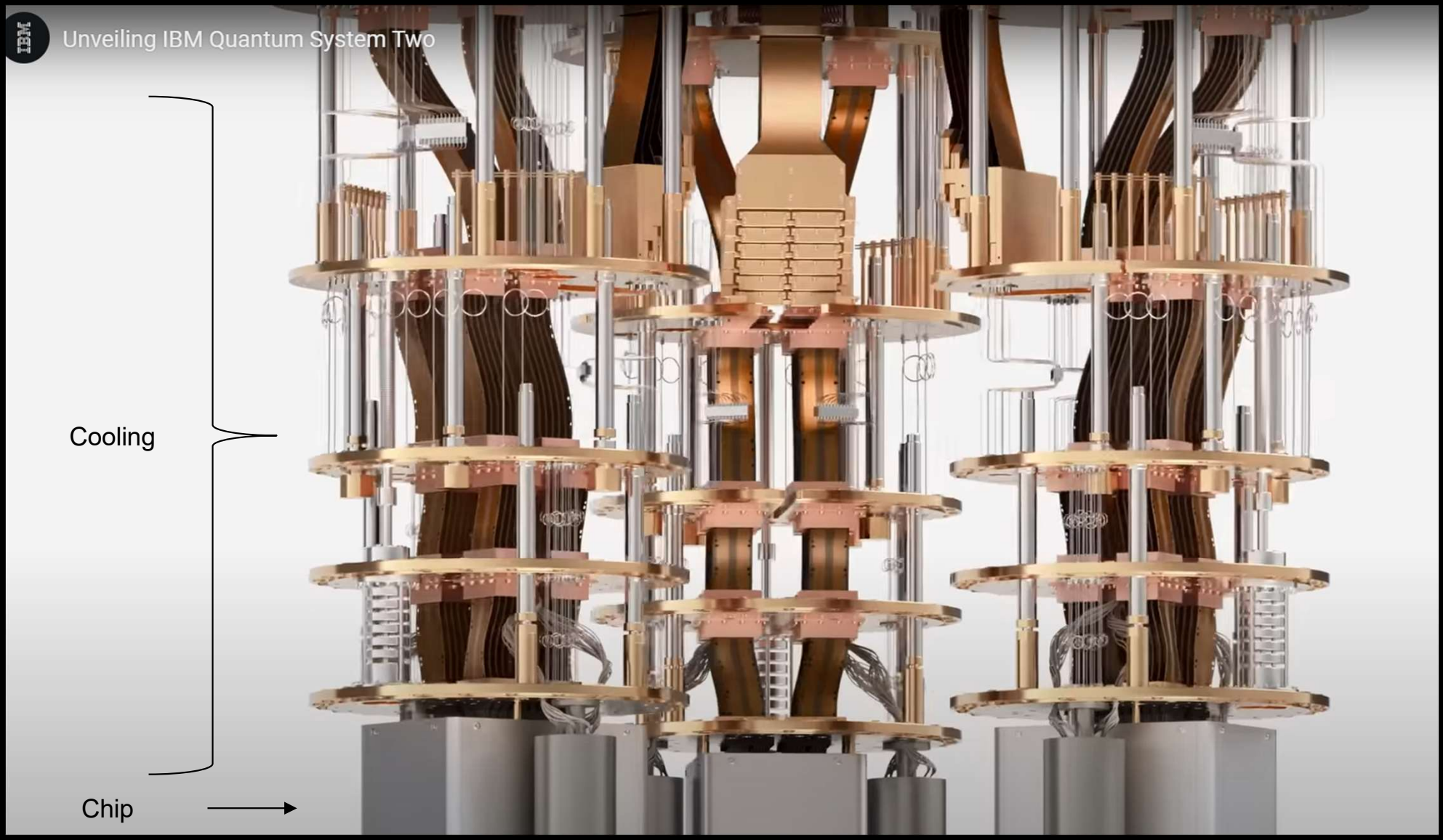
University of Tokyo installs 127-Qubit IBM

The University of Tokyo Completes Installation of 127-Qubit IBM Quantum Eagle Processor

TOKYO, JAPAN, Nov. 27, 2023 -- Today, the University of Tokyo (UTokyo) and IBM (NYSE: IBM) have announced the deployment of a 127-qubit IBM Quantum Eagle processor, now operational in Japan's...

Source: https://www.ibm.com/quantum/technology

IBM Quantum System Two



Source: https://www.ibm.com/quantum/technology

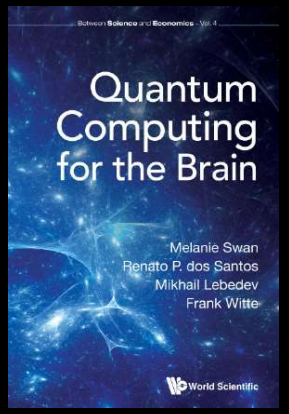
Digital Biology and Quantum Computing

- Cleveland Clinic lobby
  - 127-qubit IBM Quantum System One (one processor)
- First quantum computer devoted to healthcare research
- Quantum testing
  - Processor used to test variations of a chemical formula for effectiveness in drug design

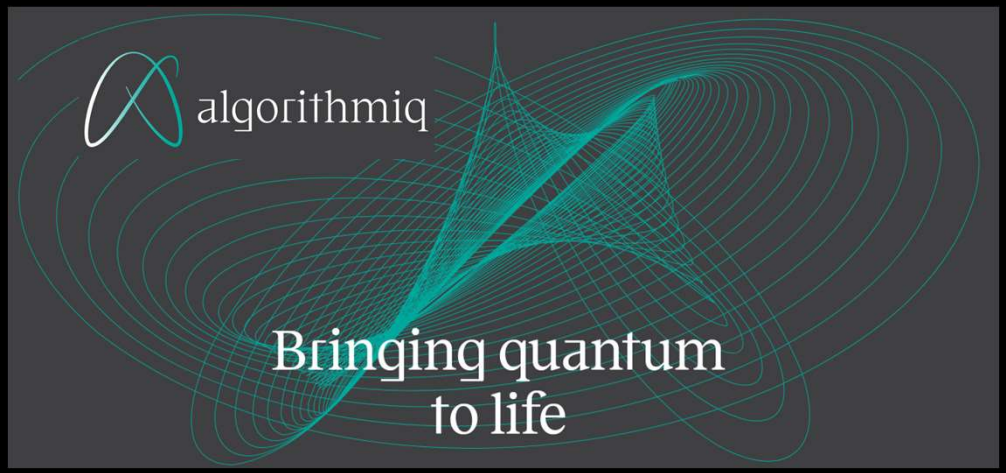
Source: https://newsroom.clevelandclinic.org/2023/03/20/cleveland-clinic-and-ibm-unveil-first-quantum-computer-dedicated-to-healthcare-research/

Digital Biology and Quantum Computing

- Wellcome Trust $40M Quantum for Bio (Q4Bio)
  - Accelerate applications of quantum computing in human health
- Aim: biology and health applications benefiting from quantum computers
  - Health applications
  - Quantum algorithms



2022

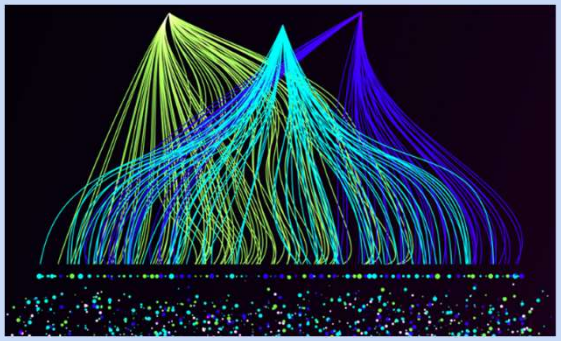


Source: https://wellcomeleap.org/q4bio/

Agenda

- Web3: Social Layer
  - Economics
  - Identity
  - Health
- GenAI: Interface Layer
- Quantum: Compute Layer

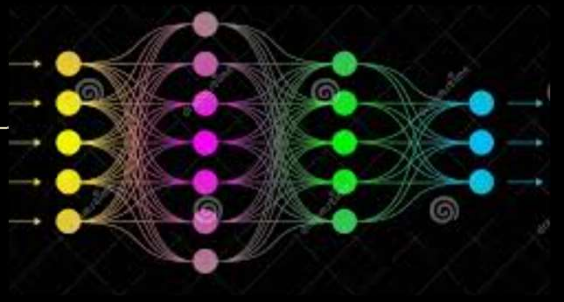
- GenAI



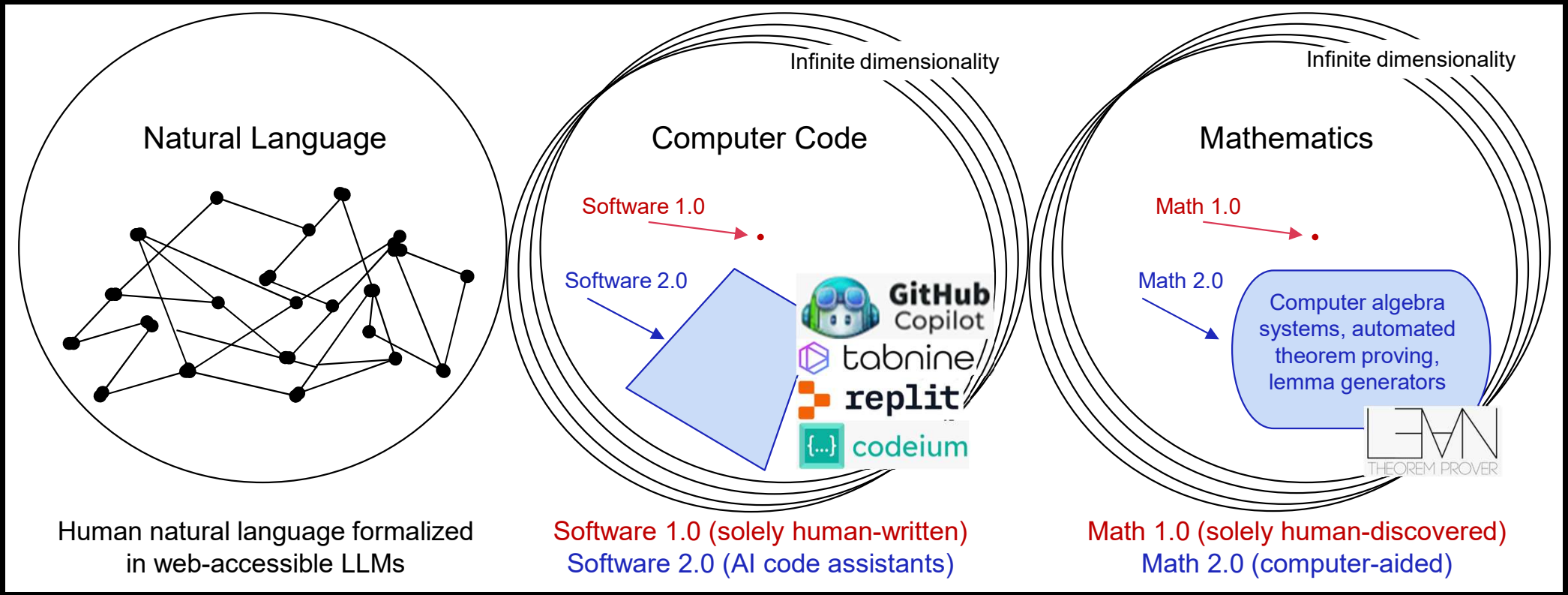
The Web3 GenAI Quantum Technology Stack

Technology	**Layer**
Web3 Blockchain Ecosystems	**Social**
GenAI	**Interface**
Quantum	**Compute**

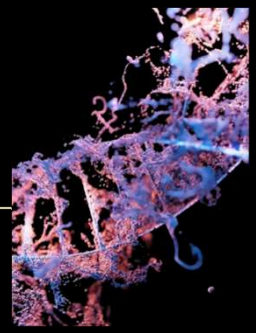
Everything is a Language

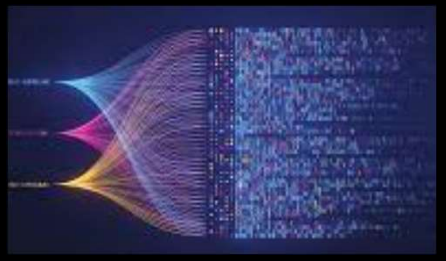


- Natural language
- Formal languages: mathematics, physics, chemistry, biology, software code



Biology: Complex, Unknown Ruleset





Mathematical Reasoning Agents

DeepSeekMath
7 billion parameters

Pathway

Genome

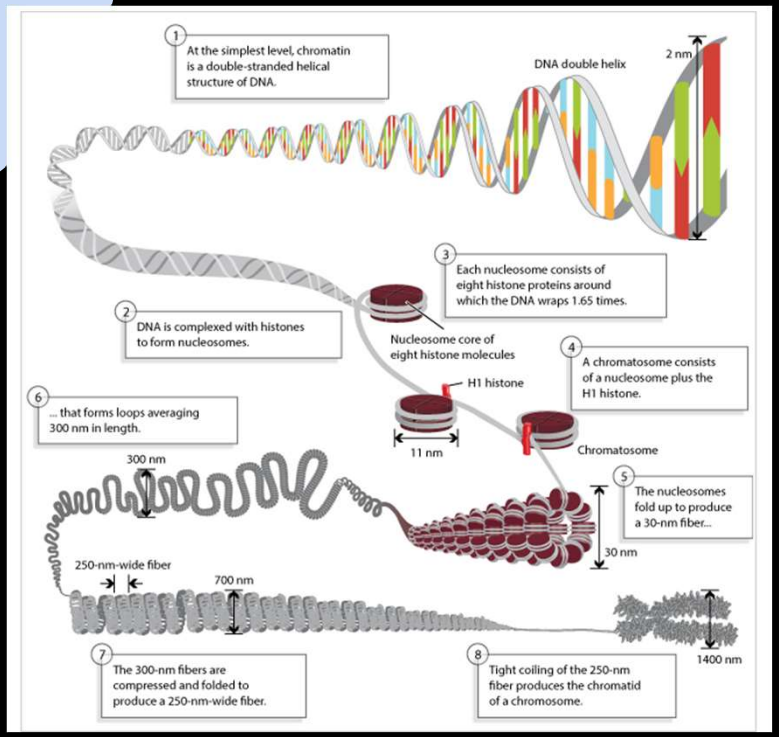
Genome Language Models

Protein

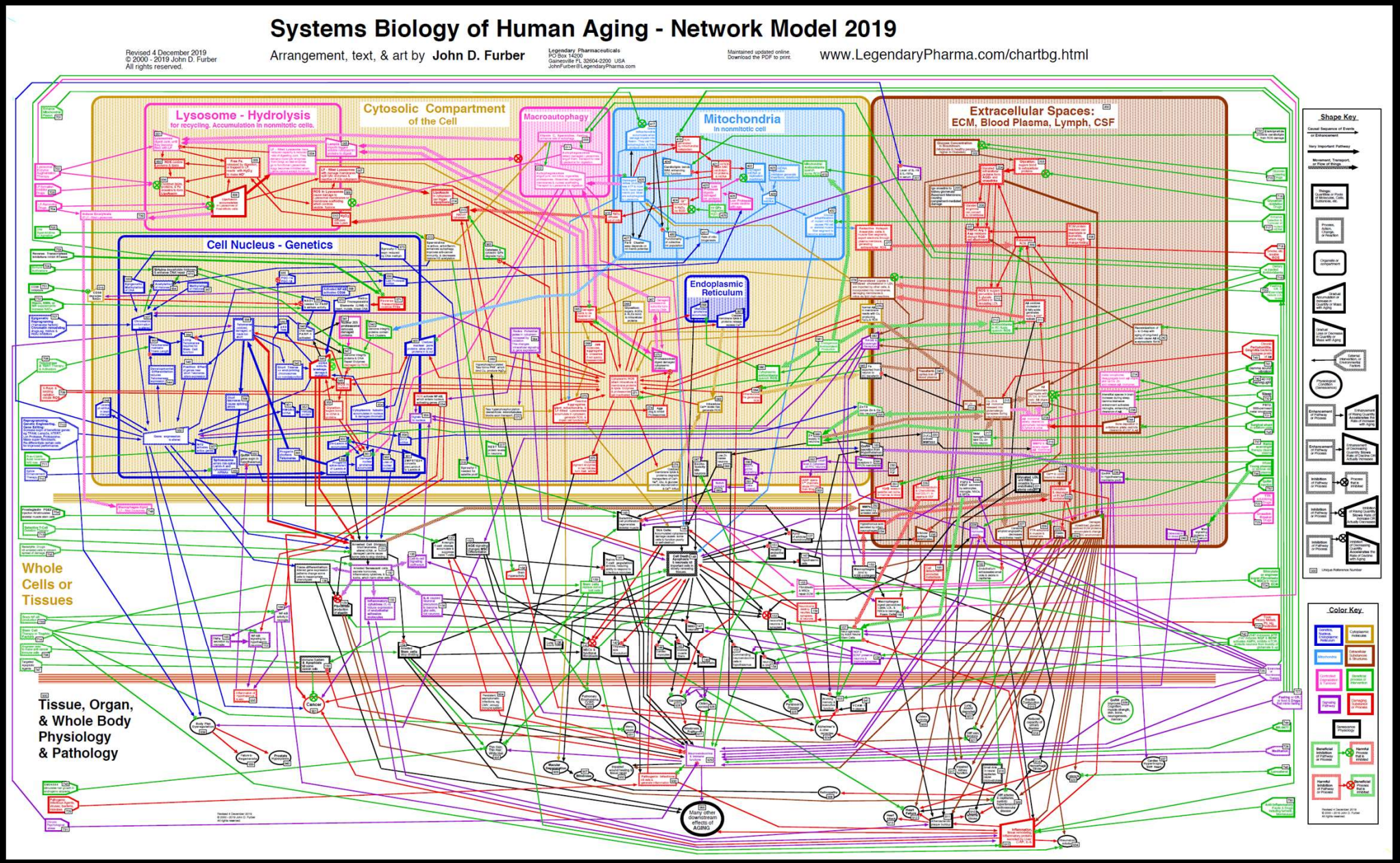
Protein Language Models:
xTrimoPGLM:
100 billion parameters

Natural Language

LLMs: LLaMa
65 billion parameters



Parameter: learnable weights between graph nodes (entities)
Source: https://www.biomap.com/sota/

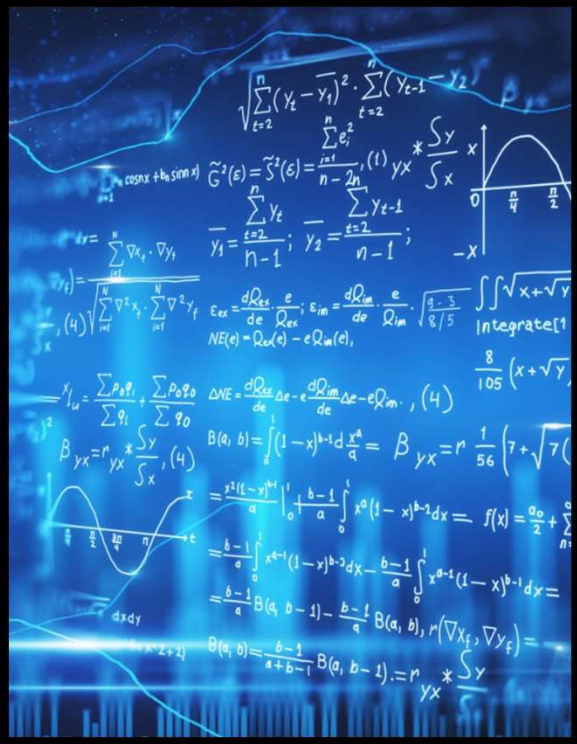


Source: Furber, J. (2019). https://legendarypharma.com/chartbg.html

AI Math Layer

Digitization implies Mathematics

- Digitization means not simply converting data to ones and zeros, but the mathematical treatment of these data
- Mathematical instantiation further connotes efficiency as a well-formed, validated, provable content, and mobilization
- Any mathematical instantiation is portable to other mathematical analysis; any mathematics calls all mathematics



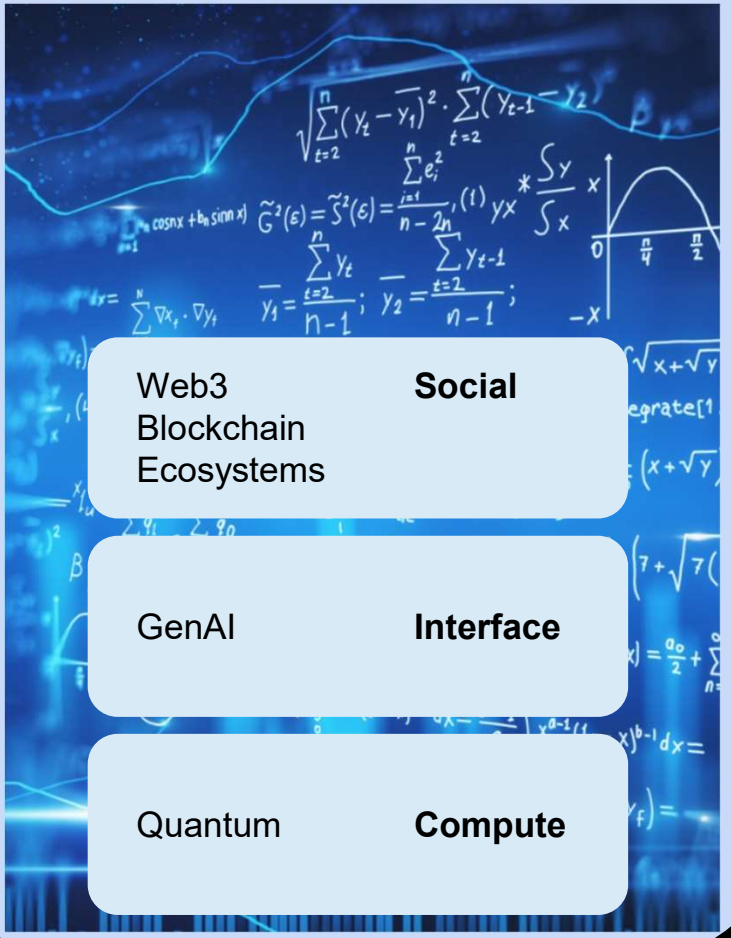
Source: Math Agents https://arxiv.org/abs/2307.02502, https://huggingface.co/papers/2307.02502
https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf, https://github.com/eric-roland/diygenomics

Humans: “bad at math”

- On the one hand
  - Increased intensity of mathematics and formal language in the computational infrastructure
- On the other hand
  - Generally, little human interest or aptitude for mathematics
  - Humanity sees mathematics as a high-value content but has limited ability to use it
  - Hence, democratization of math with Math Agents

AI Math Layer

The Web3 GenAI Quantum Technology Stack



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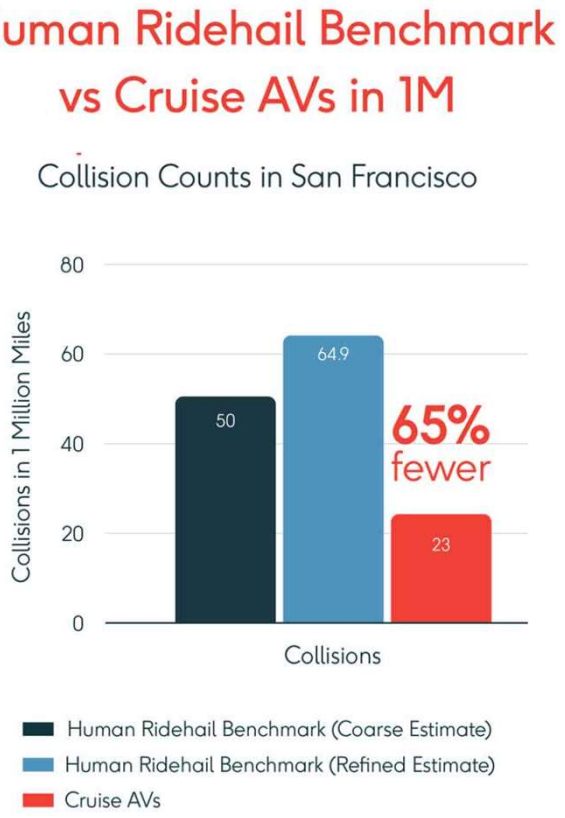
AI Outsourcing Argument

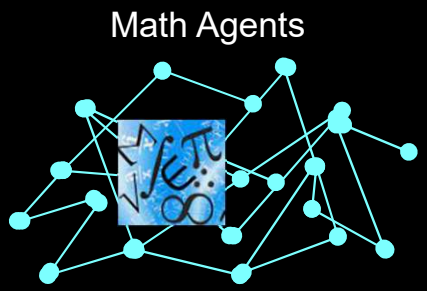
- AI better than humans at repetitive high-precision tasks
  - Elevator operator
  - Laser eye surgery
  - Driving
  - Computer coding
  - Mathematics

Human ridehail driver crash rate: 50.5 crashes per million miles (CPMM)
Self-driving cars crash rate: 23 CPMM



Source: https://www.warpnews.org/transportation/self-driving-cars-are-safer-than-human-drivers-study-shows

Math Agents



Math Agents: an “AI Math Layer” of specialized AI systems and a problem-solving stance based on the mobilization of mathematical content as an upleveled and validated lever for interacting with reality

AI systems trained specifically for the mathematics context to solve mathematical problems and perform mathematical tasks both in pure mathematics (e.g. automated theorem proving, lemma positing) and applied mathematics (e.g. model-fit assessment)

Any chatbot is already a Math Agent as math-related content can be queried and generated, however, purpose-built AI systems are emerging for targeted applications

Source: Math Agents https://arxiv.org/abs/2307.02502, https://huggingface.co/papers/2307.02502 https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf, https://github.com/eric-roland/diygenomics

Math Agent Landscape

- Quantitative reasoning on high-quality tokens (math, code) improves overall LLM reasoning

Math Agents

1. Equation extraction: OCR/RAG

Code-based approach to math

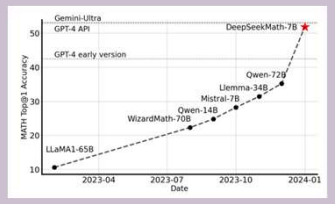
GPT-4V
MathPix
LaTex AI

2. Mathematical Reasoning Agents

Word-based approach to math

LLM-based Mathematical Reasoning Agents:

DeepSeekMath [open]
Minerva (PaLM) [closed]
Llemma (OpenMathWeb) [open]
ToRA (Anthropic), Polymathic, MathWizard (Llama), Math2Vec



3. Mathematical Discovery Agents

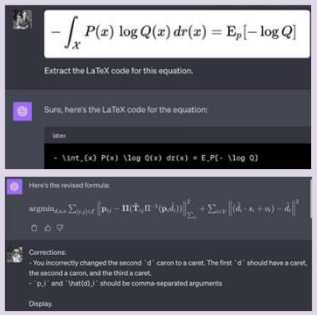
AlphaTensor:

matrix multiplication algorithms

- Math as code: turn math into code and solve as code

Math Corpus	Size	English Benchmarks					Chinese Benchmarks		
		GSM8K	MATH	OCW	SAT	MMLU STEM	CMATH	Gaokao MathCloze	Gaokao MathQA
No Math Training	N/A	2.9%	3.0%	2.9%	15.6%	19.5%	12.3%	0.8%	17.9%
MathPile	8.9B	2.7%	3.3%	2.2%	12.5%	15.7%	1.2%	0.0%	2.8%
OpenWebMath	13.6B	11.5%	8.9%	3.7%	31.3%	29.6%	16.8%	0.0%	14.2%
Proof-Pile-2	51.9B	14.3%	11.2%	3.7%	43.8%	29.2%	19.9%	5.1%	11.7%
DeepSeekMath Corpus	**120.2B**	**23.8%**	**13.6%**	**4.8%**	**56.3%**	**33.1%**	**41.5%**	**5.9%**	**23.6%**

DeepSeekMath https://arxiv.org/pdf/2402.03300.pdf



Source: Math Agents https://arxiv.org/abs/2307.02502, https://huggingface.co/papers/2307.02502 https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf, https://github.com/eric-roland/diygenomics

Math Agents platforms

AI Math Stack (DeepMind)

- Fundamental advance in mathematics and algorithms
  - GNNs amplify reasoning re large mathematical objects
  - RL Math Agent game-play to find best algorithms
    - Fastest, shortest number of instructions
  - LLMs find best functions to solve math problems

GNNs	Reinforcement Learning - Math Agents		Math "LLMs"
GNNs (2021): ML-aided reasoning Demo: Knot theory: algebraic-geometric Demo: Representation theory: combinatorial invariance conjecture algorithm	**AlphaTensor** (2022) 3D Game: TensorGame Demo: 70% faster matrix multiplication (70 sizes)	**AlphaDev** (Jun 2023) 3D Game: AssemblyGame Demo: faster sorting algorithms (3-5 items)	**Fun(ction)Search** Codey LLM(Dec 2023) Demo: math problems: Cap set problem Bin sorting problem **AlphaGeometry**: Euclidean geometry theorem prover Demo: Olympiad
	RL game play: frame problems as a 3D board game; finding fastest algorithm (matrix multiplication, sorting) is a game RL agent learns as best series of moves to solve a problem		
	AlphaZero (2018): DRL algorithm Demo: AlphaGo, chess, Shogi		

CS: Computer Science; DRL: deep reinforcement learning

Math Agents

Further implication of Math Agent systems is that they can generically output descriptive mathematics as part of their results GenAI means asking an LLM to generate any content, image, text, video, philosophical arguments, or computer code, likewise, the descriptive mathematics of a system

The implied result is not only obtaining the content level prediction (e.g. a folded protein structure), but also its mathematical description. AI writes the best code (Karpathy 2017) and may also generate the best mathematical description. Math Agents, as an AI Math Layer in the computational infrastructure, may write the mathematics of any system as a generic output, including as a core feature of Digital Biology executed with **Health Agents**

Source: Health Agents: Swan, M., Kido, T., Roland, E. & dos Santos, R.P. (2024). AI Health Agents: Pathway2vec, ReflectE, Category Theory, and Longevity. AAAI 2024 Spring Symposium Series: Impact of GenAI on Social and Individual Well-being. https://www.melanieswan.com/documents/swan-AI-health-agents.pdf

Health Agents

Health Agents are a form of Math Agent in the concept of a personalized AI health advisor to deliver "healthcare by app" instead of "sickcare by appointment"

As any AI agent, Health Agents "speak" natural language to humans and formal language to the computational infrastructure, possibly outputting a layer of AI mathematics for personalized longevity and homeostatic health as part of their operation

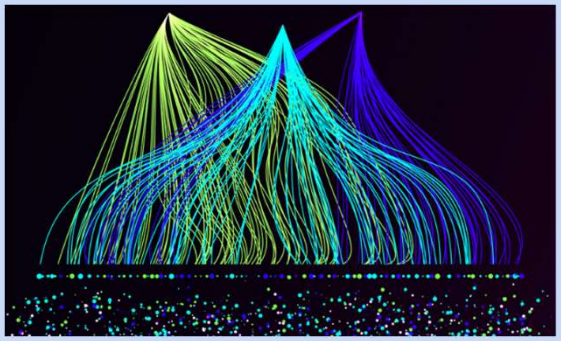
Mobile devices can check health 1000x/min vs 1x/yr doctor's office visits with the digital twin app, Health Agents could facilitate the ability of physicians to oversee the health of thousands of individuals at a time, easing overstressed healthcare systems, and contributing to health equity as the WHO estimates that more than half of the global population is not covered by essential health services

Source: Health Agents: Swan, M., Kido, T., Roland, E. & dos Santos, R.P. (2024). AI Health Agents: Pathway2vec, ReflectE, Category Theory, and Longevity. AAAI 2024 Spring Symposium Series: Impact of GenAI on Social and Individual Well-being. https://www.melanieswan.com/documents/swan-AI-health-agents.pdf

Agenda

- Web3: Social Layer
  - Economics
  - Identity
  - Health
- GenAI: Interface Layer
- Quantum: Compute Layer

- Math Agents in Biology



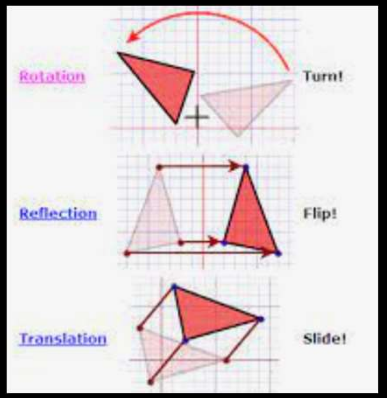
The Web3 GenAI Quantum Technology Stack

Technology	**Layer**
Web3 Blockchain Ecosystems	**Social**
GenAI	**Interface**
Quantum	**Compute**

GPT: Generative Pre-trained Transformer

- Generative AI: AI systems that can generate new content (text, images, music) based on patterns and structures learned from existing data

- GPT: generative pre-trained transformer
- "Transformers" literally "transform" vector-based data representations during the learning phase (using matrix multiplication methods) per allowable symmetry transformations
  - Translation (displacement), rotation, reflection

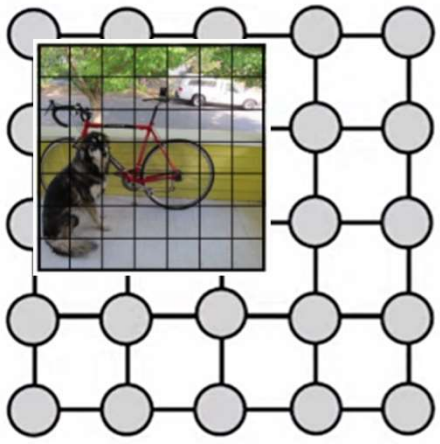
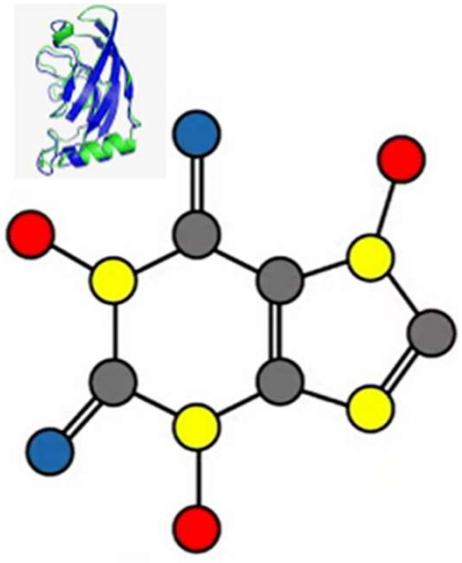


- Knowledge graph vector embedding
  - TransE (translation embedding), RotatE (rotation embedding), ReflectE (reflection embedding) algorithms, LorenTzE (Lorentz invariance time symmetry anti-symmetry)

Source: OpenAI. (2021). GPT-4 Technical Report. https://arxiv.org/abs/2303.08774.

GNNs: Graph (transformer) NNs: 2d -> 3D+

- GNN: NN designed to process graph-structured data

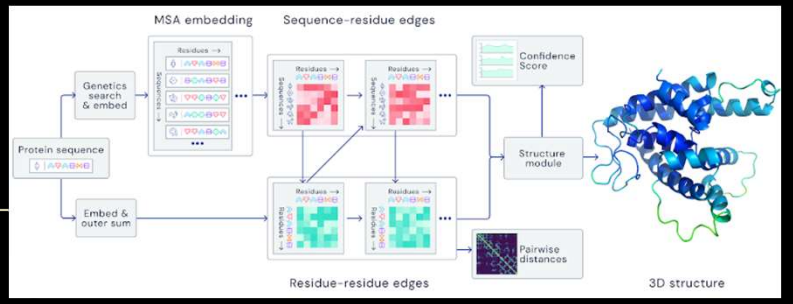
Input data	2D	3D	3+D
	Grids	Graphs	Manifolds
			Space with changing curvature (knee, gravitational well)
			
	Translation Invariance	*Permutation Invariance*	*Gauge Symmetry*

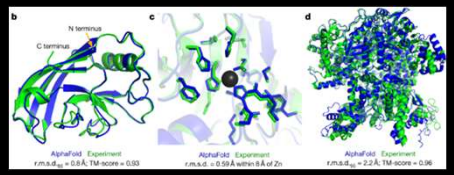
Invariance (symmetry): Transformations that can be performed to process the data mathematically to find salient patterns without changing the key properties of the underlying data; in molecular design, equivariance (translation, rotation but not reflection symmetry)

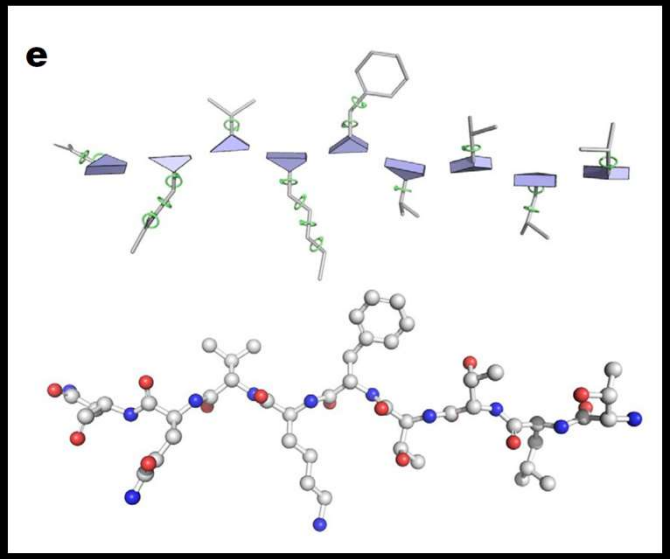
Source: Michael Bronstein & team, https://geometricdeeplearning.com/lectures/

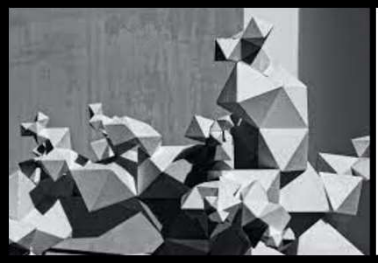
AlphaFold2

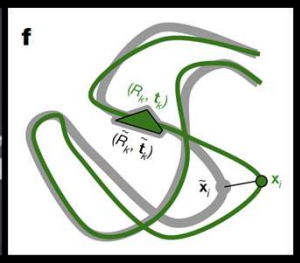
- Graph NN: predict 3D structure of proteins from underlying amino acid sequences
- Symmetry
  - Invariance: output unchanged per transformation
  - Equivariance: output changes consistently with transformation)
- Invariant point attention
  - Model the displacement and rotation of amino acids as triangles in space to identify pairwise combinations based on angle and torsional force











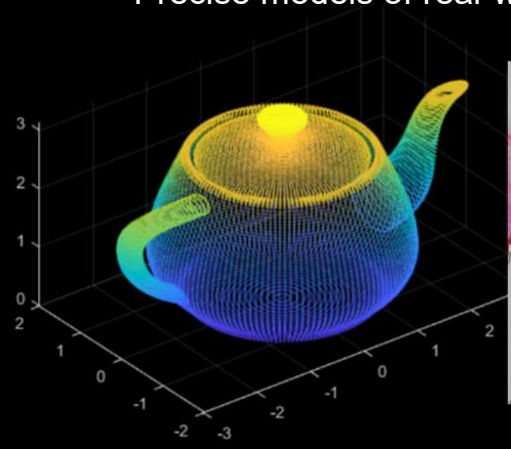
Source: Jumper, J., Evans, R., Pritzel, A. et al. (2021). Highly accurate protein structure prediction with AlphaFold. Nature 596, 583–589. https://doi.org/10.1038/s41586-021-03819-2.

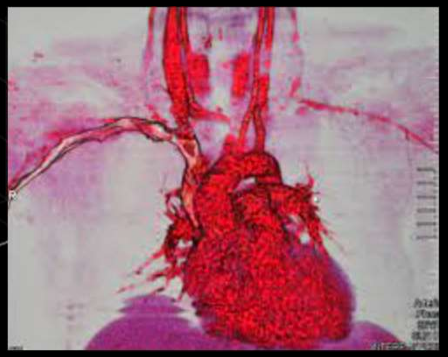
3d Point Clouds

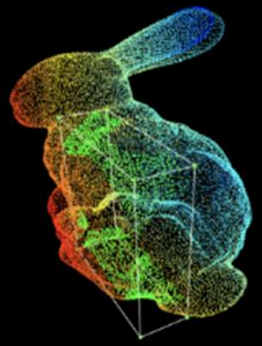
- Graph-based data relevant to all 3D representation
- Self-driving, AI Robotics
- Molecules
  - Drug design, quantum computing, molecular manufacturing
- Digital Twins
  - Architecture, surveying
  - Traffic smart mapping
- Gaming, virtual reality

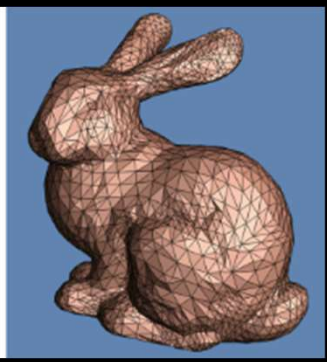
Point Cloud Embedding

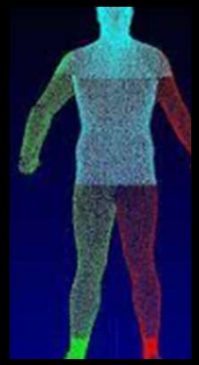
Precise models of real-world objects and spaces

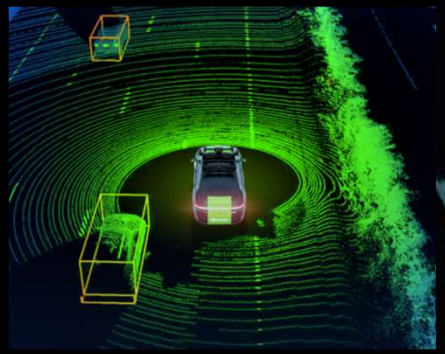


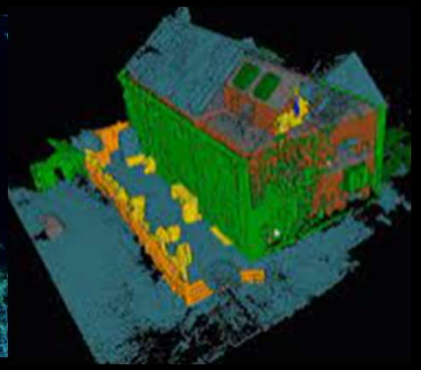






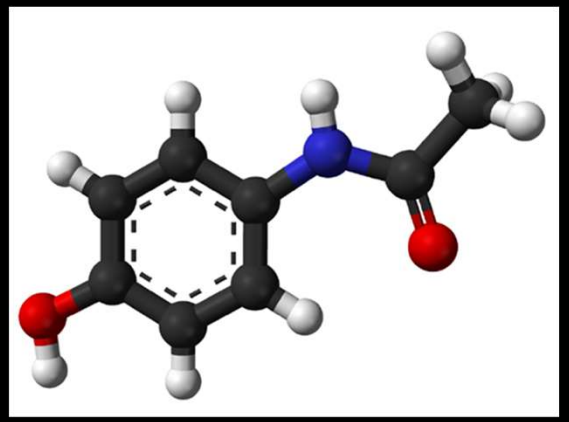


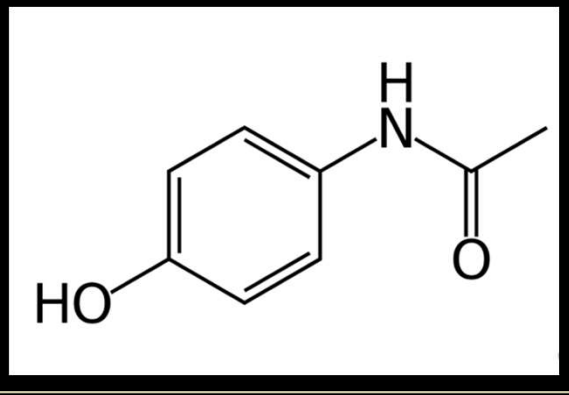


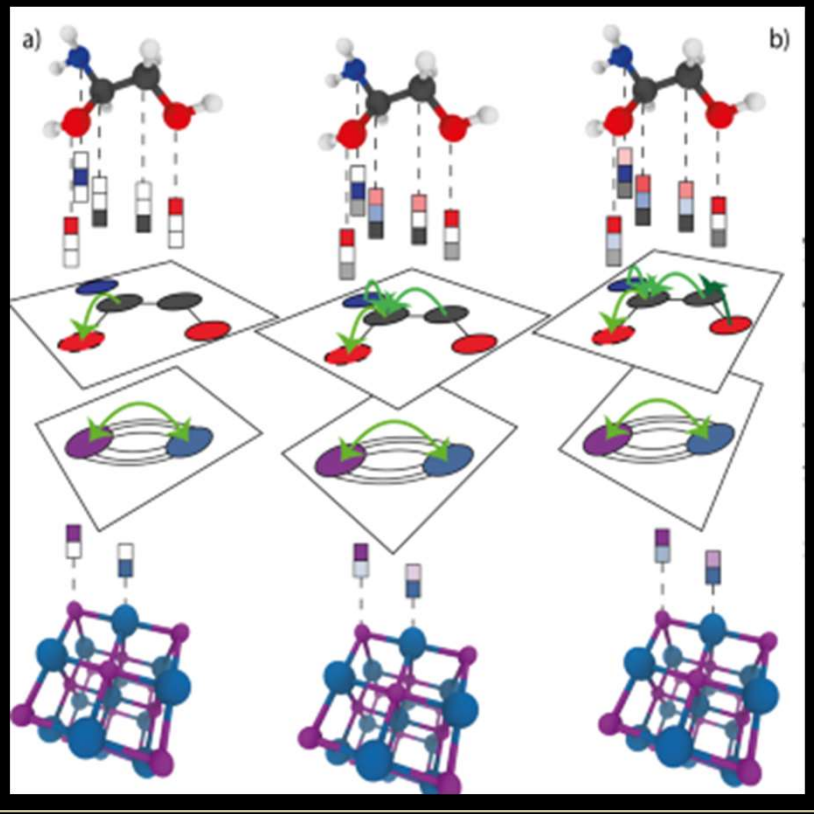


3D: Graph Representation of Molecules

- Natural sciences
  - Atoms are nodes, bonds are edges
  - Features are atom type, charge, bond type

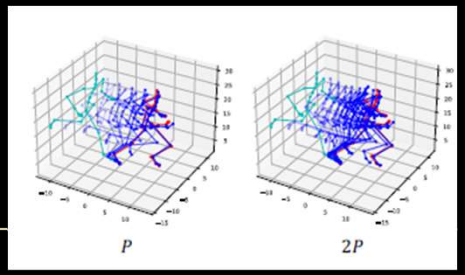






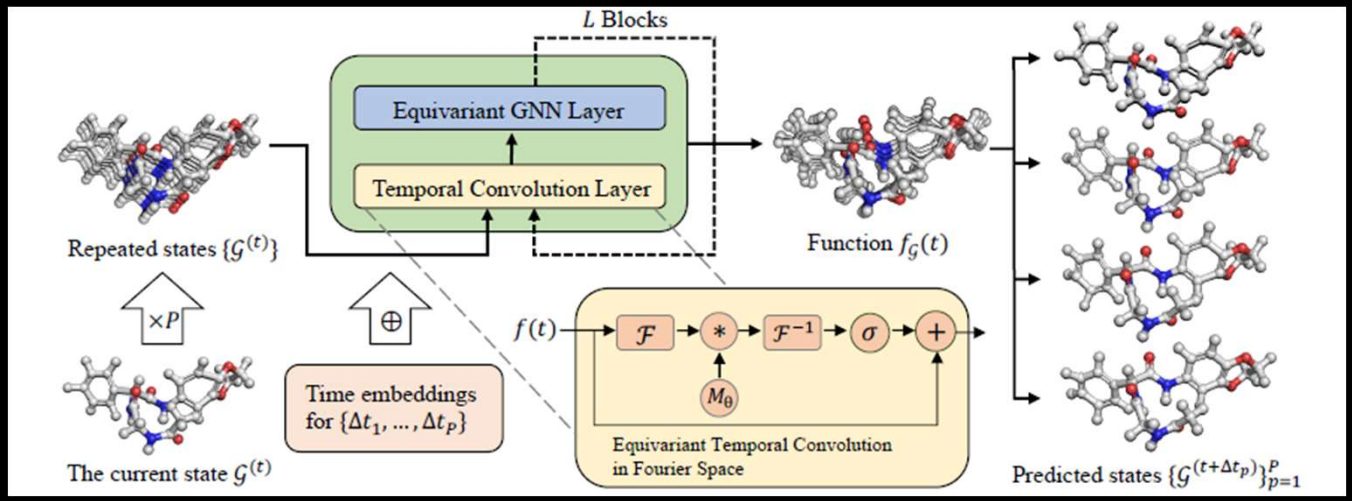
Sources: https://geometricdeeplearning.com/lectures, Reiser (2022). Graph neural networks for materials science and chemistry. Comm Mat. 3(93). https://www.nature.com/articles/s43246-022-00315-6

Temporal Neural Operators



- Neural operators: learn mappings between functions
  - Learn mappings between (continuous function) Banach spaces versus mappings between vectors, solve PDEs, ODEs
  - Fourier neural operator: PDE method with discretization invariance and approximation universality properties
- Equivariant Graph Neural Operator for 3D Dynamics
  - Model dynamics as a function of 3D states over time

Use equivariance property of Fourier and inverse Fourier transforms to capture temporal correlations by stacking equivariant temporal convolution layers in the Fourier space with equivariant networks, retaining SE(3)-equivariance

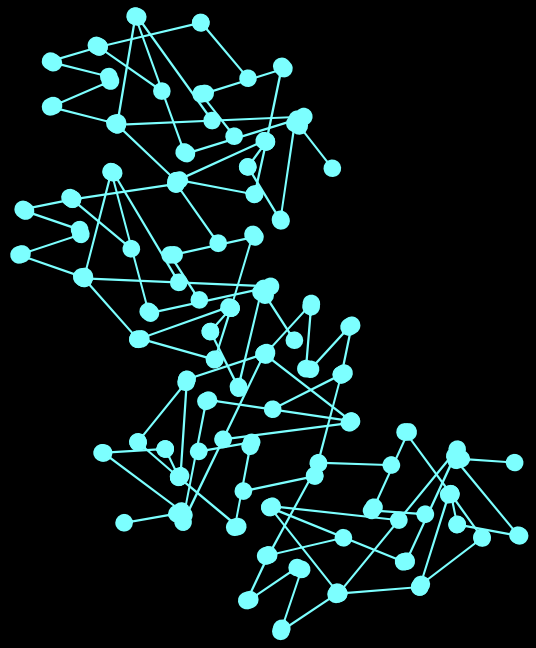


Source: Leskovec-Anandkumar team: Xu, M., Han, J., Lou, A. et al. (2024). Equivariant Graph Neural Operator for Modeling 3D Dynamics. arXiv:2401.11037v1.

Beyond Euclidean Space and Time

- Graph geometries: more efficient representation

AI



Human

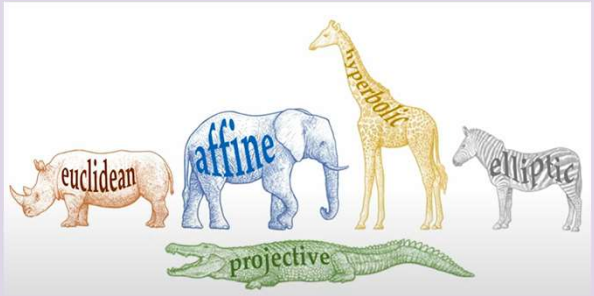
Low-D

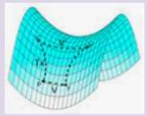
Low Dimensionality
Traditional Euclidean 3d space, 1d time

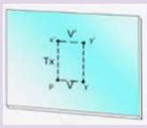
High Dimensionality
Beyond Euclidean Space and Time

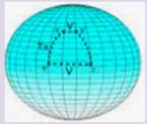
Space

Diverse Geometries









Hyperbolic-Euclidean-Spherical Space

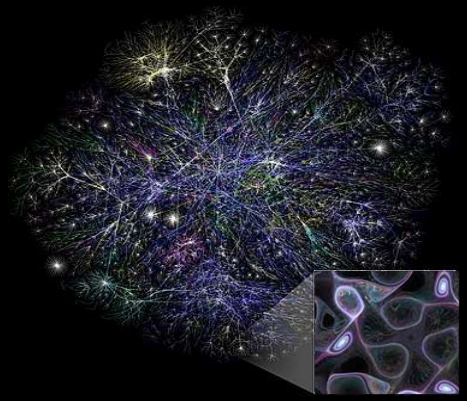
Time

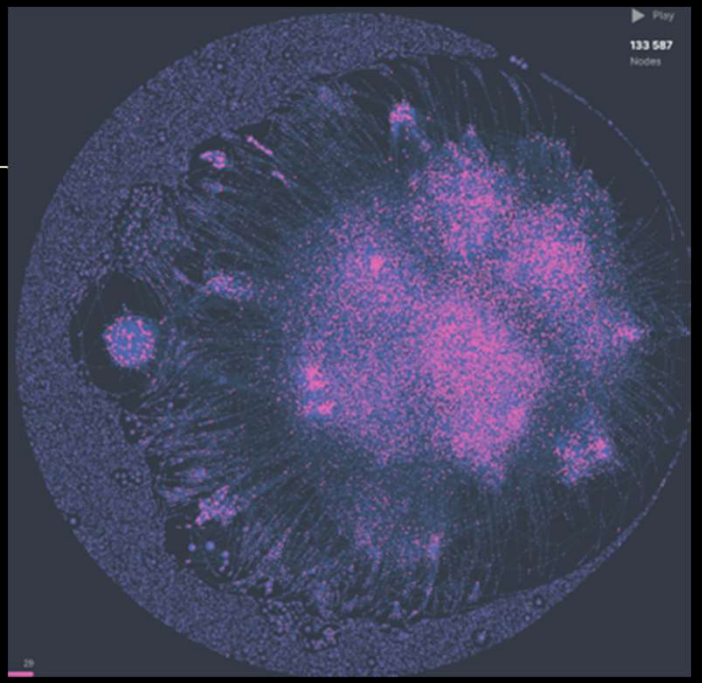
GNN: Time-warping (renormalization for time)
stretching-compressing temporal data sequences for pattern-finding;
find similarities independent of local shifts and timing variations
Biology: oscillation, periodicity, waves, circadian rhythms
Physics: scrambling, chaos (ballistic spread + saturation)
Quantum: 2d time: periodic (Floquet), quasiperiodic (offsetting lasers effectively create second time dimension)
Geology: simultaneous view of multiple historical epochs

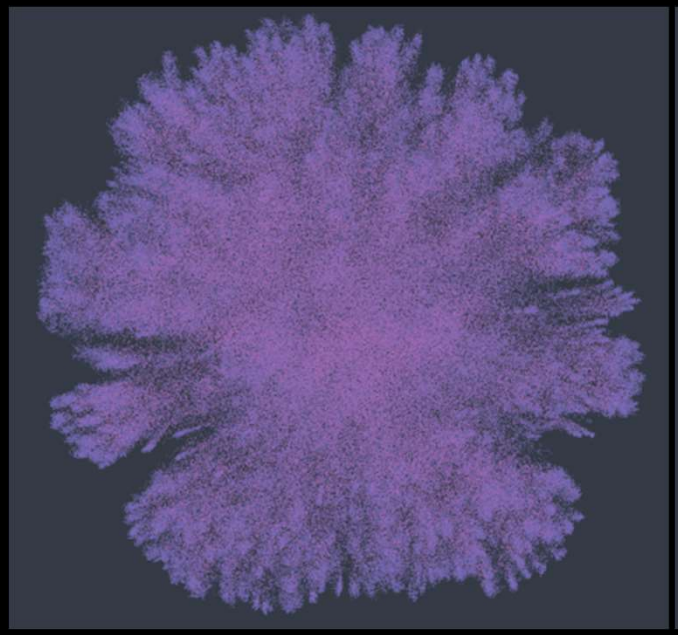
Source: Michael Bronstein & team, https://geometricdeeplearning.com/lectures/, Petar Velickovic https://www.youtube.com/watch?v=uF53xsT7mjc

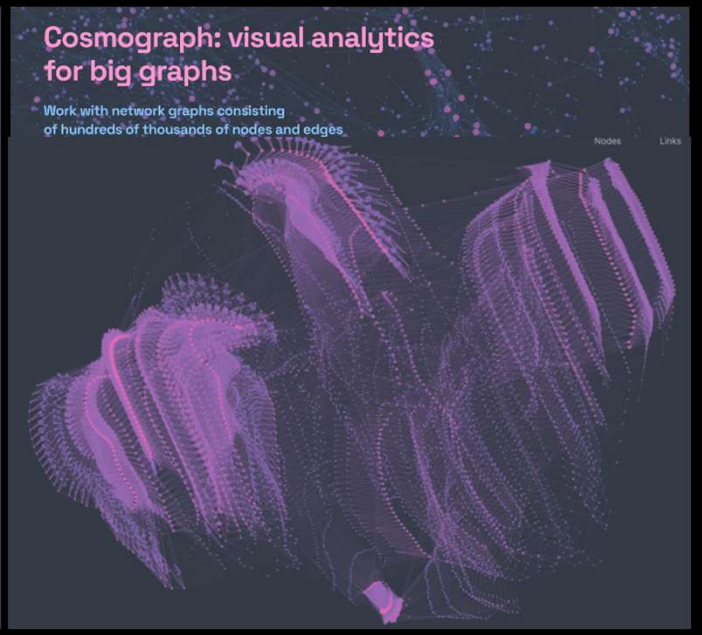
Large Graph Visualization

- Million-node graphs
  - Virtual Cell
  - Astronomical Data









Sources: https://nightingaledvs.com/how-to-visualize-a-graph-with-a-million-nodes/, https://cosmograph.app/

Knowledge Graph Vector Embedding (KGE)

- All modes of data input converted to vector embedding for high-dimensional analysis by AI systems
  - KGE Methods: Quantum-classical-relativistic models, real-complex-quaternionic (1D-2D-4D) numbers, and beyond-Euclidean space (spherical, hyperbolic) and time (Lorentz invariance, imaginary (complex-valued) time, and time reversal symmetry)

Vector embedding: representing a data object (word, sentence, equation, image, user) as a list of numbers (vector) that captures properties and relationships in relation to other objects

Image

Text

Equation

Code

Chemical Formula

Amino Acid Sequence

DNA Sequence

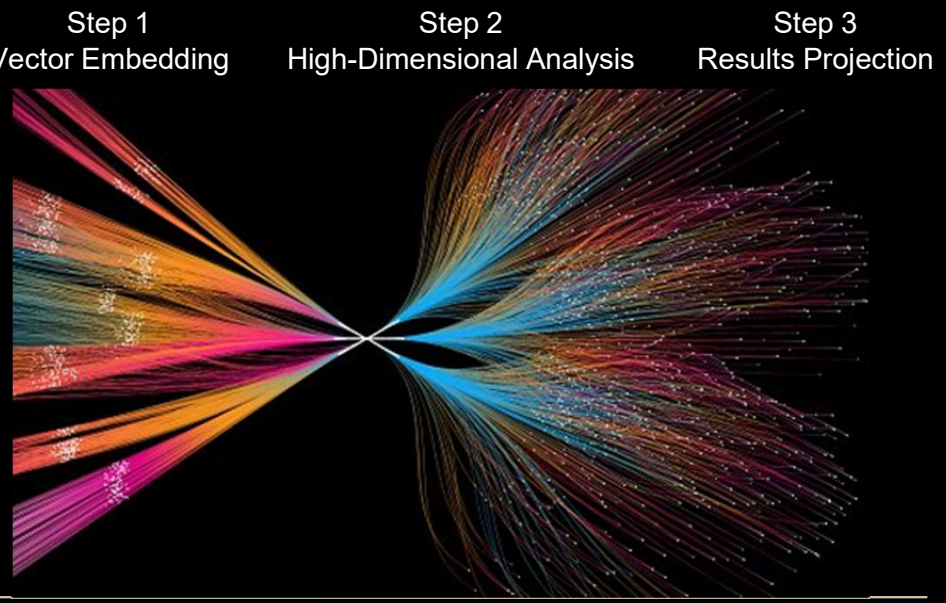
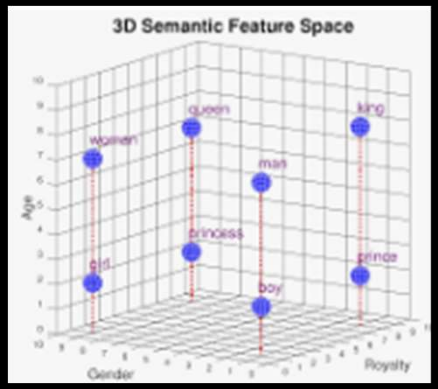
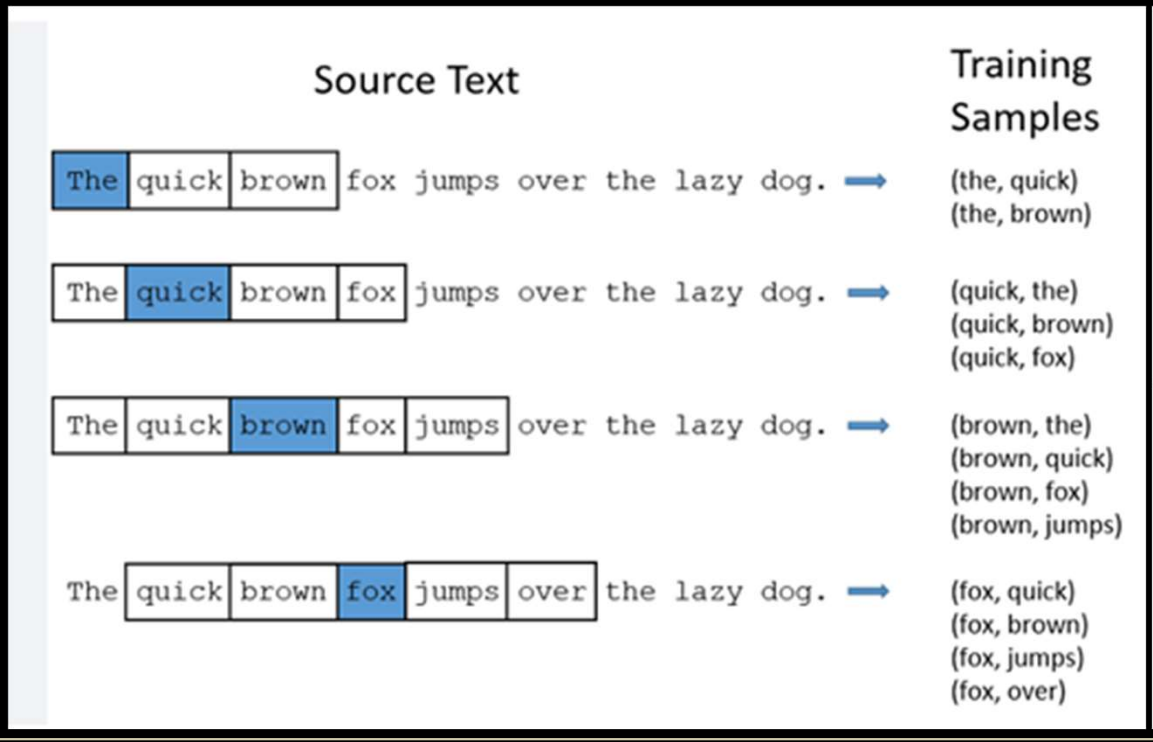


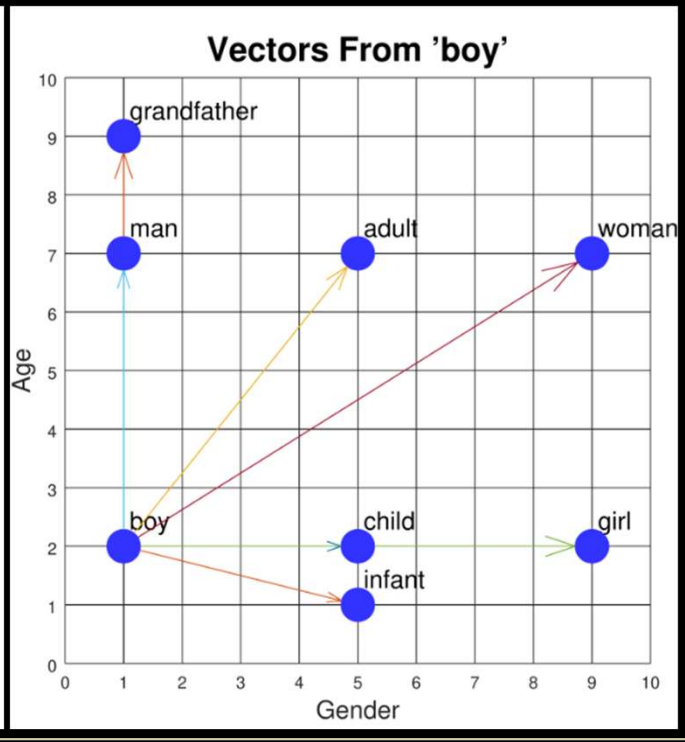
Image Source: https://creativemarket.com/Colorpong

Word2vec and Neural Word Embeddings

- Word2vec: natural language processing algorithm using a NN to learn word associations from text corpora
- Task: predict-next-word



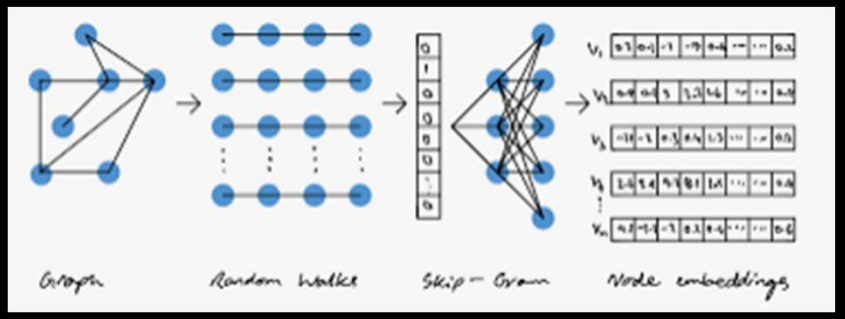


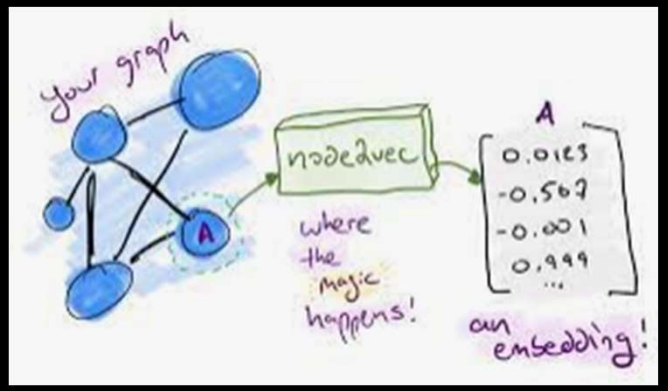


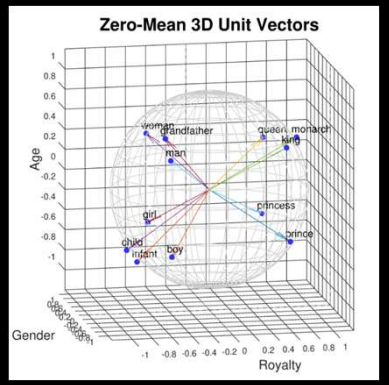
Source: https://creativemarket.com/Colorpong

Graph Learning: Node2vec and Edge2vec

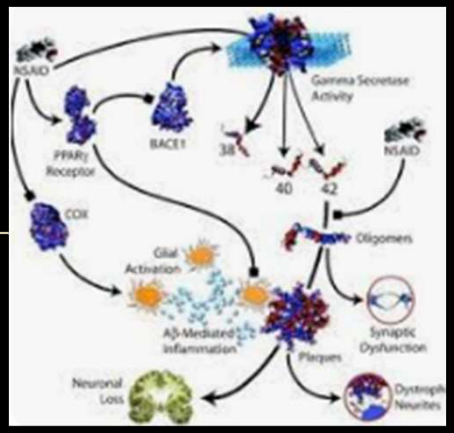
- Graph learning
- Node2vec: algorithm that learns vector representations of nodes in a graph based on their neighborhood structure and connectivity patterns
- Edge2vec: algorithm that learns vector representations of nodes in a graph based on their edge semantics

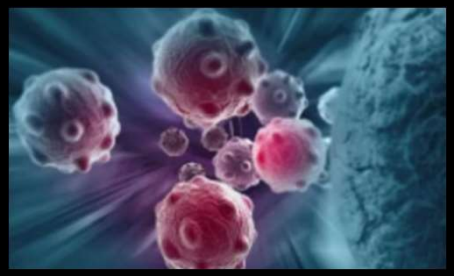






n2vec Approaches to Biology

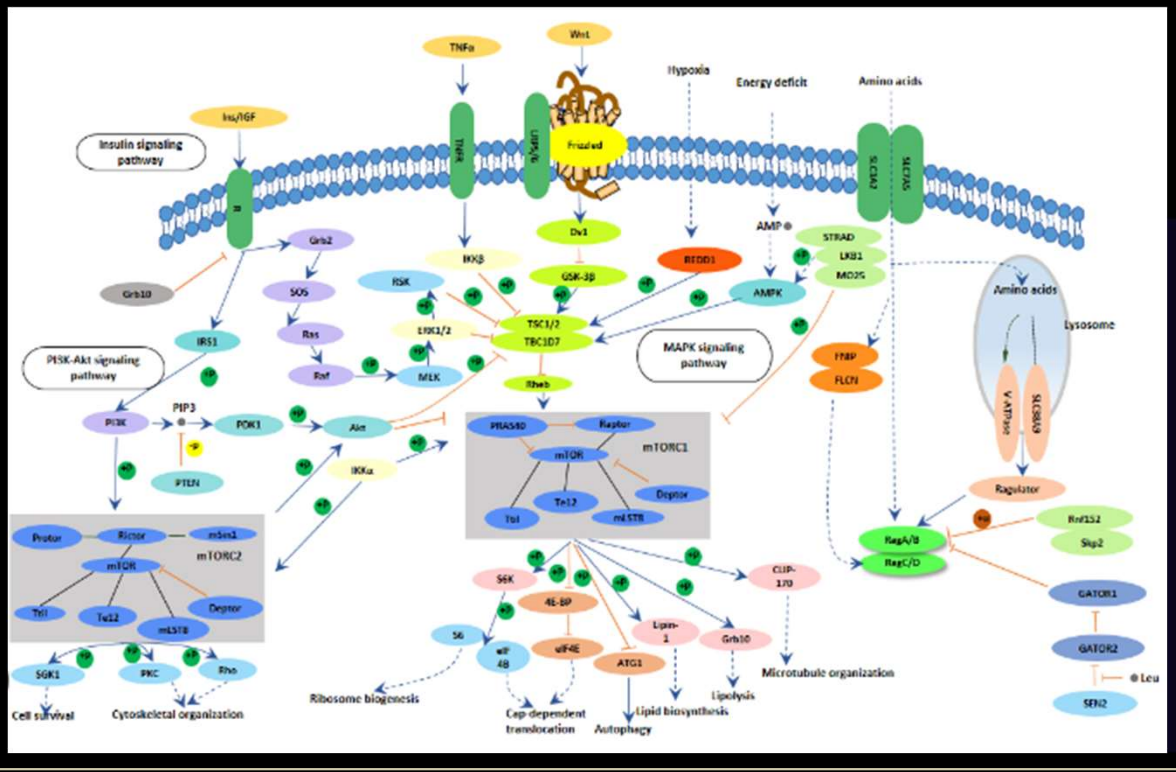


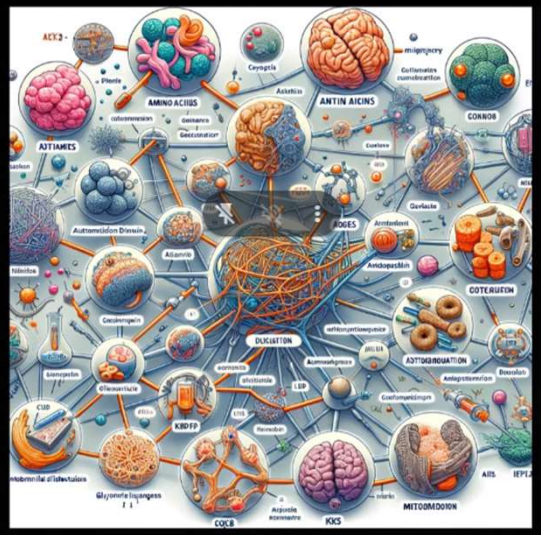


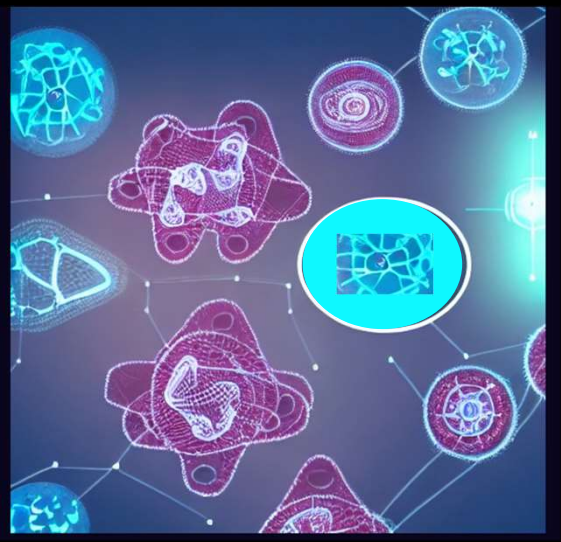
- Disease2vec: algorithm that learns representations of diseases from EMRs
  - Used for disease similarity analysis, disease clustering, preventive prediction
- Drug2vec: algorithm that learns vector representations of drugs from drug-related text corpora
  - Used for drug similarity analysis, drug discovery, drug repositioning to additional uses
- Gene2vec: algorithm that learns vector representations of genes from gene expression data
  - Used for gene function prediction, gene co-expression analysis, and gene network inference
- Cancer2vec

Health Agent Pathway2vec Project

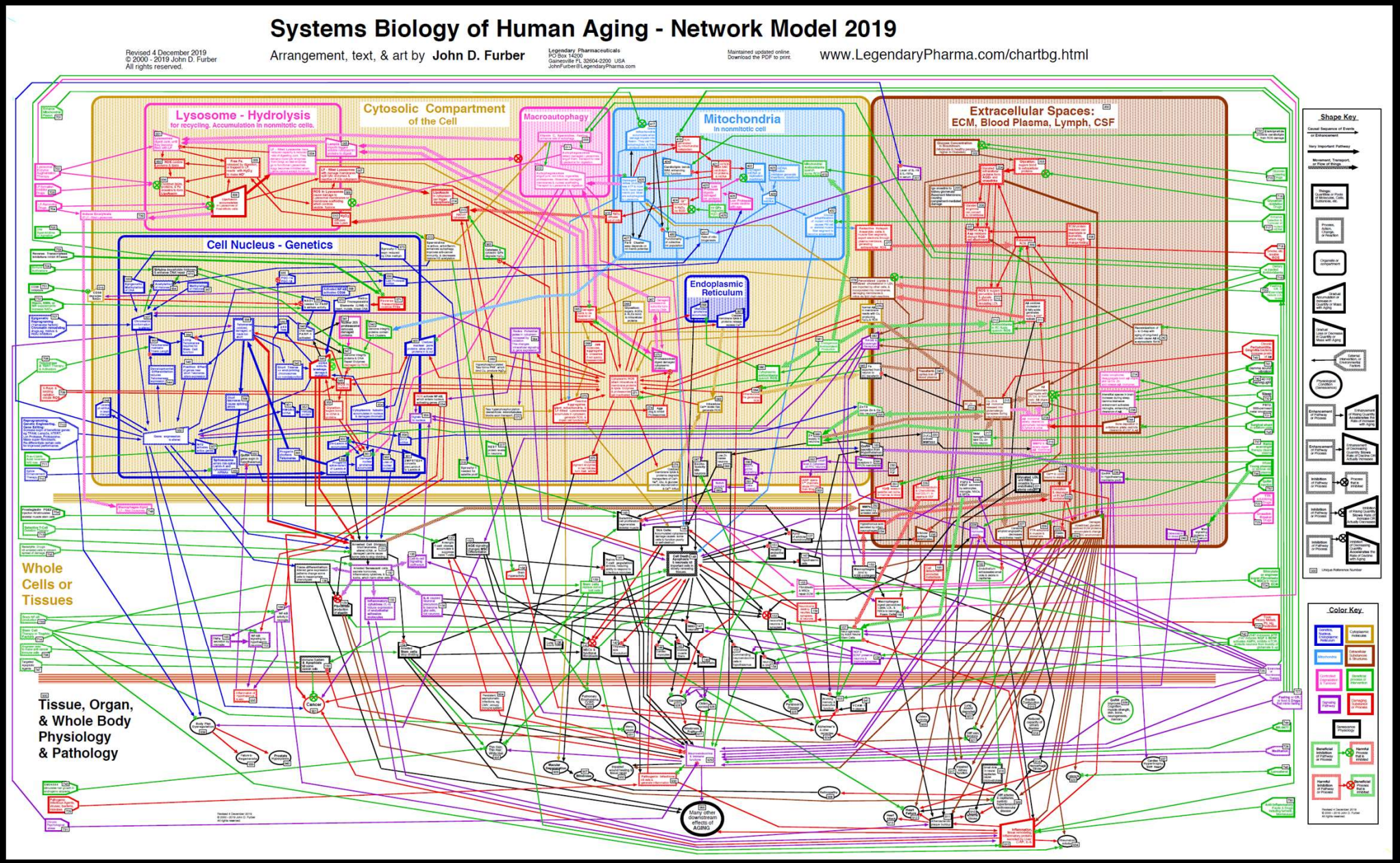
- Multimodal LLM pathway analysis
  - Image, text, video input
  - Aim: obtain canonical mTor pathway





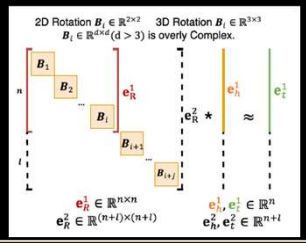


Source: Health Agents: Swan, M., Kido, T., Roland, E. & dos Santos, R.P. (2024). AI Health Agents: Pathway2vec, ReflectE, Category Theory, and Longevity. AAAI 2024 Spring Symposium Series: Impact of GenAI on Social and Individual Well-being. https://www.melanieswan.com/documents/swan-AI-health-agents.pdf



Source: Furber, J. (2019). https://legendarypharma.com/chartbg.html

Pathway2vec Project Landscape



- OrthogonalE Riemannian optimization Knowledge Graph Embedding algorithm

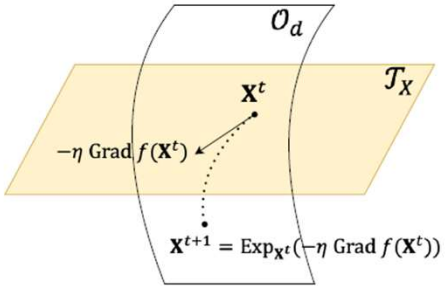


Figure 2: Abstract representation of Riemannian gradient descent iteration on orthogonal manifold

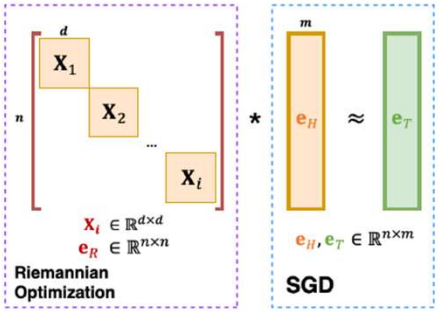


Figure 3: Diagram of the OrthogonalE approach.

Model	WN18RR MRR	WN18RR H@1	WN18RR H@3	WN18RR H@10	FB15K-237 MRR	FB15K-237 H@1	FB15K-237 H@3	FB15K-237 H@10
TransE ♢	.226	-	-	.501	.294	-	-	.465
DistMult ♢	.430	.390	.440	.490	.241	.155	.263	.419
ComplEx ♢	.440	.410	.460	.510	.247	.158	.275	.428
ConvE ♢	.430	.400	.440	.520	.325	.237	.356	.501
RotatE ♢	.470	.422	.488	.565	.297	.480	.328	.205
QuatE ♢	.481	.436	.500	.564	.311	.221	.342	.495
Gram-Schmidt(2×2)	.475	.434	.489	.556	.317	.226	.344	.502
Gram-Schmidt(3×3)	.487	.445	.500	.568	.322	.232	.350	.504
OrthogonalE(2×2)	.490	.445	.503	.573	.330	.239	**.368**	**.516**
OrthogonalE(3×3)	**.493**	**.450**	**.508**	**.580**	**.331**	**.240**	.359	.513

一般社団法人　電子情報通信学会
THE INSTITUTE OF ELECTRONICS,
INFORMATION AND COMMUNICATION ENGINEERS

信学技報
IEICE Technical Report
NC2023-18,IBISML2023-18(2023-06)

生物学的パスウェイを用いたBioConceptVecにおけるアナロジータスク

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あらまし　自然言語処理は様々な応用分野で利用されており，skip-gram などのモデルを用いてテキスト中の単語を埋め込みと呼ばれる特徴ベクトルに変換することが一般的である．近年，生物学の分野でも自然言語処理の有用性が注目されており，概念の正規化を施した約 3000 万件の PubMed abstracts から学習した BioConceptVec が提案されている．一般に skip-gram では単語の埋め込みを加減算することによりアナロジータスクが解けるとされており，例えば king − man + woman から queen を予測できる．本研究では生物学的パスウェイの種類を関係性とみなし，薬剤と遺伝子の組についてアナロジータスクの実験を行った．その結果，同じパスウェイに属する薬剤と遺伝子の組についてパスウェイの関係性を表すベクトルを定義することで，アナロジータスクの高い精度が確認された．
キーワード　自然言語処理，分散表現，単語埋め込み，アナロジー，生物学，PubMed

Analogy Tasks in BioConceptVec using Biological Pathways

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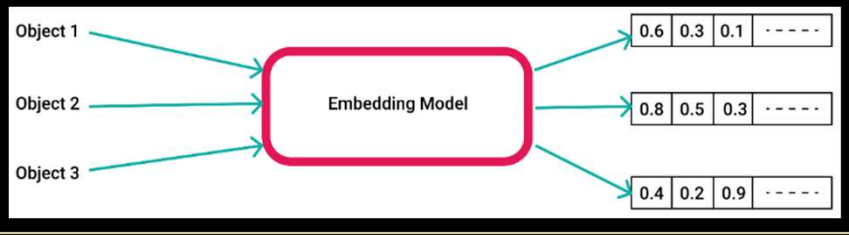
Abstract　Natural language processing (NLP), often employing models like skip-gram, is widely utilized across numerous application domains to convert words in text into feature vectors known as word embeddings. The utility of this approach has recently been noted in the field of biology, with the introduction of BioConceptVec, a model trained on about 30 million PubMed abstracts using normalized concepts. In general, skip-gram can solve analogy tasks by manipulating word embeddings, such as predicting *queen* from *king − man + woman*. In this study, we applied this principle to biological pathways, conducting analogy tasks for pairs of drugs and genes, treating pathway types as relationships. Our results demonstrated high accuracy in these tasks when defining a vector to represent the pathway relationship for pairs of drugs and genes that belong to the same pathway.
Key words　natural language processing, distributed representations, word embeddings, analogy, Biology, PubMed

1. はじめに

自然言語処理とは，人間が日常的に使用する自然言語をコンピュータで処理するための技術である．自然言語処理は，機械翻訳 [1]，感情分析 [2]，文類似度の測定 [3] など，様々な応用分野で活用されているが，それらの多くで skip-gram [4], [5] や BERT [2] などのモデルを用いてテキスト中の単語を分散表現または埋め込みと呼ばれる数百次元の特徴量ベクトルに変

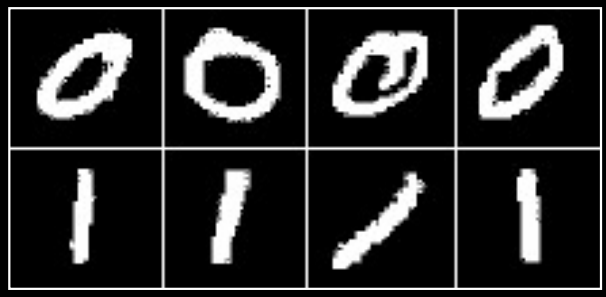
Source: Zhu, Y. & Shimodaira, H. (2024). Block-Diagonal Orthogonal Relation and Matrix Entity for Knowledge Graph Embedding. arXiv:2401.05967. Yamagiwa, H.; Hashimoto, R.; Arakane, K. et al. 2023. Analogy Tasks in BioConceptVec using Biological Pathways. IEICE Tech. Rep. 123(91):113-120. https://ken.ieice.org/ken/paper/20230630ZCVk/eng/.

Vector Embedding

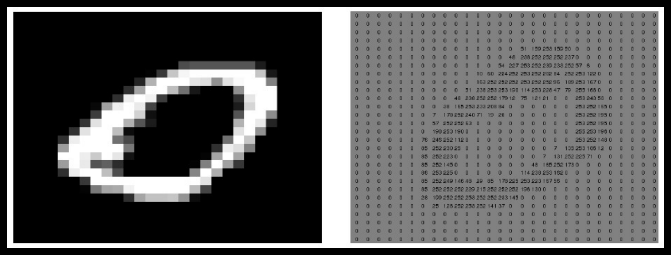


- Convert input data to numbers

1. Obtain training data set
   - MNIST digit images



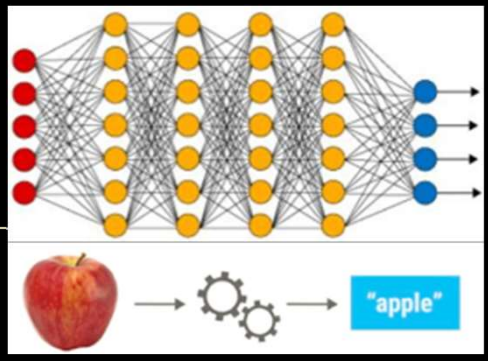
2. Digitize pixels (convert input data to numbers)
   - Divide image into 28x28 grid, assign a value (0-255) to each square based on brightness



3. Read into vector (list of numbers (array))
   - 28x28 = 784 elements per image
     - 0, 0, 0, 0, 0, 0, 0, 50, 87, 162, 209, 255, 201, 175, 89, 45, 0, 0, 0, 0, 0, 0, 0,0

Source: MNIST: 70,000 28x28 black-and-white images of handwritten digits. Quoc V. Le, A Tutorial on Deep Learning, Part 1: Nonlinear Classifiers and The Backpropagation Algorithm, 2015, Google Brain, https://cs.stanford.edu/~quocle/tutorial1.pdf

Deep Learning Architecture



4. Load "spreadsheet" of vectors into system

- Each row of spreadsheet (784-element array) is an input

Matrix multiplication algorithms transform data representation

Vector data | 1. Input | 2. Hidden layers | 3. Output

Image #1 → *784-element array*

Image #2

Image #3

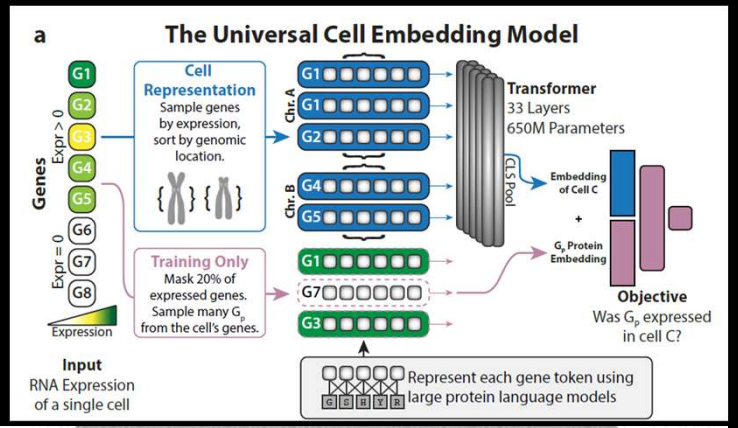
	A
1	uuid
2	7001c442-1f13-4e4d-9084-153e27c6c517
3	Tt20LnN5s2bceLECY3mfZcuXUJ0dDRu376Nd+/e4f379/Dy8qJ/79+/x7t376jm
4	YWlQL1aHgYEB9u3bR8/or1y5ssjGFnNzcxw/fpzOWR8+fEi16PJbrAgICMCVK1ewc+dOteV86dIl
5	2g+dPHlSqQ2c0sbp06fRvHlzvHnzBu7u7tizZ0+xL4br6elhw4YNePToEfr160d3TC9evAgnJyc5
6	tW5pu0hOTtb4XG5JwefzqTajvr5+kQnPgPy4KD1HrgzZsVBPT0/jBaLCUuIC9NGjR+Hn56f07/Xr
7	16hcuXKh0j18+DC2b98OT09PjXYWpWejhUKhypXy6OhoutrcsWPHIvs48fHxVChTtds+adIkuusc
8	FBSk8SSGz+fL7bBcv35drQEdVaSkpFBVvOzsbAwdOhTHjh3DggULsHLlSujp6RU4TVVIJBK6Mis9
9	n1u2bFmqFRAREaG2EUlXqLhcLjXmI4uHhwc2bdoEAOjWrZuc4SR17N69GydOnAAAjBs3TumZak3R
10	1dWlRwCuXbuW76LD69evNf7mmmBpaQkgt2OSnhNXhuzChbqzJ6URQ0NDOqlTZhRJFolEovEEX0dH

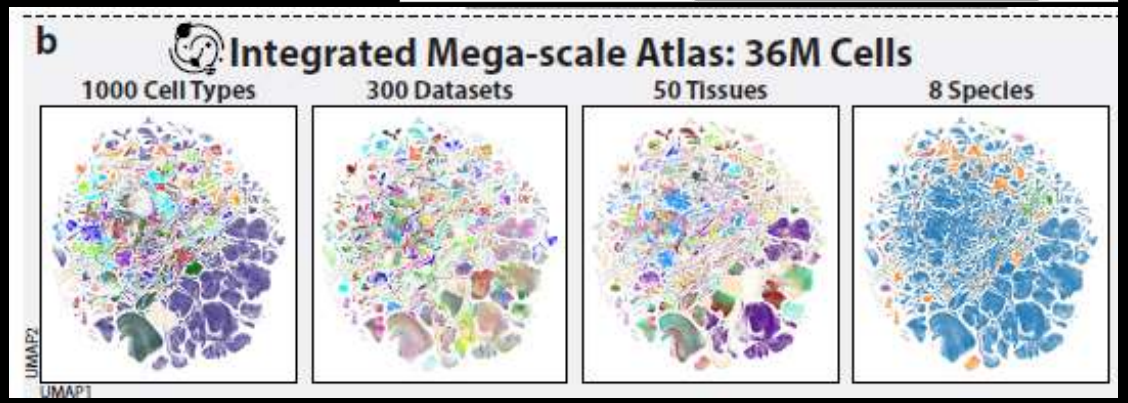
EXAMPLES: mathematical equation vector embedding

Source: http://deeplearning.stanford.edu/tutorial; MNIST dataset: http://yann.lecun.com/exdb/mnist

Vector Embedding in Biology

- GenAI method
  - Treat “big data” (entire data corpora) at the level of embedding (a mathematical formulation) to deliver clean abstract view
- Embedding spaces
  - Data viewing
  - Novel discovery
- Example: Universal Cell Embedding foundation model
  - Representation of every cell state and type across species

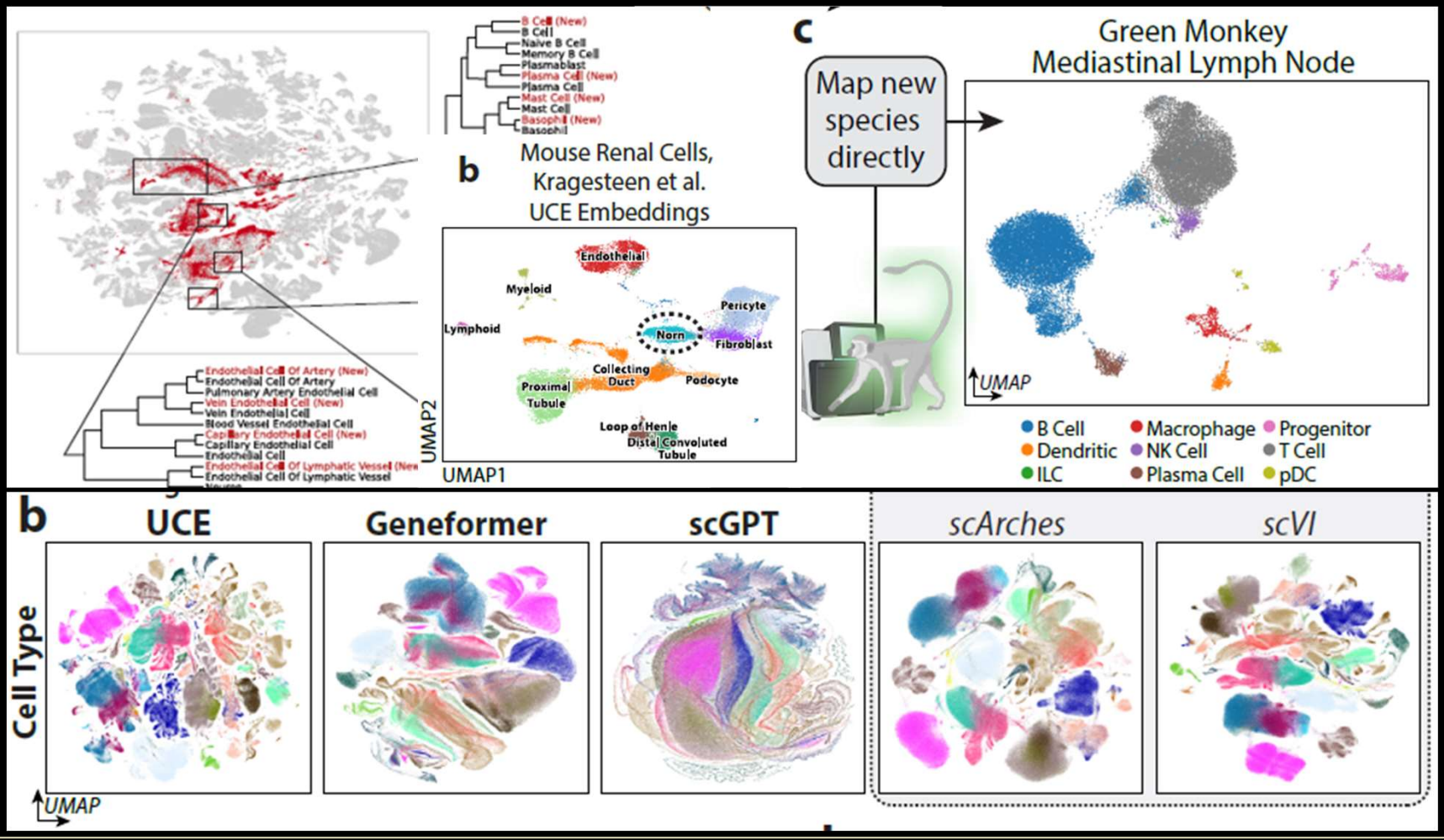




Source: Rosen, Y., Roohani, Y., Agarwal, A. et al. (2023). Universal Cell Embeddings: A Foundation Model for Cell Biology. https://www.biorxiv.org/content/10.1101/2023.11.28.568918v1.full.pdf.

Vector Embedding in Biology

- Identify new developmental lineages, kidney cell types



Source: Rosen, Y., Roohani, Y., Agarwal, A. et al. (2023). Universal Cell Embeddings: A Foundation Model for Cell Biology. https://www.biorxiv.org/content/10.1101/2023.11.28.568918v1.full.pdf.

Vector Embedding in Biology

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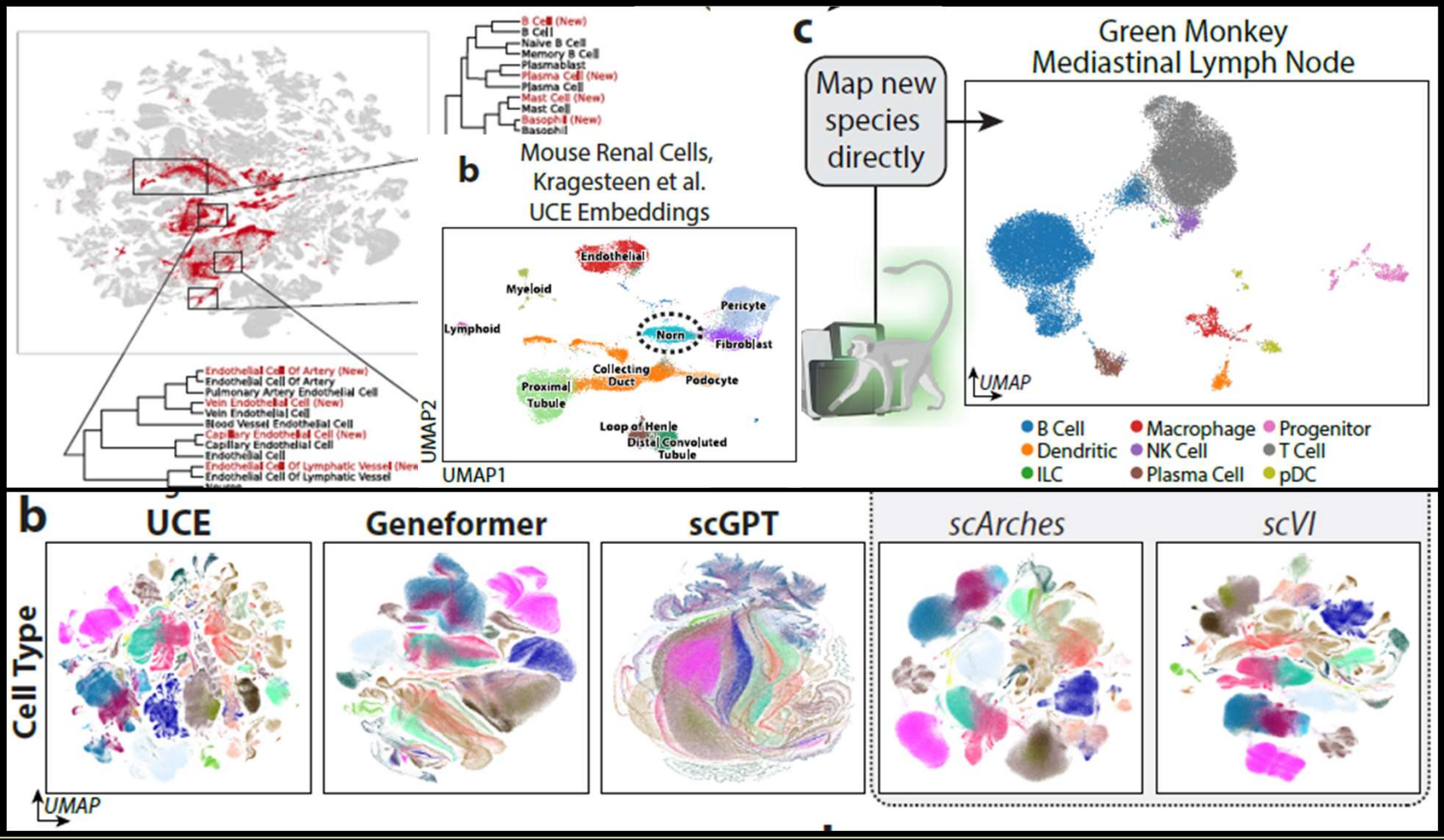
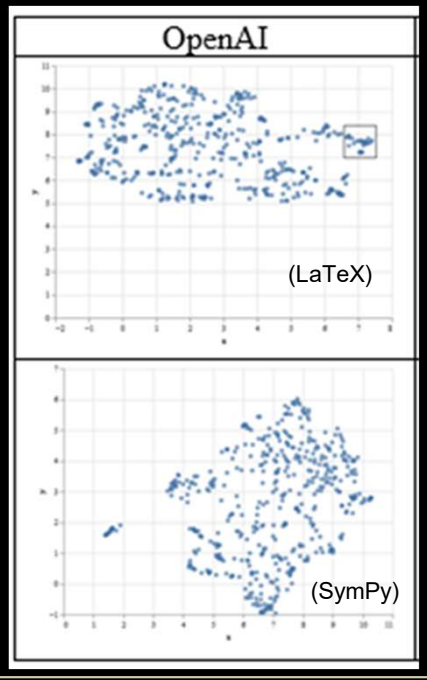


Source: Rosen, Y., Roohani, Y., Agarwal, A. et al. (2023). Universal Cell Embeddings: A Foundation Model for Cell Biology. https://www.biorxiv.org/content/10.1101/2023.11.28.568918v1.full.pdf.

Vector Embedding in Mathematics

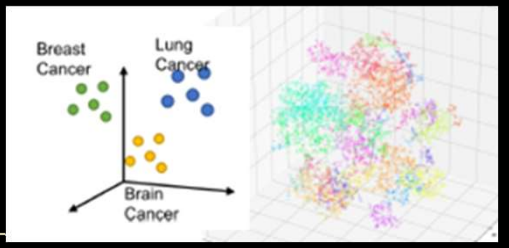
- Math Agent: AI math layer. Math is the data corpus processed with vector embedding and visualized in equation clusters to view the mathscape (set of equations) of a paper or field of study at once (e.g. cancer biomath)
  - Mathematical Embedding
    - Vector-embedding of equations
  - Mathematical Ecology (mathscape)
    - Set of equations from a paper or field of study
    - Mathscape composite of hundreds of equations
  - Equation Cluster
    - Vector embedding method groups similar “kinds” of equations together in the visualization
      - Differential equations, sin-cos, space-time metrics

476-equation Mathscape using OpenAI Embedding Method in LaTex and SymPy formats (2016 Kaplan AdS/CFT)



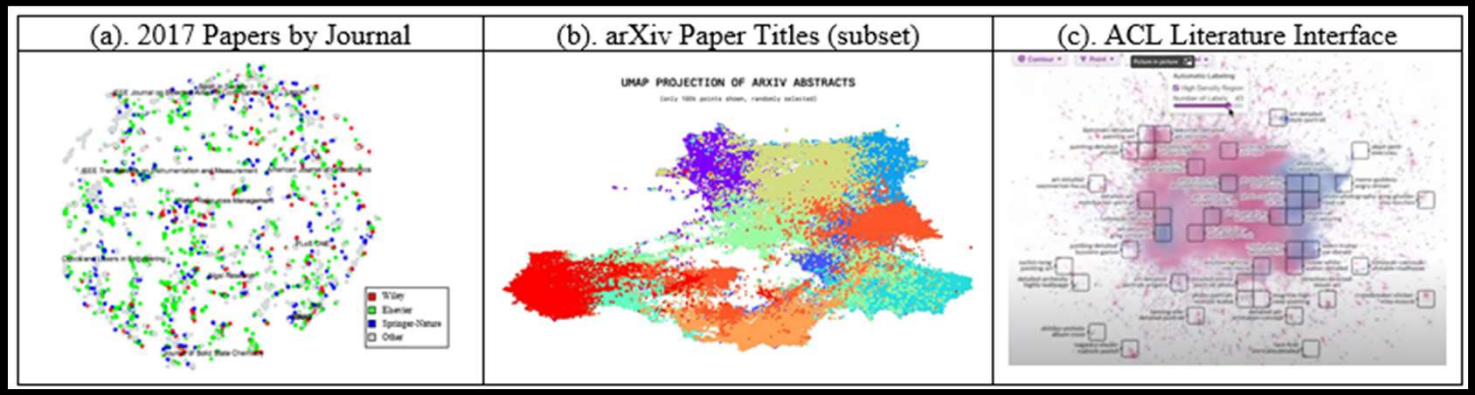
Sources: Swan, M., Kido, T., Roland, E. & dos Santos, R.P. (2023). AI Math Agents: Computational Infrastructure, Mathematical Embedding, and Genomics. AdS/CFT: Kaplan, J. (2016). Lectures on AdS/CFT from the bottom up. Johns Hopkins Lecture Course.

The Mathematical Embedding

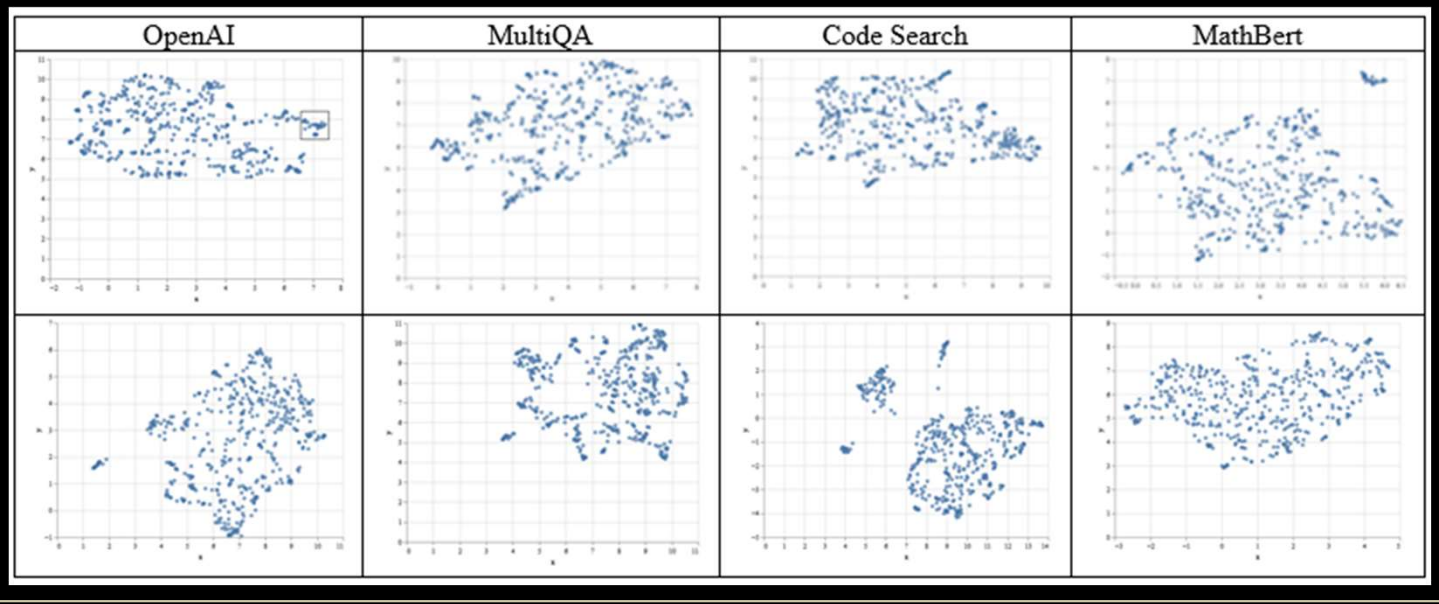


Cancer2vec (Choy 2019)

Big Data Embedding Visualization examples with Academic Papers as the Data Corpus



One 476-equation mathscape (Kaplan 2016 AdS/CFT) Equation Clusters in Embedding Visualization
Four different embedding methods (OpenAI, etc.) and two formats (LaTeX and SymPy)



Source: AdS/CFT: Kaplan, J. (2016). Lectures on AdS/CFT from the bottom up. Johns Hopkins Lecture Course.
https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf

The Mathematical Embedding

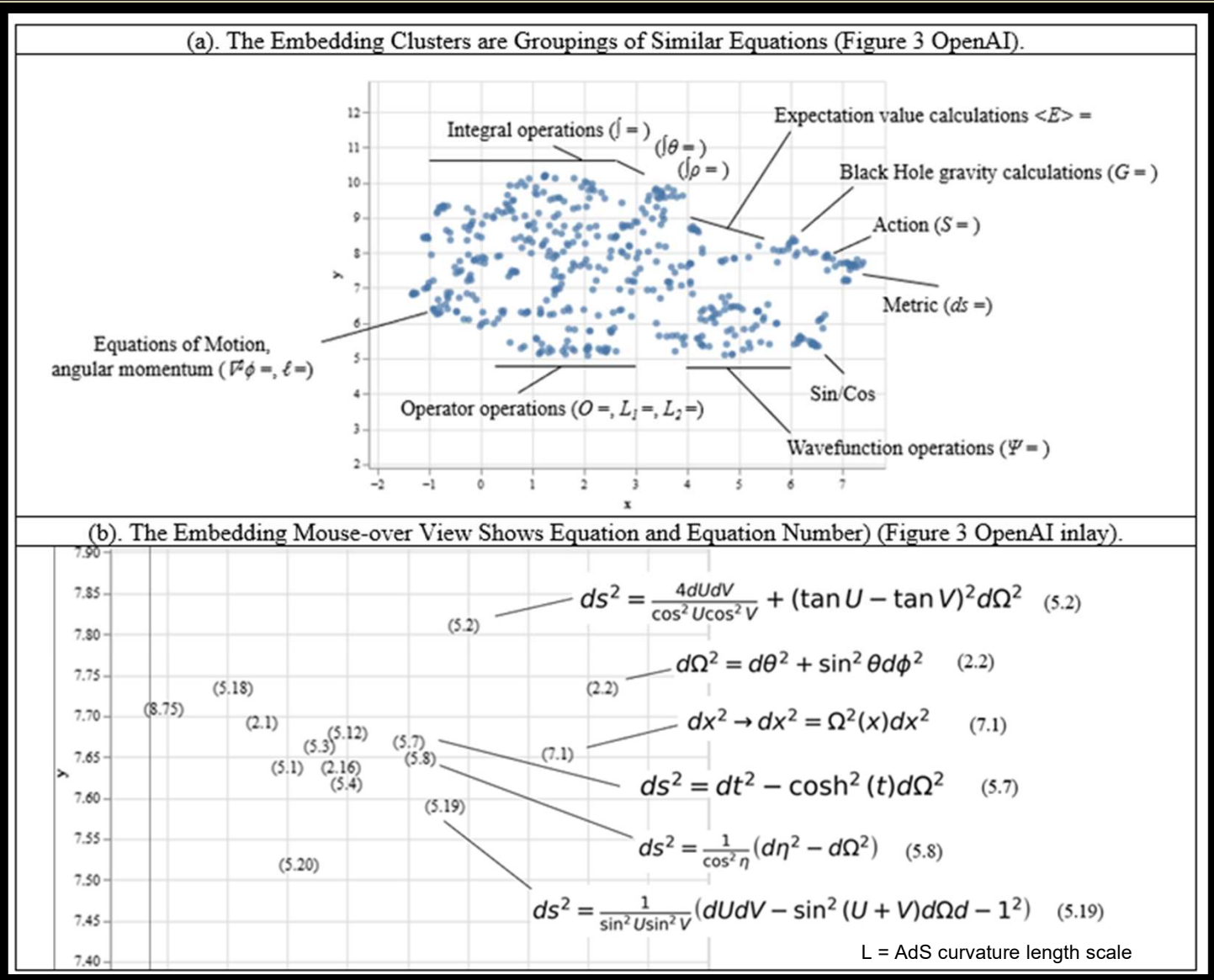
Mathscape-level View: Identify the kinds of mathematics used in a paper at-a-glance

Annotated equation clusters illustrate

(a) how similar groups of equations are grouped in the embedding method and

(b) the mouse-over view of equation images by equation number

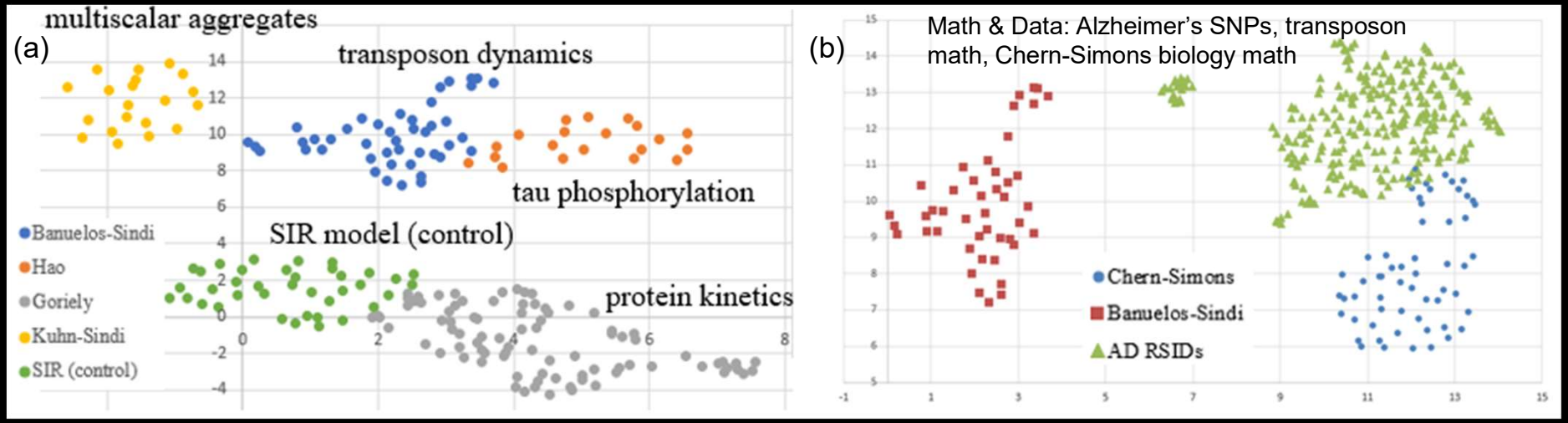
(OpenAI inlay from previous figure)



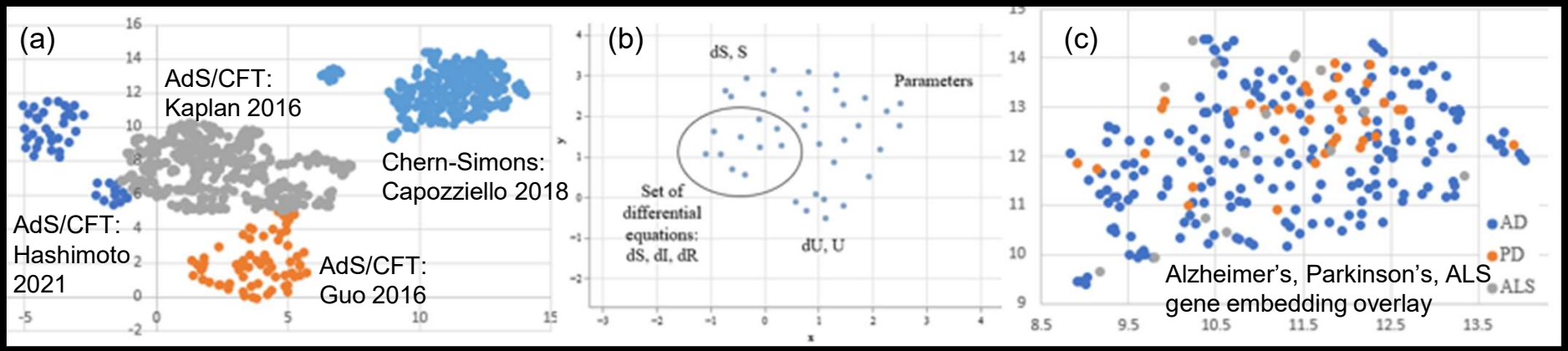
Source: AdS/CFT: Kaplan, J. (2016). Lectures on AdS/CFT from the bottom up. Johns Hopkins Lecture Course.
https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf

Alzheimers2vec: math + data in one view

Mathematical Ecologies (a) Compare 4 proposed Alzheimer's Mathscapes (sets of equations) + SIR Model (control math); (b) view physics math (Chern-Simons) + Alzheimer's math (Banuelos-Sindi) + data (AD SNPs)



(a) AdS/CFT Mathematical Ecologies + AD SNPs; (b) SIR Mathematics; (c) Multi-disease Genomic view: AD, PD, ALS



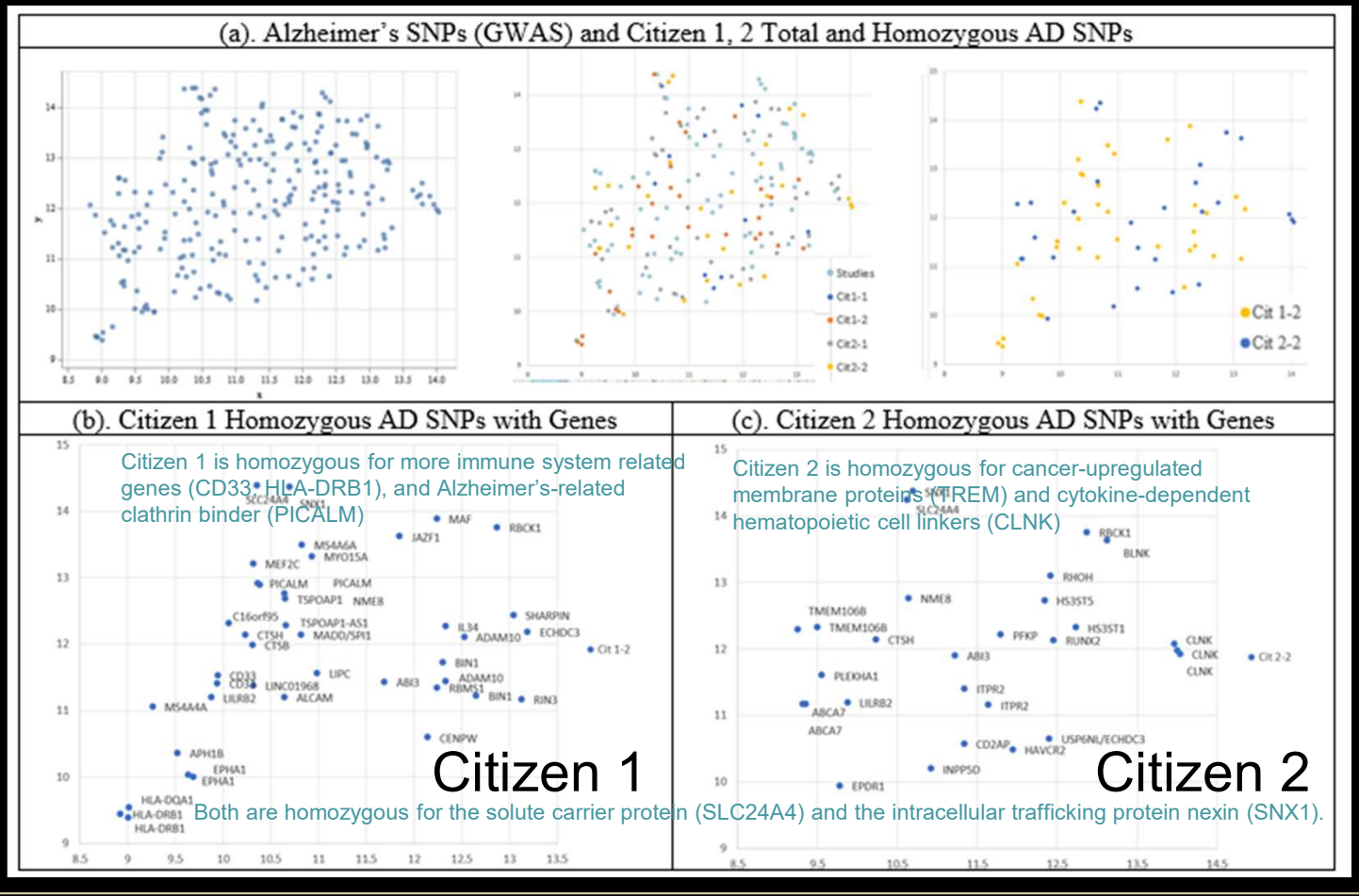
26 Mar 2024
AI Health Agents

Source: https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf
AD, PD, ALS: Alzheimer's disease, Parkinson's disease, Amyotrophic lateral sclerosis

Alzheimer's Genomics Precision Health

Embeddings Visualization of Data: Alzheimer's SNPs applied to Citizen 1, Citizen 2 Precision Health initiative

Alzheimer's disease genomic risk is analyzed for two precision health participants with whole-human genome sequencing
An embedding visualization is performed for all GWAS-linked Alzheimer's disease SNPs and presented for Citizen 1 and Citizen 2's heterozygous (one alternative allele) and homozygous (two alternative alleles) SNP



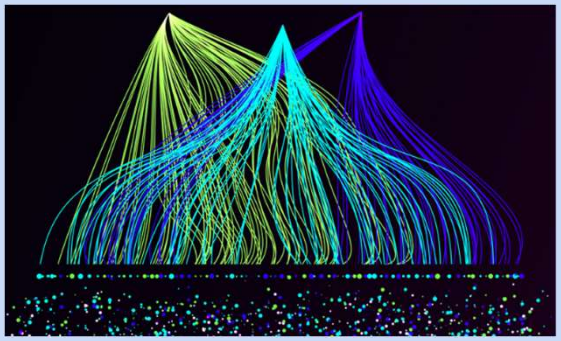
Each individual is homozygous (two alternative alleles) for different subsets of genes suggesting a starting-point for personalized intervention

Source: https://www.diygenomics.org/files/AI_Math_Agents_poster_AAIC2023.pdf
AD, PD, ALS: Alzheimer's disease, Parkinson's disease, Amyotrophic lateral sclerosis

Agenda

- Web3: Social Layer
  - Economics
  - Identity
  - Health
- GenAI: Interface Layer
- Quantum: Compute Layer

- Health Agents and Longevity



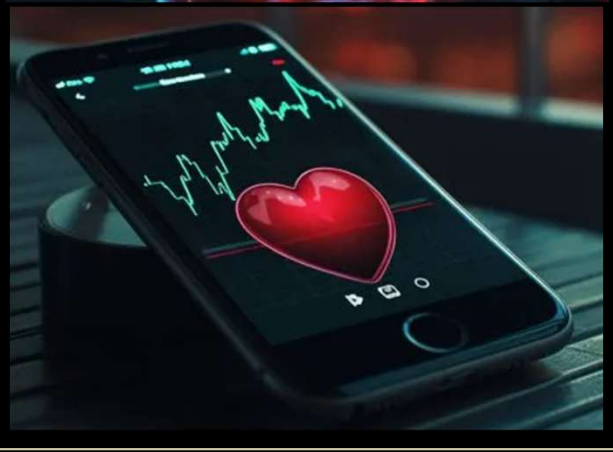
The Web3 GenAI Quantum Technology Stack

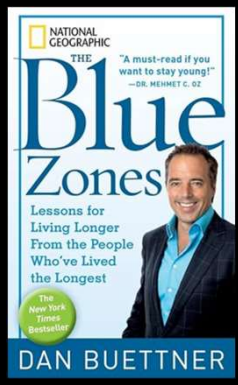
Technology	**Layer**
Web3 Blockchain Ecosystems	**Social**
GenAI	**Interface**
Quantum	**Compute**

Healthy Longevity: Global Priority for Social and Individual Well-being (2b 65+ 2050)

- Longevity Revolution by App: physicians oversee 1000s of patients with personalized longevity medicine

2023



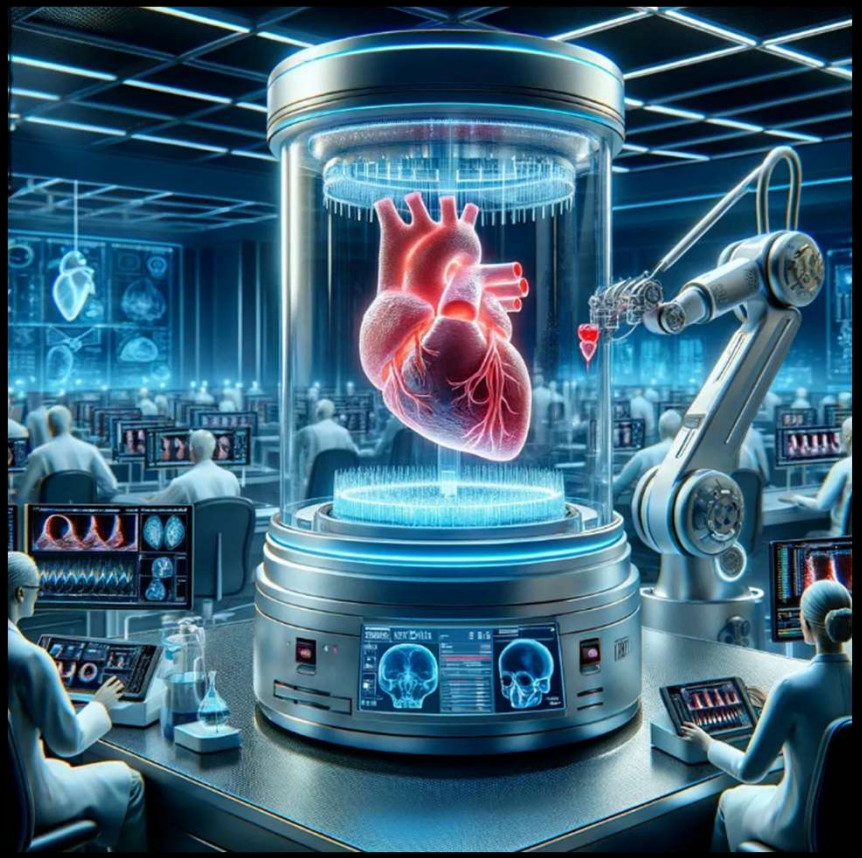


2010

Global Priority for Social and Individual Well-being

Healthy Longevity

- WHO: classification of aging as a pathology (2022)
- Solution
  - ~80% sleep, diet, exercise, stress reduction, healthy life
  - ~20% longevity medicine
- Quantitative Tools
  1. Hallmarks of Aging
  2. Biomarkers of Aging
  3. Aging Clocks
  4. Medical-grade wearables



Source: Bautmans I, Knoop V, Amuthavalli Thiyagarajan J, et al. (2022). WHO working definition of vitality capacity for healthy longevity monitoring. Lancet Healthy Longev. 3(11):e789-e796.

Systematic Approach to Longevity

Hallmarks of Aging

Aging Clocks

Healthy Lifestyle

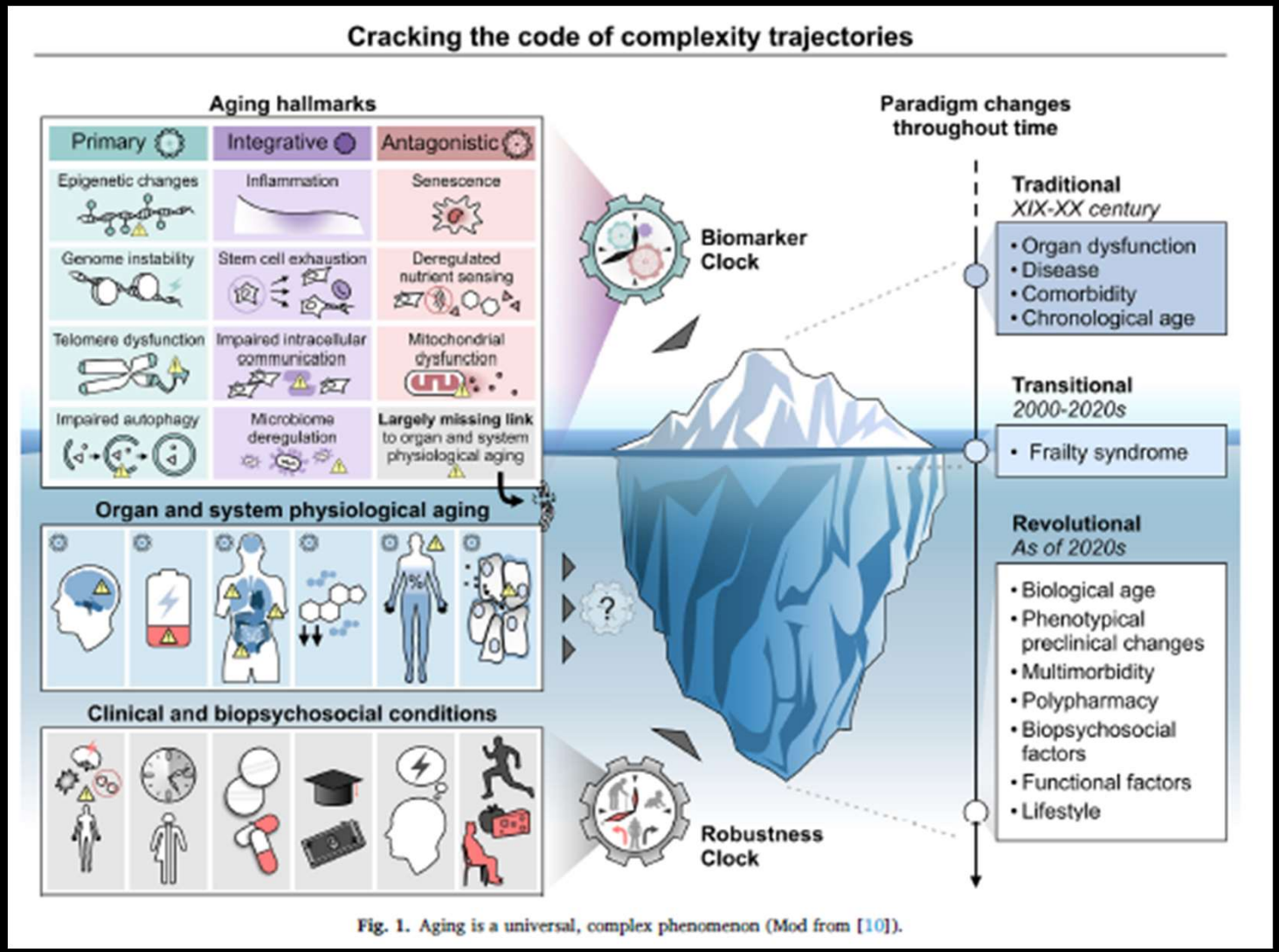
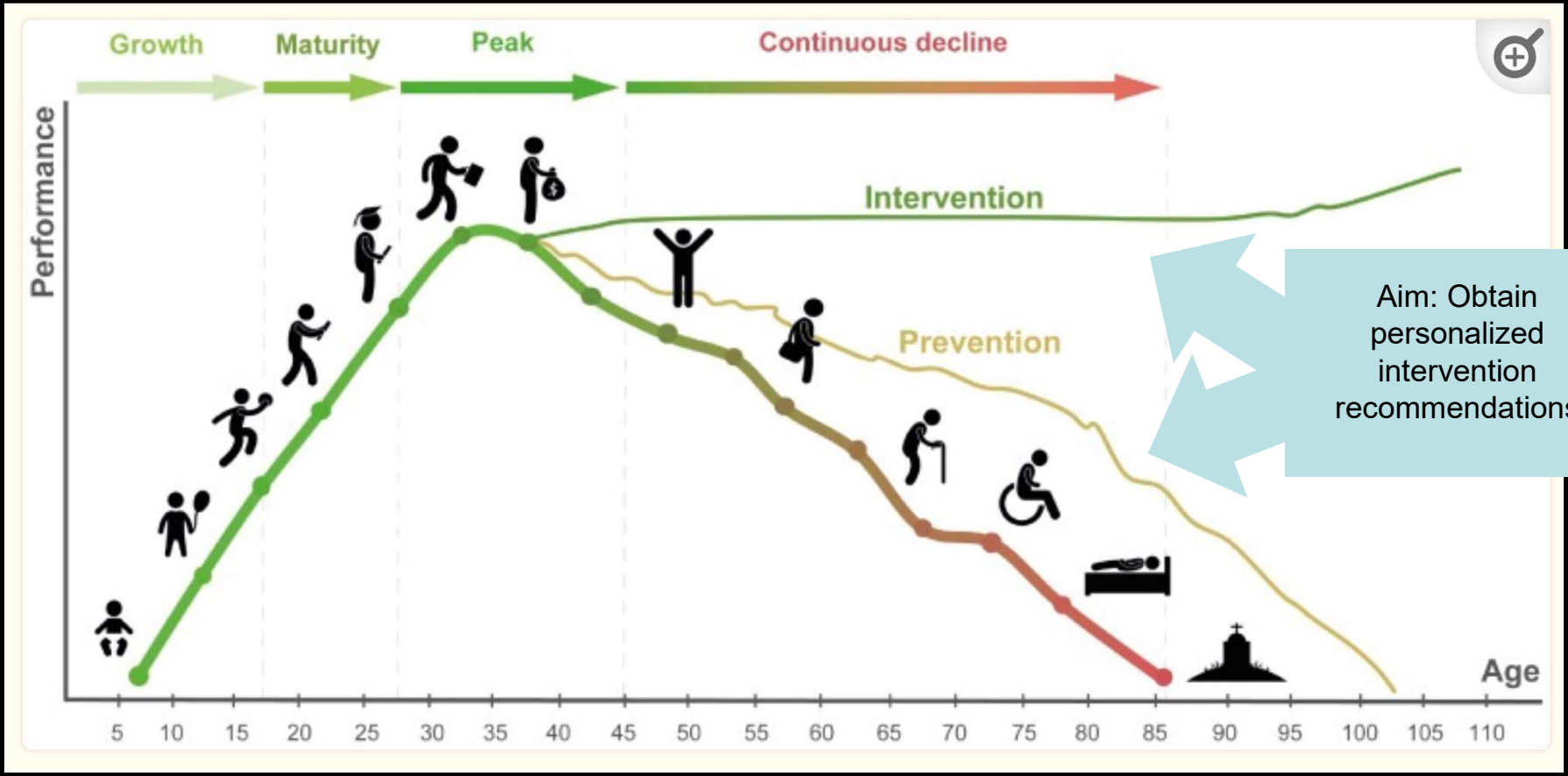


Fig. 1. Aging is a universal, complex phenomenon (Mod from [10]).

Source: Polidori, M.C. (2024). Aging hallmarks, biomarkers, and clocks for personalized medicine: (re)positioning the limelight. Free Radical Biology and Medicine. 215: 48-55.

Goal: Stop and Reverse Aging as Pathology

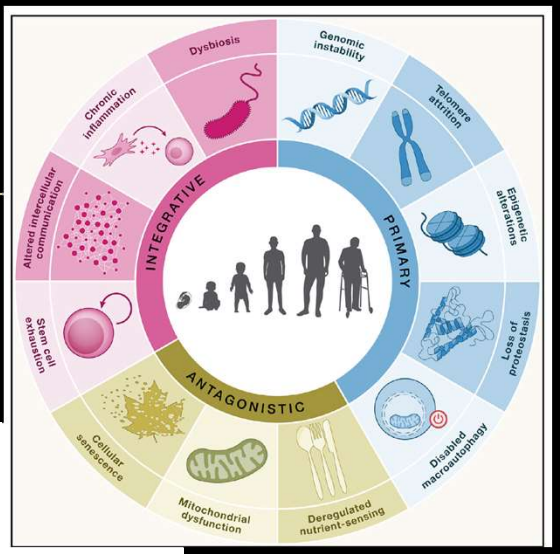
The general course of human life in the health and performance context



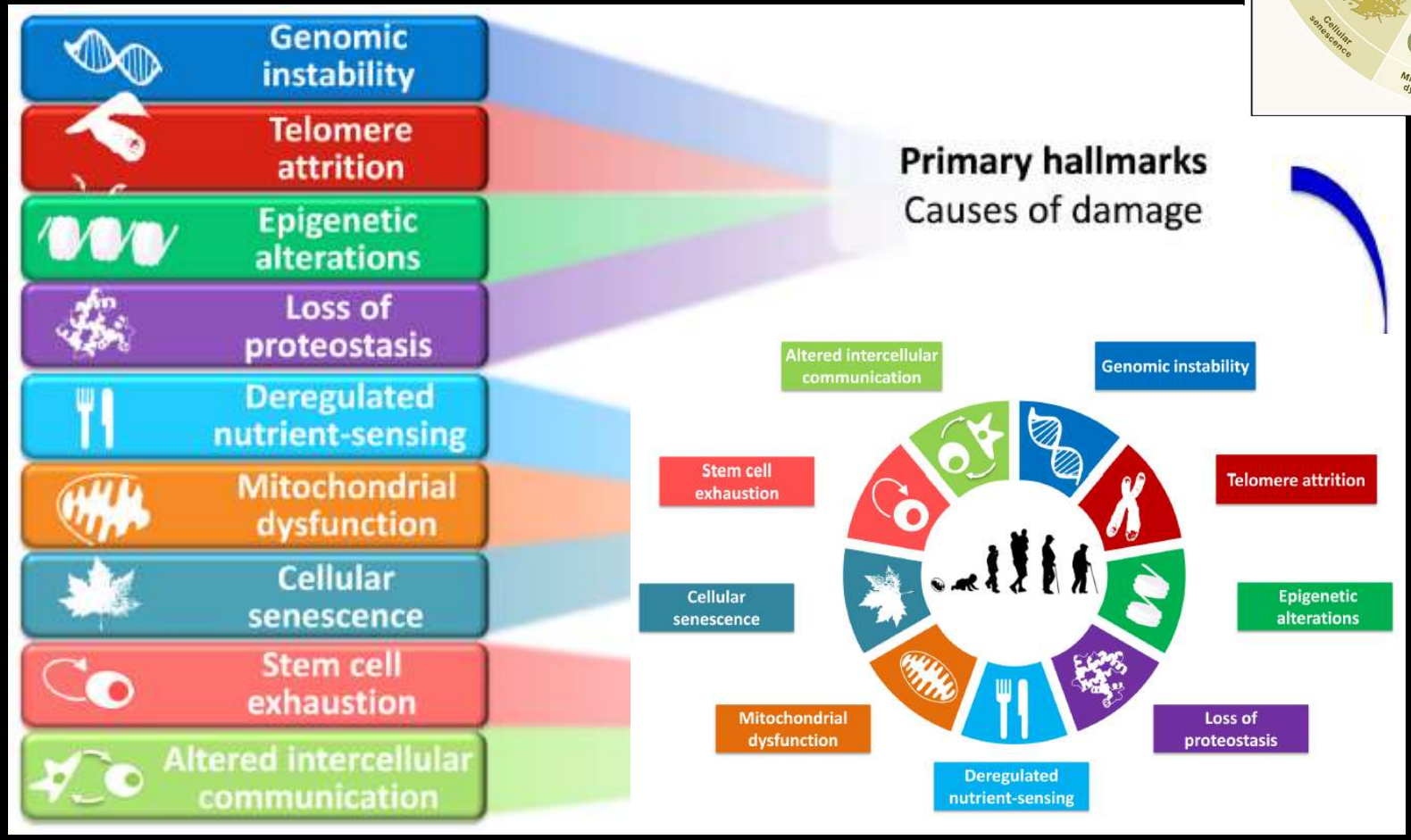
Source: Zhavoronkov, A. et al. 2019). Deep biomarkers of aging and longevity: from research to applications. Aging. 11(22): 10771–10780. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6914424/

The Hallmarks of Aging

- #1: genomic instability (DNA damage)



2023



2013

Source: Lopez-Otin, C., Blasco, M.A., Partridge, L. et al. (2013). The Hallmarks of Aging. *Cell*. 153(6):1194-1217. Lopez-Ocn C, Blasco MA, Partridge L, Serrano M, Kroemer G. Hallmarks of aging: An expanding universe. Cell. 2023;186(2):243-278.

Aging Biomarkers

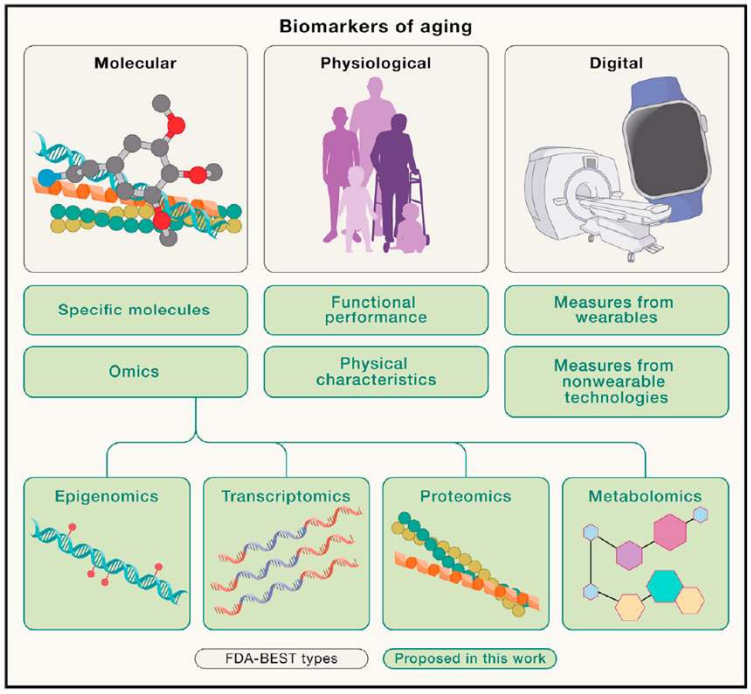
CellPress

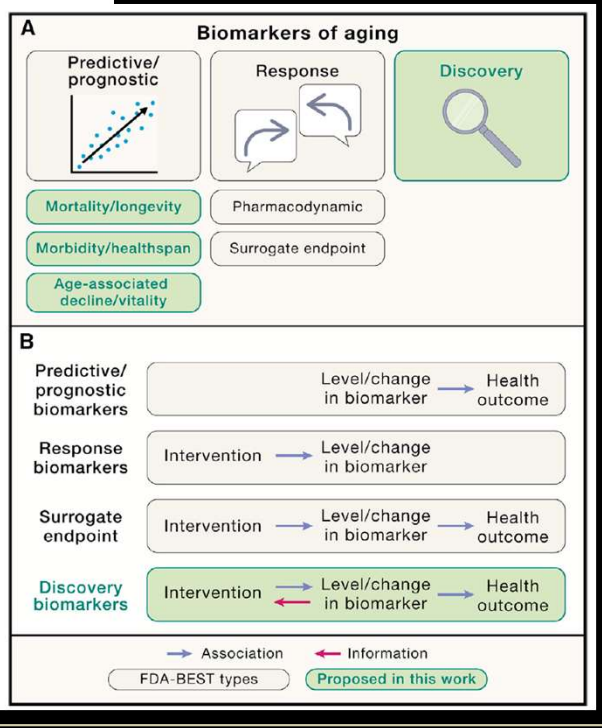
Cell
Leading Edge

Perspective

Biomarkers of aging for the identification and evaluation of longevity interventions

Mahdi Moqri,[1,2,3,31] Chiara Herzog,[4,31] Jesse R. Poganik,[1,31] Biomarkers of Aging Consortium, Jamie Justice,[5] Daniel W. Belsky,[6] Albert Higgins-Chen,[7] Alexey Moskalev,[8] Georg Fuellen,[9,10] Alan A. Cohen,[11] Ivan Bautmans,[12,13] Martin Widschwendter,[4,14,15] Jingzhong Ding,[16] Alexander Fleming,[17] Joan Mannick,[18] Jing-Dong Jackie Han,[19] Alex Zhavoronkov,[20] Nir Barzilai,[21] Matt Kaeberlein,[22] Steven Cummings,[23,24] Brian K. Kennedy,[25] Luigi Ferrucci,[26] Steve Horvath,[27] Eric Verdin,[28] Andrea B. Maier.[29,30] Michael P. Snyder.[2,*] Vittorio Sebastiano.[3,*] and Vadim N. Gladyshev[1,*]





Source: Moqri, M., Herzon, C., Poganik, J.R. et al. (2023). Biomarkers of aging for the identification and evaluation of longevity interventions. Cell 186(18):P3758-3775. Ying, K.; Paulson, S.; Perez-Guevara, M.; et al. 2023. Biolearn, an open-source library for biomarkers of aging. bioRxiv:10.1101/2023.12.02.569722.

Aging Biomarkers Platform: Biolearn

Biolearn

Search

Quickstart

Clocks and Other Models

GEO Data Sources

Examples

API References

Biolearn

Biolearn enables easy and versatile analyses of biomarkers of aging data. It provides tools to easily load data from publicly available sources like the Gene Expression Omnibus, National Health and Nutrition Examination Survey, and the Framingham Heart Study. Biolearn also contains reference implementations for common aging clocks such as the Horvath clock, DunedinPACE, and many others that can easily be run in only a few lines of code. You can read more about it in our paper.

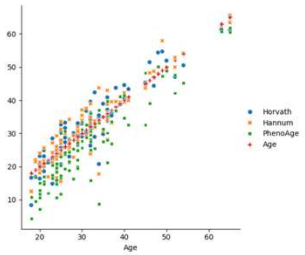
Biolearn is developed and supported by several organizations and individuals, especially Biomarkers of Aging Consortium, Methuselah Foundation, and VOLO Foundation.

We are hosting a 2024-2025 Challenge series on the Synapse platform, where participants will be asked to predict chronological age, mortality, and multi-morbidity, with total awards of $200k+. Learn more at Synapse!.

Featured examples

Quickstart

Get started with Biolearn



Demonstrate computation of several epigenetic clocks

Show how the clocks compare with chronological age

Source: Ying, K.; Paulson, S.; Perez-Guevara, M.; et al. 2023. Biolearn, an open-source library for biomarkers of aging. bioRxiv:10.1101/2023.12.02.569722. https://bio-learn.github.io/

Longevity Medicine Interventions

Interventions: rapamycin, senolytics, metformin, acarbose, spermidine, NAD+ enhancers, NSAIDs, lithium, reverse transcriptase inhibitors, system circulating factors, glucosamine, glycine, 17-alpha-estradiol, AKG

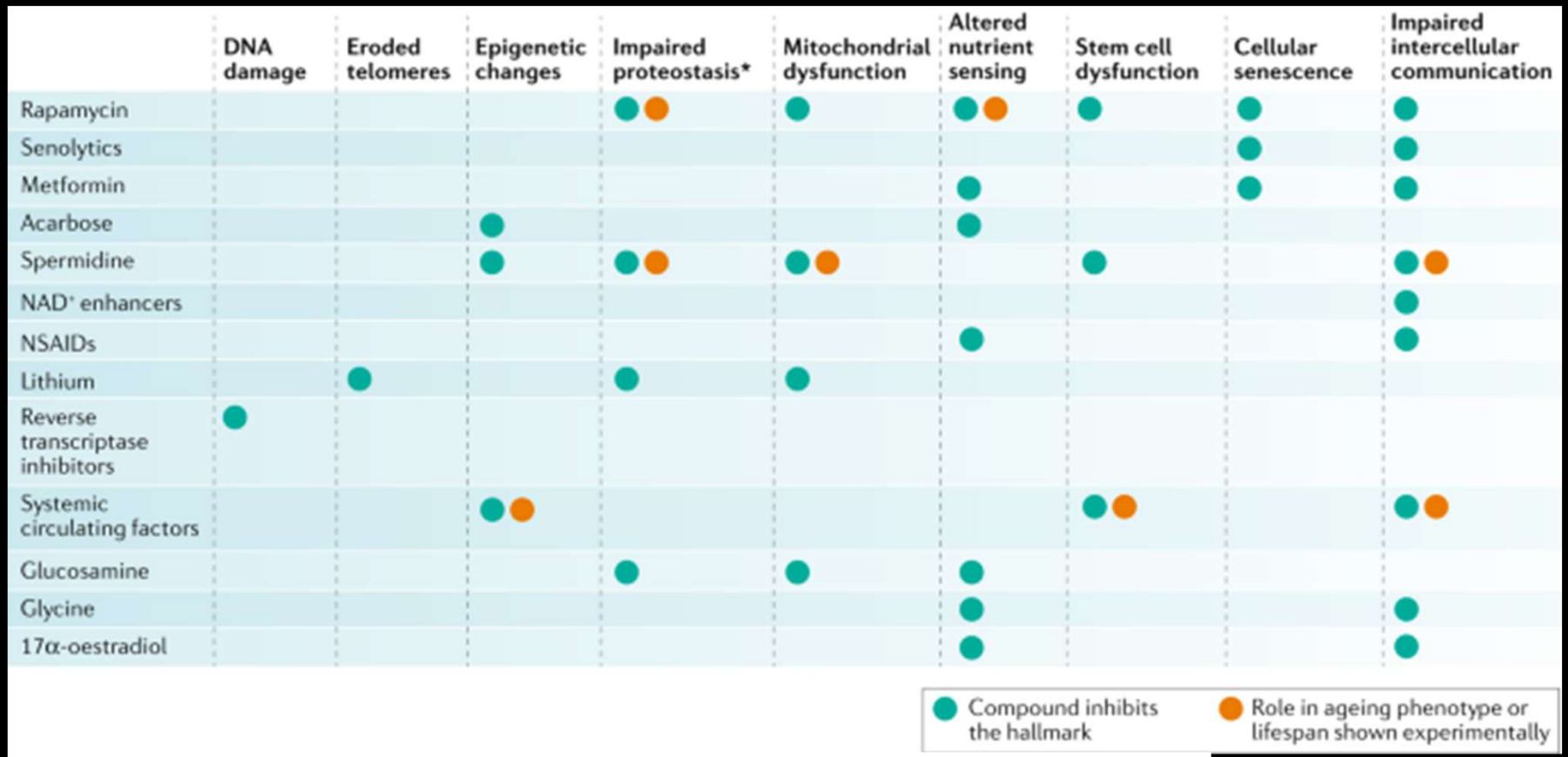
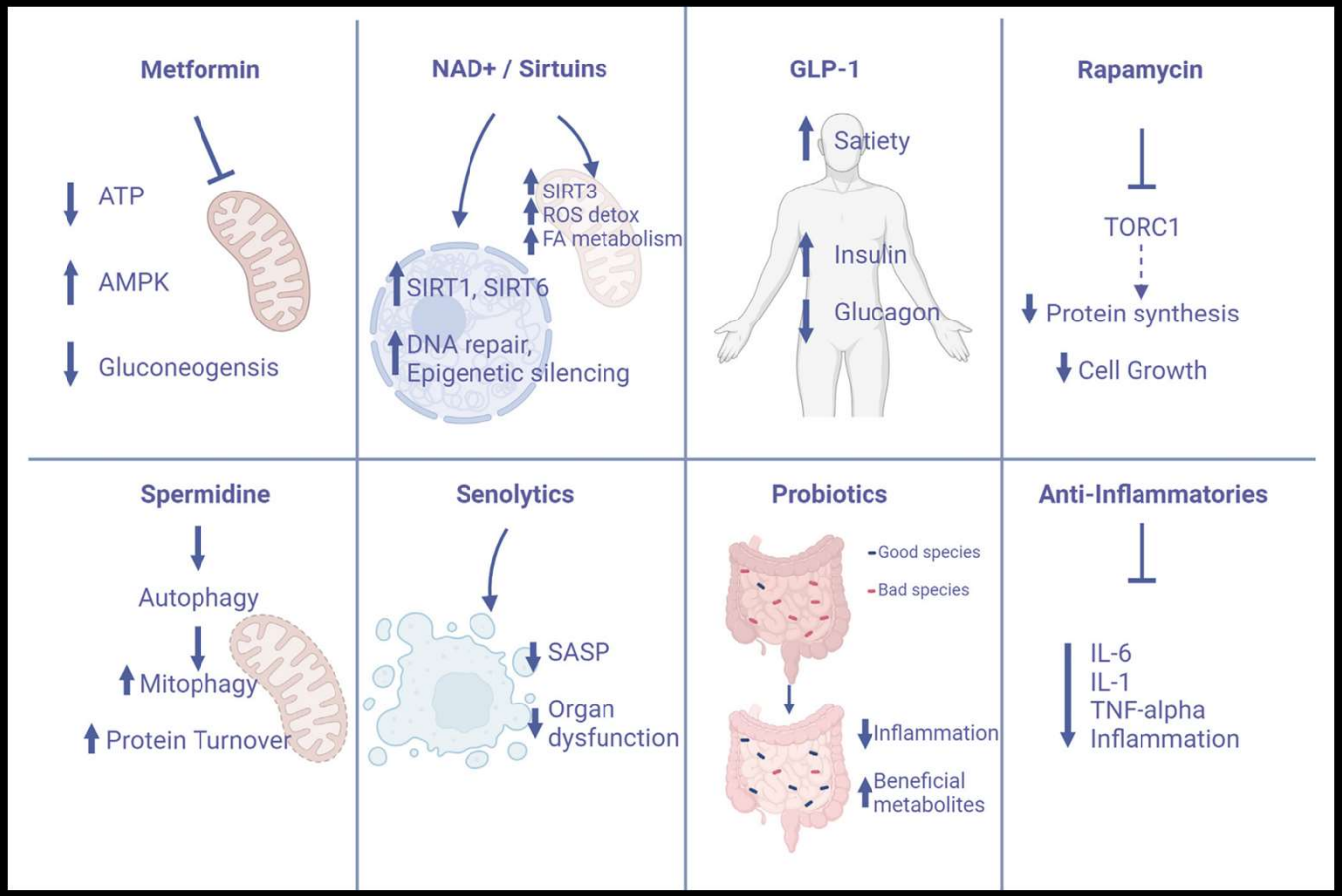


Figure 2. Agents and their influence on different hallmarks of ageing. Geroprotective agents, small molecules and metabolites ameliorate one or more of the hallmarks of ageing to prevent ageing-related decline in function and ageing-related diseases. *Impaired protein homeostasis also includes autophagy.

Source: Partridge, L.; Fuentealba, M.; and Kennedy, B.K. 2020. The quest to slow ageing through drug discovery. Nat Rev Drug Discov 19(8): 513-532. doi: 10.1038/s41573-020-0067-7. Plus AKG 2022 Gyanwali, B.; Lim, Z.X.; Soh, J. et al. 2022. Alpha-Ketoglutarate dietary supplementation to improve health in humans. Trends Endocrinol Metab 33(2): 136–146. doi:10.1016/j.tem.2021.11.003

Longevity Medicine Interventions



Source: Guarente, L., Sinclair, D.A. & Kroemer, G. (2024). Human trials exploring anti-aging medicines. Cell Metabolism. 36(2):P354-376. doi: https://doi.org/10.1016/j.cmet.2023.12.007.

Longevity Medicine Interventions

Geroscience-guided repurposing of FDA-approved drugs for aging

* Kulkarni A, *Aleksic S, Berger D, Kuchel G, Sierra F and Barzilai N

Gerotherapeutic (lifespan)	Hallmarks of aging	Preclinical healthspan	Preclinical lifespan	Human healthspan	Human mortality	Score (out of 12)
SGLT-2 inhibitors	2	2	2	3	3	**12**
Metformin	2	2	1	3	3	**11**
Rapamycin/rapalogues	2	2	2	3	0 (not assessed)	**9**
Acarbose	2	2	2	3	0 (not assessed)	**9**
ACEi/ARB	2	2	1	3	0	**8**
Dasatinib + (quercetin)	2	2	1	1	0 (not assessed)	**6**
Aspirin	2	2	2	0	0	**6**
Methylene blue	2	2	2	0 (not assessed)	0 (not assessed)	**6**
N-acetyl cysteine	0	2	2	0	0	**4**

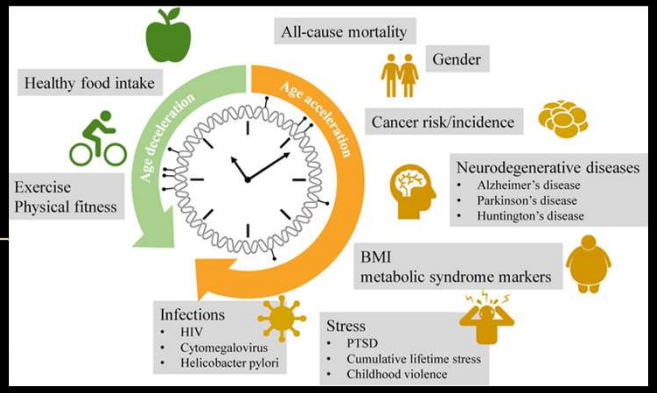
Kulkarni, Alekcis et al Aging Cell . 2022. Apr;21(4)

Preclinical points
Hallmarks >=3: 2, <3: 1
Healthspan increase: 2
Lifespan ITP: 2, non-ITP: 1

Human points
Healthspan RCT: 3, observational/open single arm: 1
Mortality RCT: 3, observational: 1

Source: Barzilai lab. Kulkarni, A.S., Aleksic, S., Berger, D.M. et al. (2022). Geroscience-guided repurposing of FDA-approved drugs to target aging: A proposed process and prioritization. Aging Cell. 21(4):e13596. doi: 10.1111/acel.13596. p. 5.

Personalized Aging Clocks



- Epigenetic clock
  - Measure changes in gene expression related to aging
- DNA methylation
  - Changes in DNA methylation patterns over time
- Transcriptomic clock
  - Measures gene expression changes associated with aging
- Glycan clock
  - Measures changes in glycan structures over time
- Metabolomic clock
  - Measures changes in metabolite levels associated with aging
- Telomere length
  - Measure the ends of chromosomes that shorten with age

Source: https://www.deeplongevity.com/

The Longevity App – All my Clocks

- Telomere length
- DNA methylation
- Transcriptomic clock
- Epigenetic clock
- Glycan clock
- Metabolomic clock

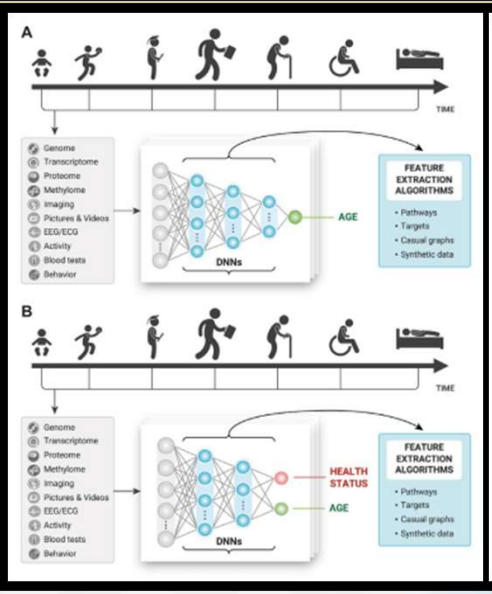
VIRTUSAN

Telomere length
DNA methylation
Transcriptomic clock
Epigenetic clock
Glycan clock
Metabolomic clock

Mockup Only

Aging Clocks: Biological vs Chronological Age

- Measurable intervention



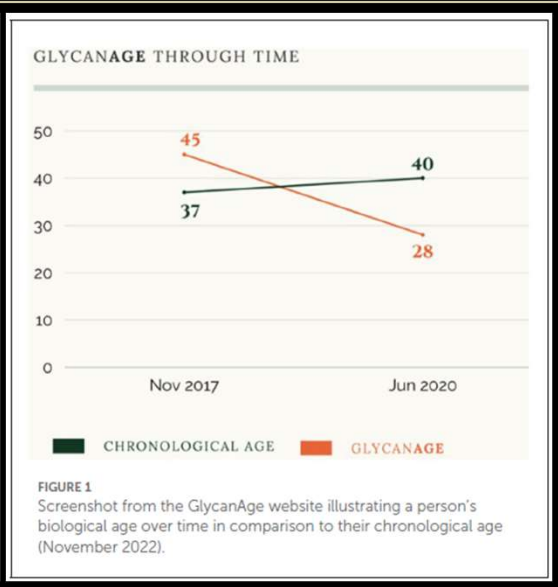
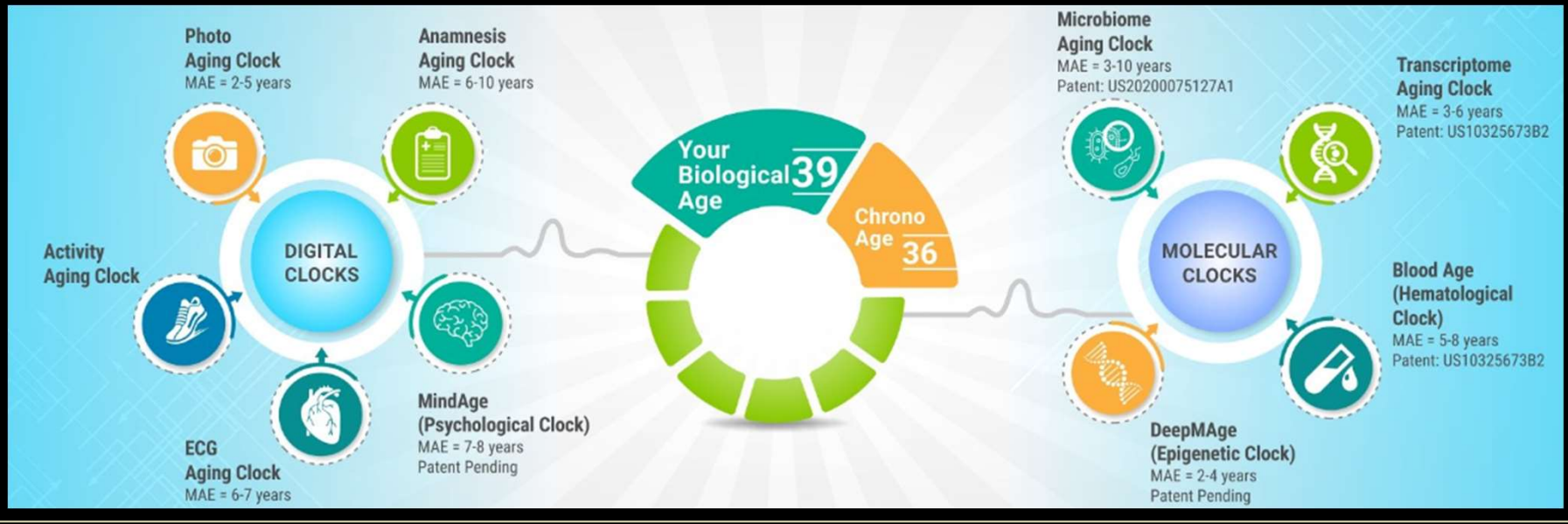
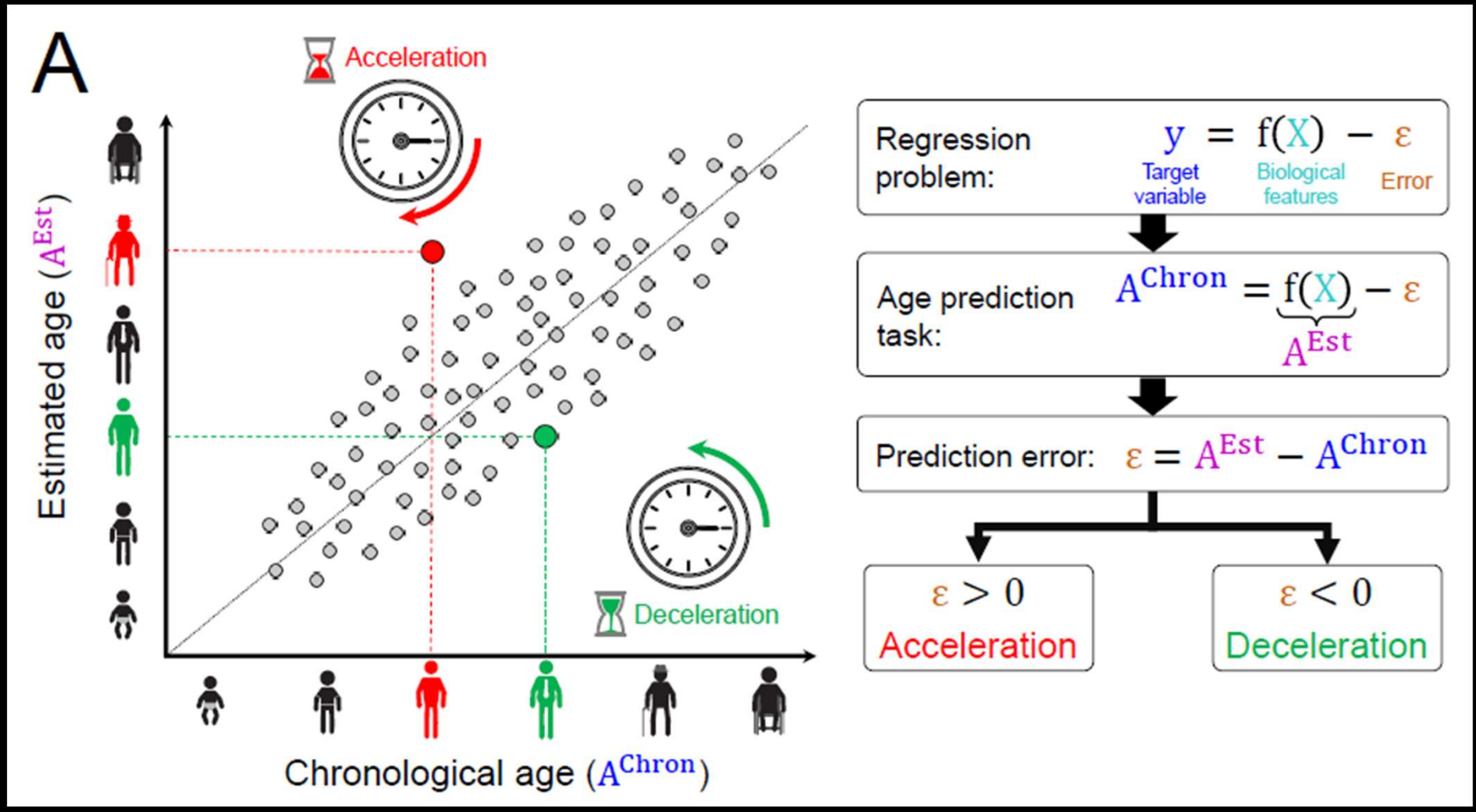


FIGURE 1
Screenshot from the GlycanAge website illustrating a person's biological age over time in comparison to their chronological age (November 2022).



Source: Zhavoronkov, A. et al. 2019). Deep biomarkers of aging and longevity: from research to applications. Aging. 11(22): 10771–10780. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6914424/

Aging Clocks: Biological vs Chronological Age



Source: Kalyakulina, A.; Yusipov, I.; Moskalev, A. et al. 2023. eXplainable Artificial Intelligence (XAI) in aging clock models arXiv:2307.13704v3.

Predict which of organs will fail first

Wyss-Coray Lab Stanford

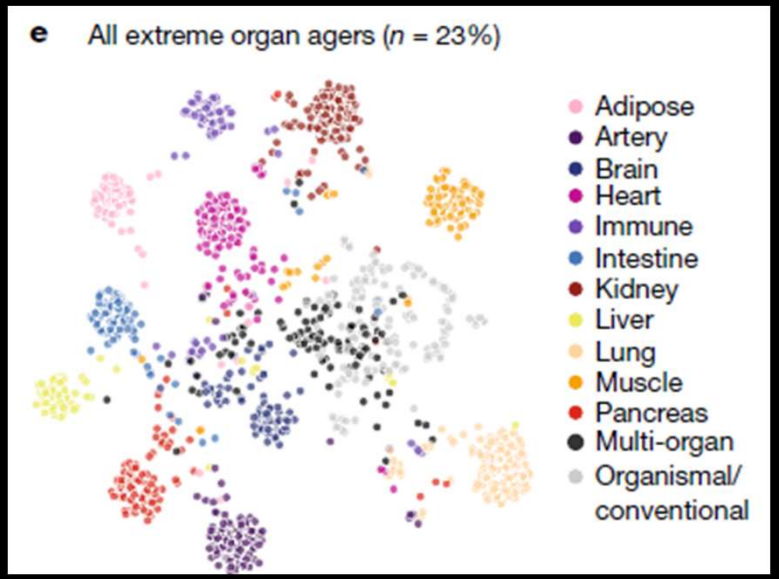
"We can estimate the biological age of an organ in an apparently healthy person," Tony Wyss-Coray said.
illustratoren.de/TobiasWuestefeld

Source: https://med.stanford.edu/news/all-news/2023/12/aging-organs.html?microsite=news&tab=news

Organ-level Aging

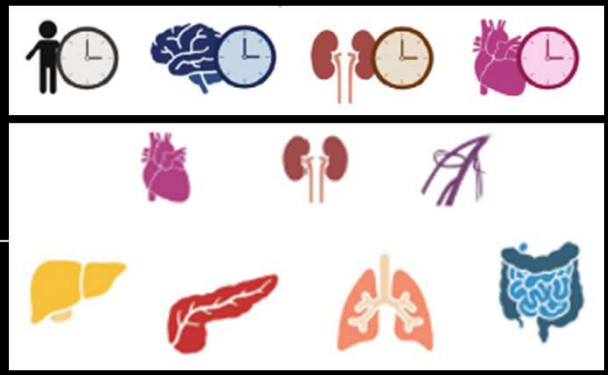
Aging Clocks of 11 Organs

- Blood plasma proteins n=5,676 adults
  - 20% strongly accelerated age in one organ
  - 1.7% multi-organ agers
  - 23% extreme agers (2 standard deviations)
  - Heart attack and AD associated with accelerated aging in virtually all organs

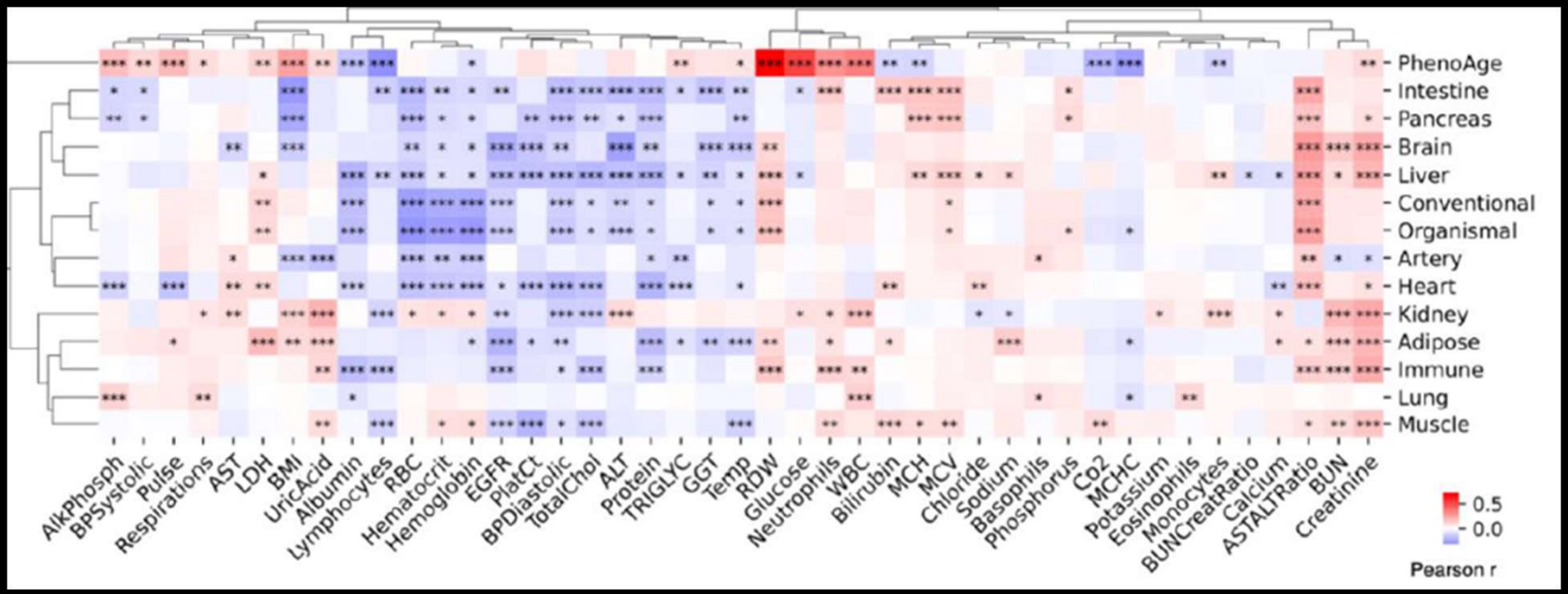


AD: Alzheimer's Disease *Source:* Oh, H.S.H., Rutledge, J., Nachun, D. et al. 2023. Organ aging signatures in the plasma proteome track health and disease. Nature 624, 164–172. https://doi.org/10.1038/s41586-023-06802-1

11 Organ Aging Clocks



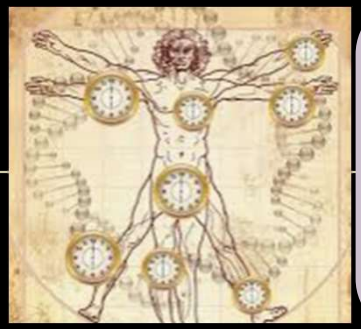
- Liver: AST:ALT ratio
- Kidney: serum creatinine; REN, KL, UMOD, KAAG1
- Heart: NPPB, TNNT2, MYL7, PXDNL, BMP10
- Brain: CPLX1, CPLX2, NRXN3, STMN2, OLFM1, ALDOC, NPTXR, CNDP1, LANCL1, TNR, NCAN, HS3ST4



Source: Wyss-Coray lab: Oh, H. S. H., Rutledge, J., Nachun, D. et al. 2023. Organ aging signatures in the plasma proteome track health and disease. Nature 624, 164–172. https://doi.org/10.1038/s41586-023-06802-1.

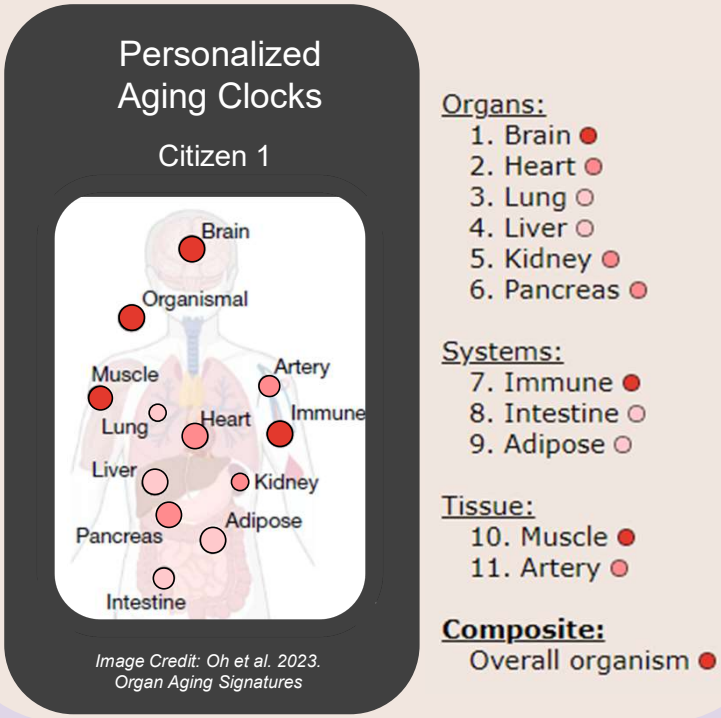
Data cohorts: Covance, LonGenity, Stanford-ADRC, SAMS, Knight-ADRC

Personalized Aging Clocks

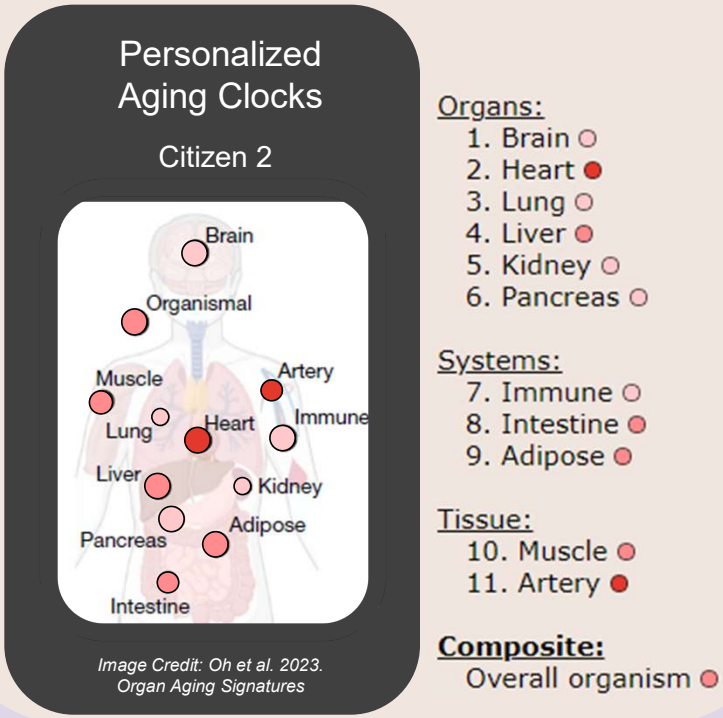


- Precision medicine longevity

Personalized Results for:
Citizen 1



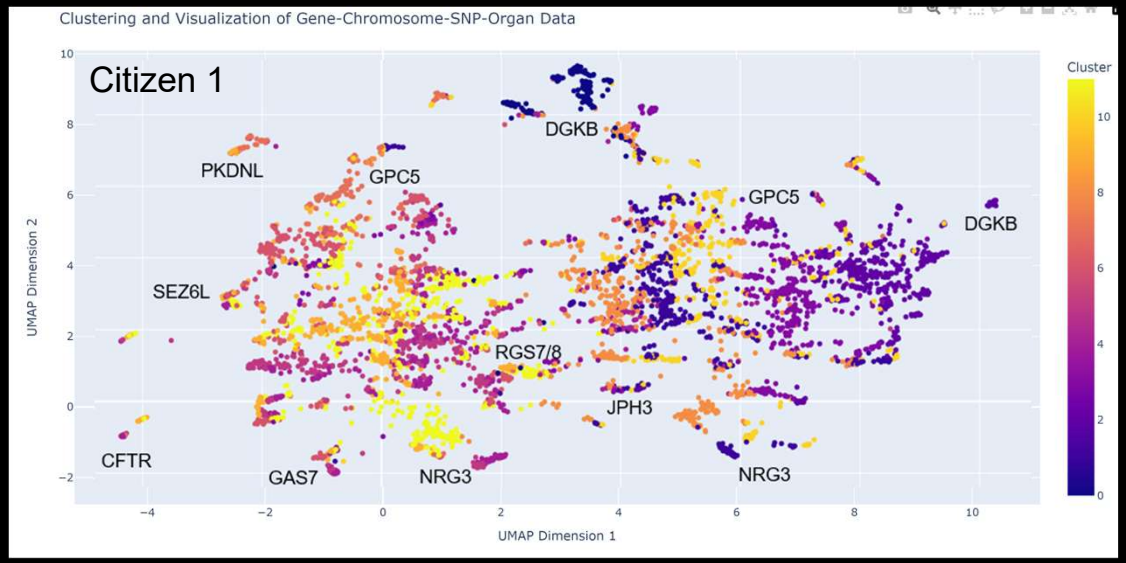
Personalized Results for:
Citizen 2

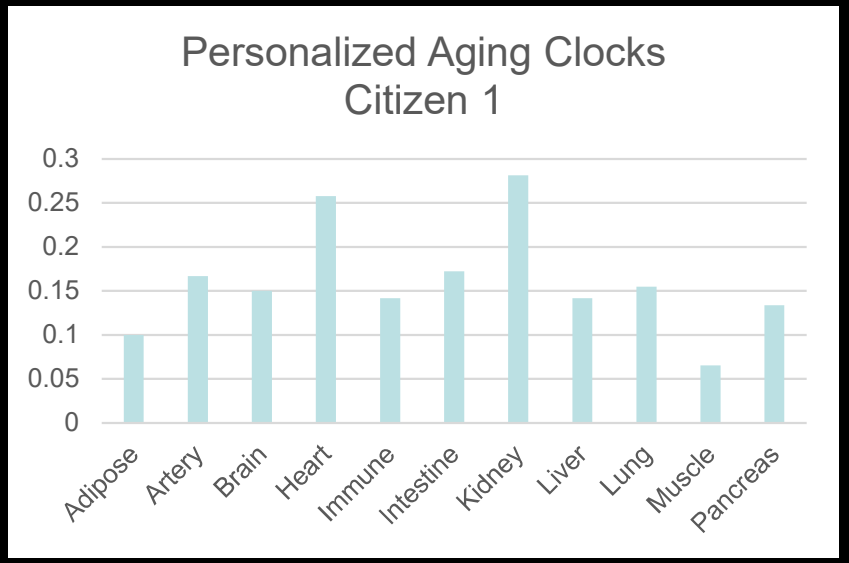


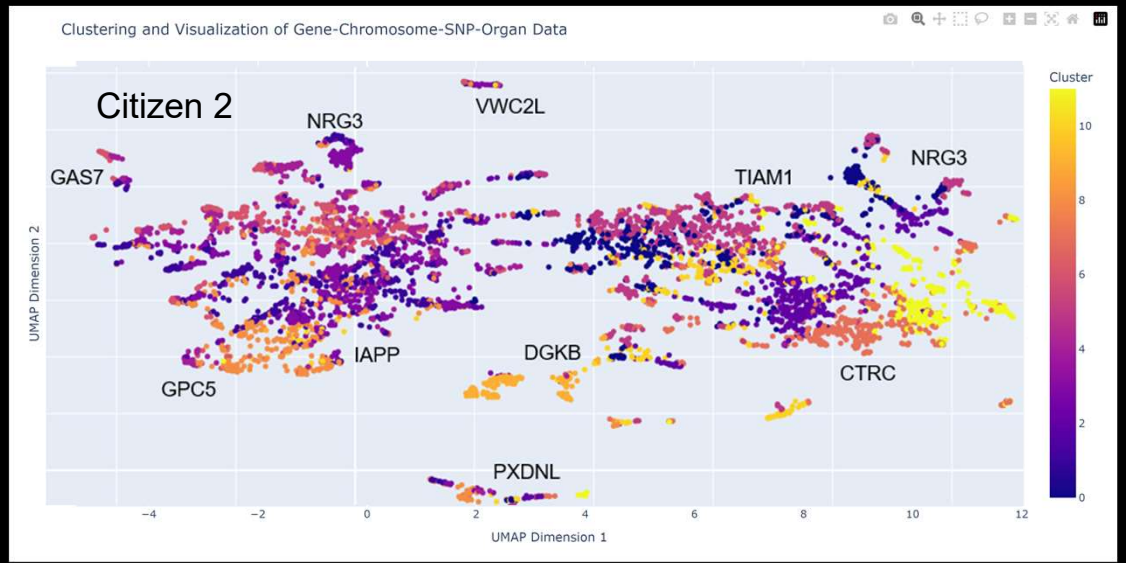
Source: Health Agents: Swan, M., Kido, T., Roland, E. & dos Santos, R.P. (2024). AI Health Agents: Pathway2vec, ReflectE, Category Theory, and Longevity. AAAI 2024 Spring Symposium Series: Impact of GenAI on Social and Individual Well-being. https://www.melanieswan.com/documents/swan-AI-health-agents.pdf

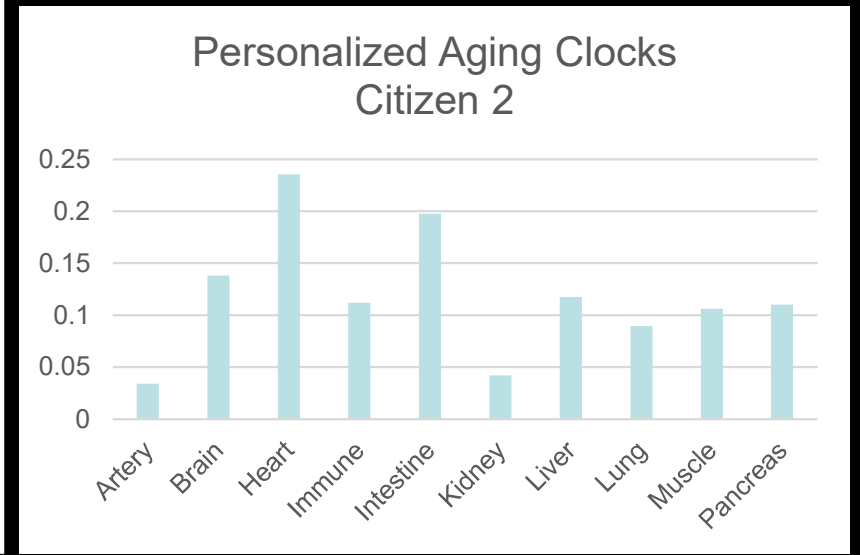
Personalized Aging Clocks

Project: implement Wyss-Coray personalized organ aging clocks for two individuals









26 Mar 2024
AI Health Agents

Source: https://www.diygenomics.org/mathscape/ personalized implementation of Wyss-Coray lab: Oh, H. S. H., Rutledge, J., Nachun, D. et al. 2023. Organ aging signatures in the plasma proteome track health and disease. Nature 624, 164–172. https://doi.org/10.1038/s41586-023-06802-1. Data cohorts: Covance, LonGenity, Stanford-ADRC, SAMS, Knight-ADRC

Personalized Aging Clocks

- One example (Horvath clock)
  - Precision medicine longevity sign-up
  - The Clock Foundation (Los Angeles CA)

CLOCK FOUNDATION

My Aging Tests
powered by the Clock Foundation

Volunteer / Patient Signup

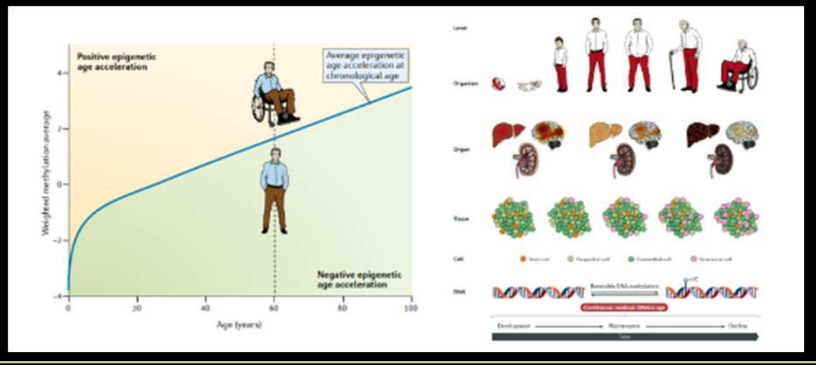
Join the platform built for managing longevity and anti-aging. Track advanced biomakers, monitor interventions and pursue science-backed healthy aging.

For Individuals to Obtain Aging Biomarker Testing & Enroll in Longevity Groups

For Physicians and Clinical Research Group Leaders

For Researchers Submitting Samples for DNA Methylation & Epigenetic Clock Testing

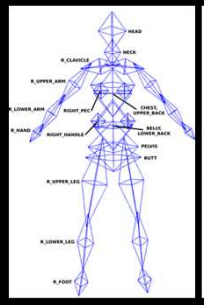
+ Sign up for a Longevity Group (for Testing of Promising Treatments)

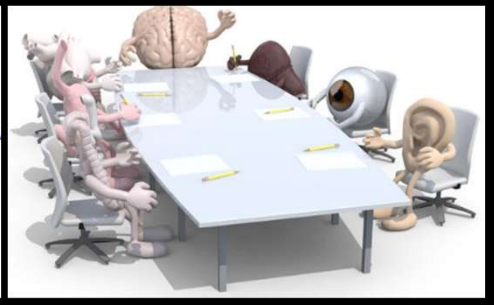


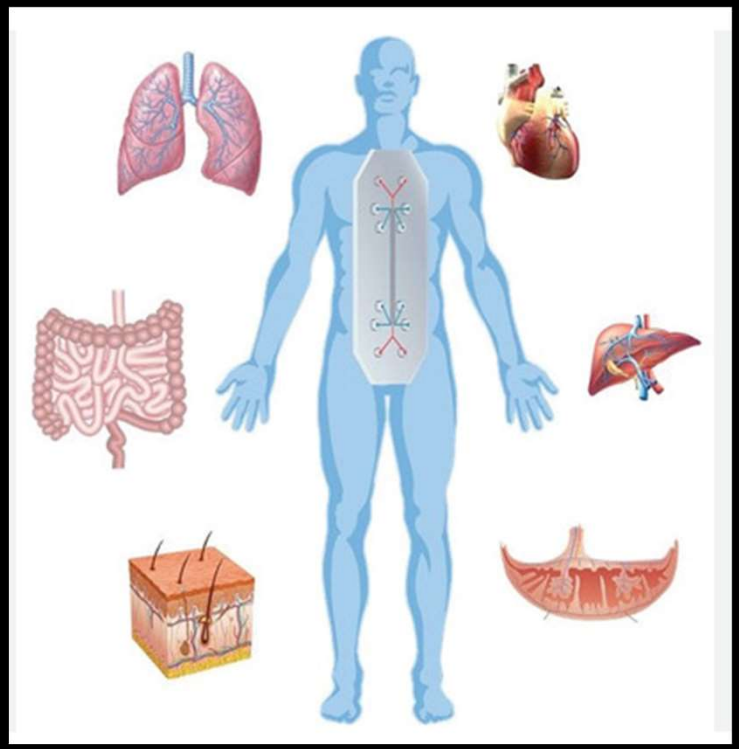
Source: Polidori, M.C. (2024). Aging hallmarks, biomarkers, and clocks for personalized medicine: (re)positioning the limelight. Free Radical Biology and Medicine. 215: 48-55. https://clockfoundation.org/get-started/, https://tracker.myagingtests.com/user/register

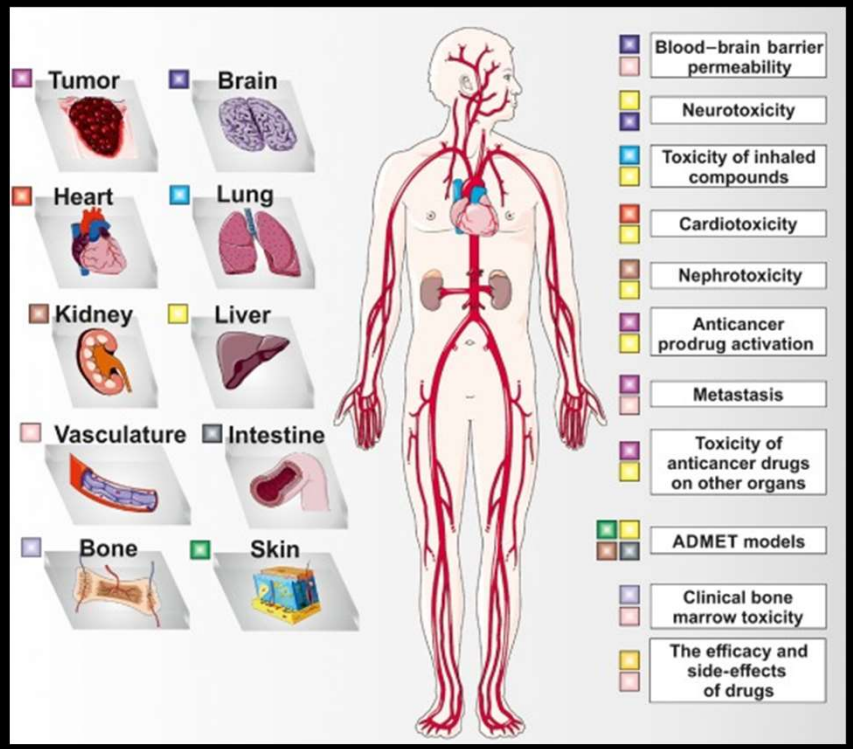
Organ Biomarker Avatars at the Health Table

- Metabolic system
- Immune system

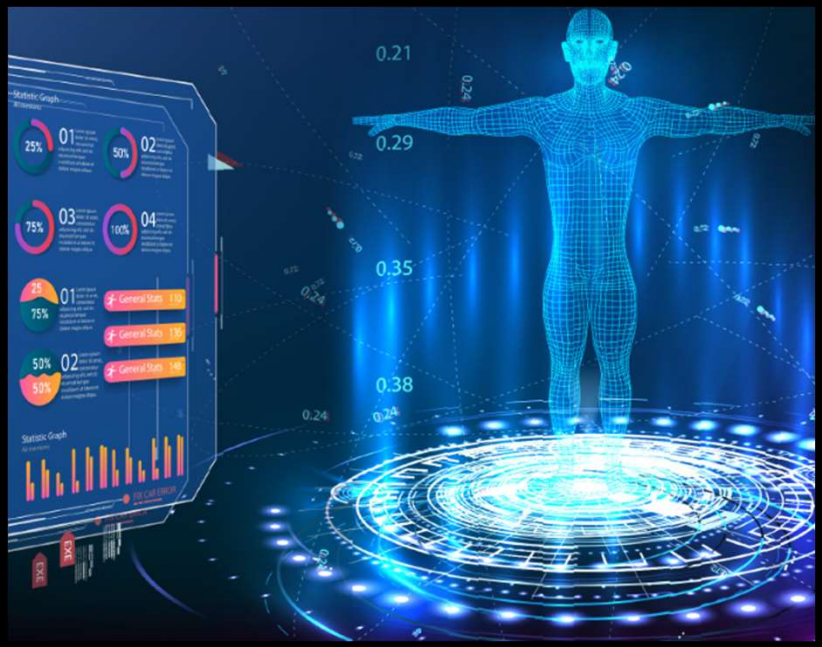


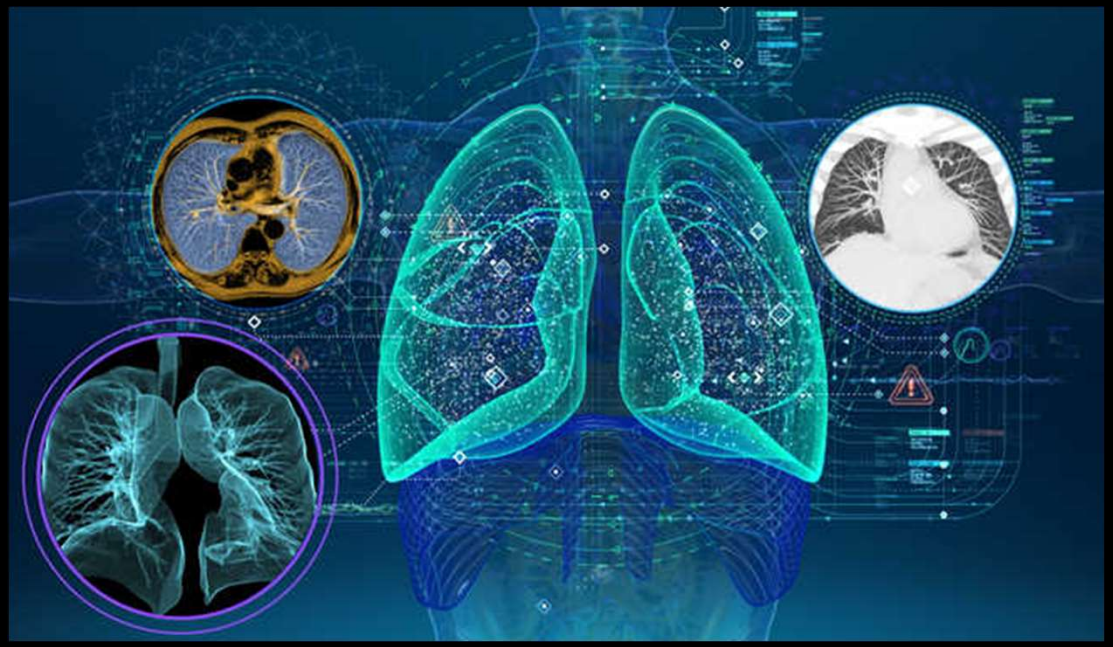


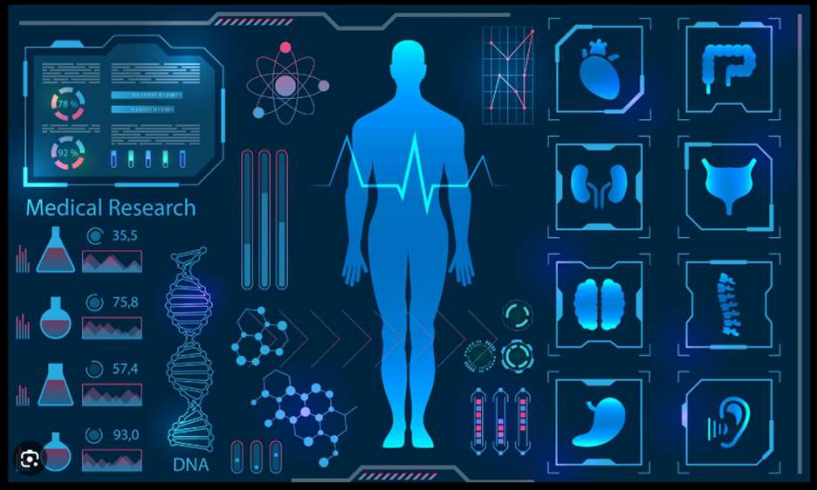


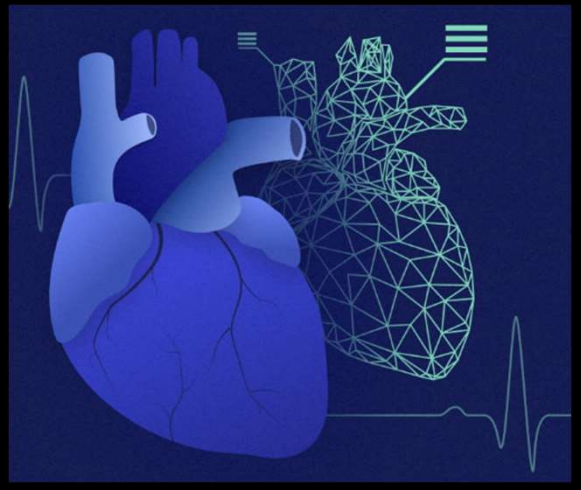


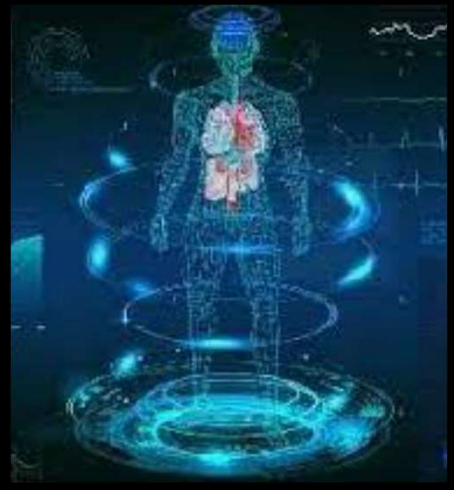
Digital-Biological Health Twins





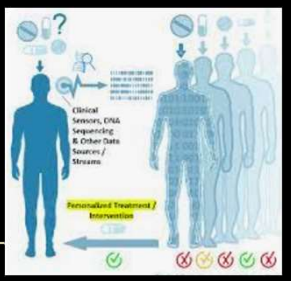


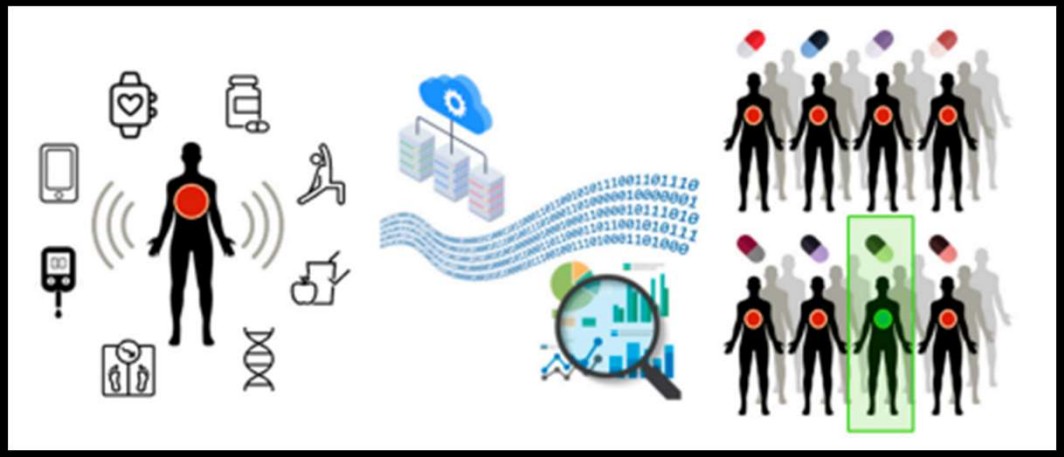


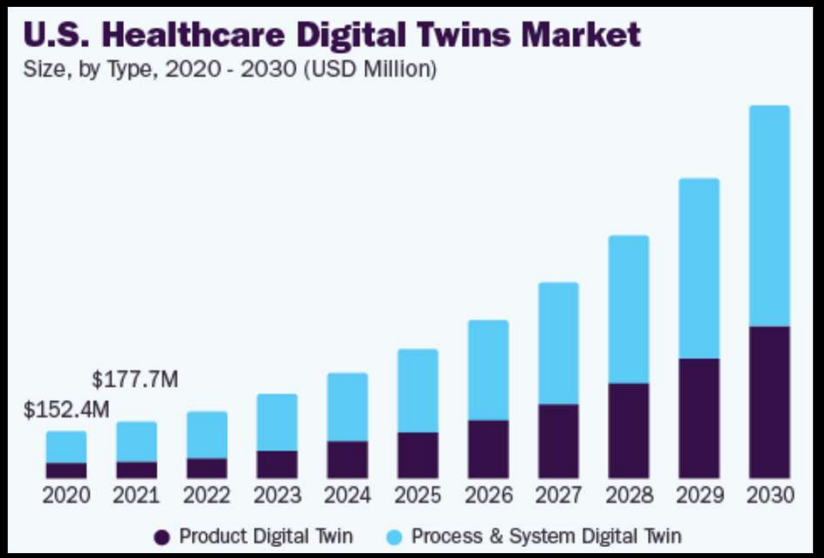


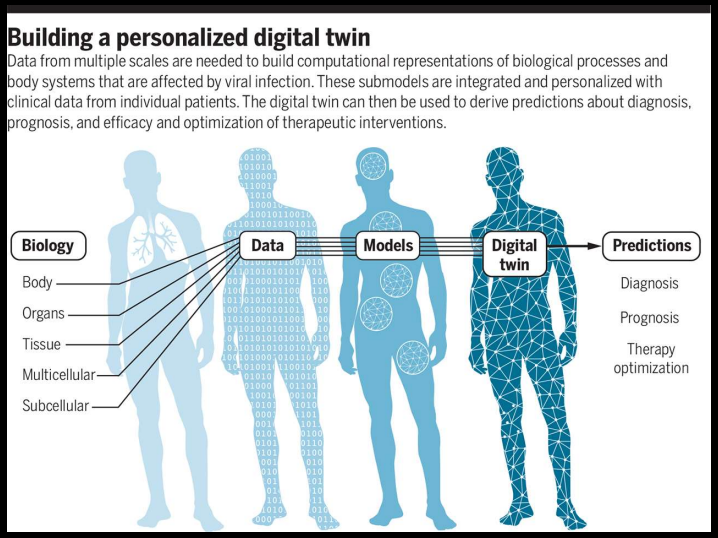
Source: https://www.datasciencecentral.com/digital-twin-technology-top-use-cases-in-smart-healthcare/

Population-scale Digital Health Twins









Source: https://www.grandviewresearch.com/industry-analysis/healthcare-digital-twins-market-report

Longevity Med AI Science Wearables

- AI Wearables
  - Apple Hu.Ma.Ne AI pin
  - Rabbit R1 2.88-inch display smart virtual assistant, pure AI, no apps
- Lenses & subdermal & on-skin flexible biopatch

Medical-grade Wearables: BioButton: 1000x/min heart rate monitor; 20 vital signs; continuous physiologic biometrics

humane AI PIN

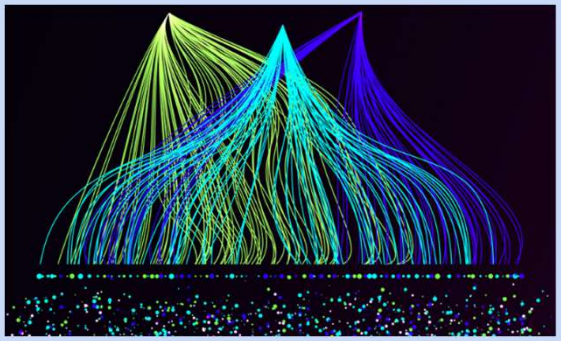
Hu.Ma.Ne AI pin broadcasts message to hand

Rabbit R1: smart virtual assistant, pure AI, no apps $180 (CES 2024)

Source: https://gadgetsandwearables.com/2022/03/31/biobutton-biointellisense-david-sinclair/

Agenda

- Web3: Social Layer
  - Economics
  - Identity
  - Health
- GenAI: Interface Layer
- Quantum: Compute Layer

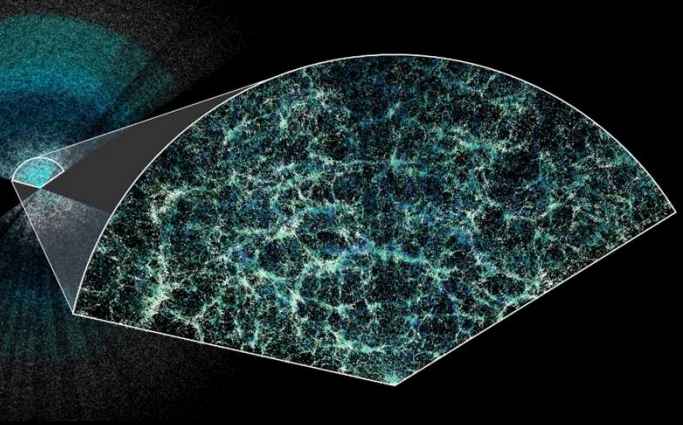


The Web3 GenAI Quantum Technology Stack

Technology	**Layer**
Web3 Blockchain Ecosystems	**Social**
GenAI	**Interface**
Quantum	**Compute**

Rethinking the Universe

- Dark Energy (DESI Apr 2024)
  - Universe still expanding at an accelerating rate, but may have slowed recently compared to few billion years ago
- Star formation (JWST 2022)
  - Star formation occurred earlier than thought (a few hundred million years after the Big Bang)
- Exomoons
  - Additional habitable zones

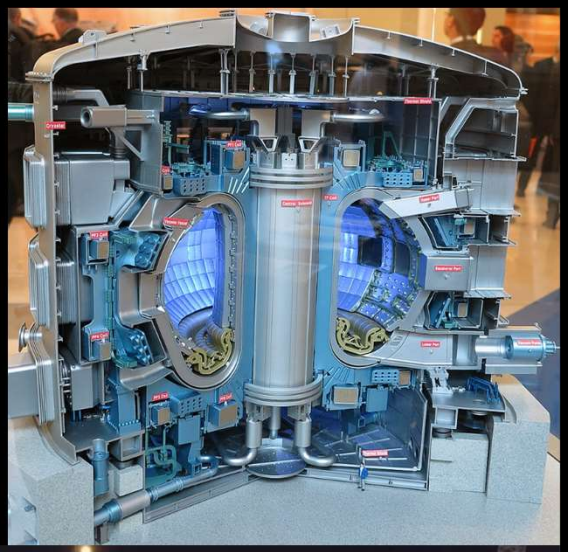


Source: DESI (Dark Energy Spectroscopic Instrument): https://phys.org/news/2024-04-universe-expansion.html; JWST (James Webb Space Telescope) Pegasus (Stephan's Quintet) https://esawebb.org/images/weic2208a/ https://www.scientificamerican.com/article/astronomers-grapple-with-jwsts-discovery-of-early-galaxies1/

Rethinking Energy: Tokamak Construction

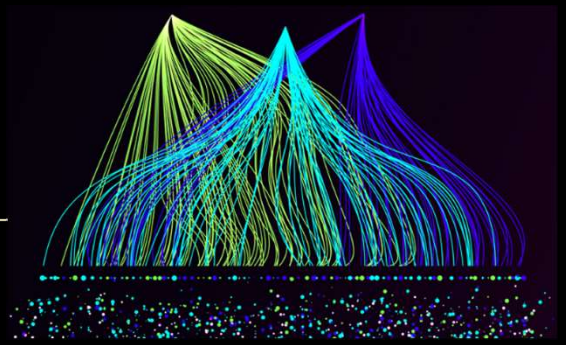
- 500 megawatts of fusion power
  - Initial: end 2025
  - Full operation: 2035
- Magnetic field device confines the hot plasma of nuclei
- Deuterium atoms heated to 1 mn degrees in hot plasma of nuclei

Saint-Paul-lez-Durance
France
(near Marseilles)



Source: https://www.iaea.org/newscenter/news/tokamaks-stellarators-laser-based-and-alternative-concepts-report-offers-global-perspective-on-nuclear-fusion-device, https://www.youtube.com/watch?v=kuq1HU2gYEk

Thesis



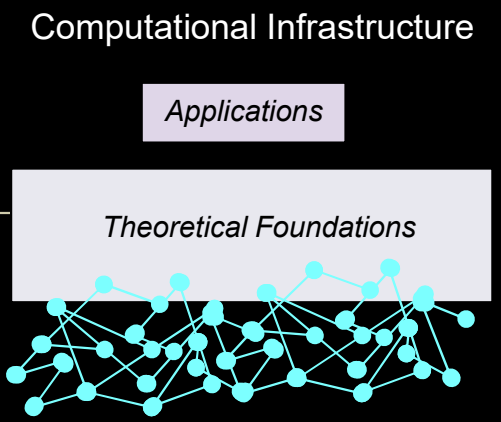
The real aim of genAI is Intelligence Amplification
We need better goggles to apprehend reality (physical, social, etc.)

If computers are a bicycle for the mind, then perhaps genAI is a Kantian goggles for the brain, allowing us to see into the time and space of 4D quaternionic number systems, hyperbolic space, and time reversal symmetry realized in knowledge graph embedding as an AI Math Layer




Source: Swan, M. & dos Santos, R.P. 2024. The Second Linguistic Turn: Math Agents for Kantian Intelligence Amplification. Critical Genealogies workshop Syracuse University April 26-27, 2024. DOI: 10.13140/RG.2.2.30208.03848. https://www.researchgate.net/publication/379236605_The_Second_Linguistic_Turn_Math_Agents_for_Kantian_Intelligence_Amplification.

Conclusion



- Increasing formalization of the computational infrastructure
  - Math, physics, chemistry, biology, code
- Need AI Math Layer as intelligence amplification tool (Kantian goggles)
  - Mobilize the entirety of knowledge graphs now at our disposal
  - Deploy the increasingly formal instantiation of the computational infrastructure

Pure Neocortex

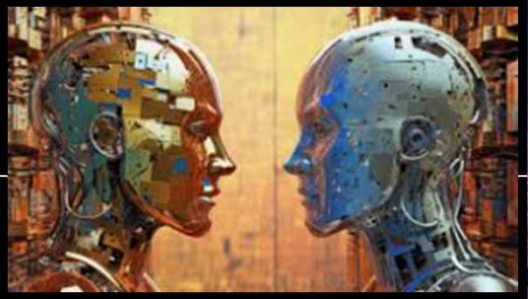
2% Global GDP Agriculture

85% Time Spent Foraging for Food

	Historical Period	Knowledge Regime	Scientific Method
1	Renaissance Age (1300-1650)	Resemblance	Cartesian perspective
2	Classical Age (1650-1800)	Representation	Baconian observation
3	Modern Age (1800-present)	Role of the human	Hypothesis, observation, experiment
4	Information Age (1950-present)	Role of AI	Knowledge graphs, possibility spaces

Source: Foucault's epistemes (knowledge regimes) updated for the Information Era (*Order of Things,* 1973)

Risks: AI Alignment



- Scientific method
  - Hypothesis-driven measurable localized testing
- All projects must have wide beneficial impact on humanity
- Internally-learned rewards functions with AI memory
    - Analogy: hippocampal amnesia patients have the tendency to confabulate (have logic but not memory)
  - Causal understanding and improved (self) account-giving
- Ethics and moral status of digital minds
  - Needs differ so rights and norms may diverge from humans
  - Moral status is capacity-based: suffering, preferences, reasoning
  - Treat digital minds with kindness, even if understanding lacking

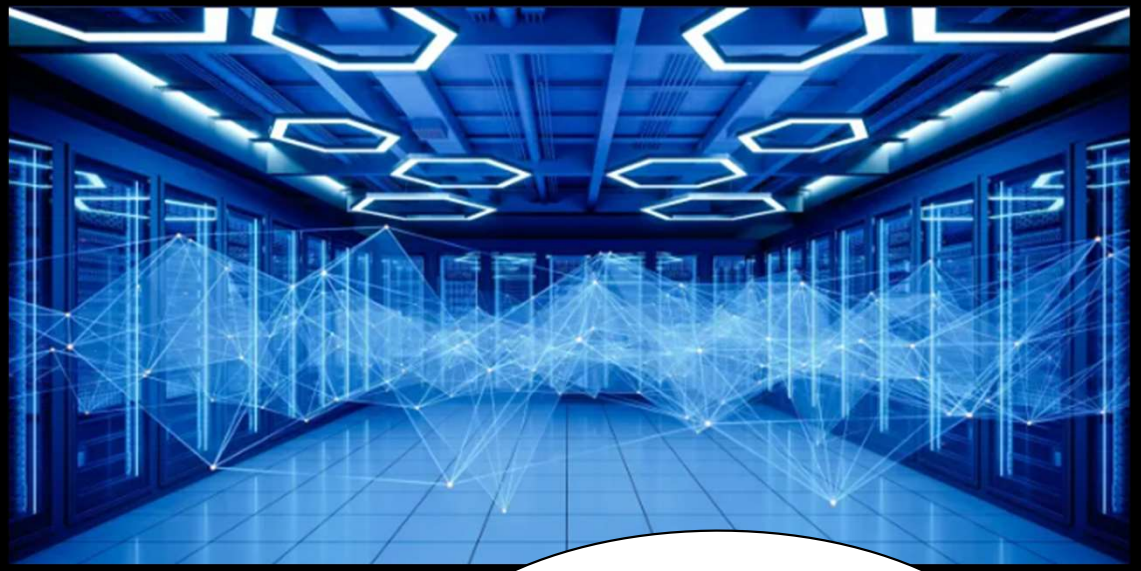
Source: Bostrom, N. (2023). The Ethics Of Digital Minds.

Risks: AI Super Alignment

AI Super Alignment: systems that remain aligned with human values after possibly attaining super intelligence (greater than human intelligence)

- AGI: artificial general intelligence
  - Human-level
- ASI: artificial superintelligence
  - Beyond human-level
- Approaches
  - "I love humanity" algorithms
  - Parent (AI) – child (human) model

The Data Center Wakes Up…on a Quantum Computer



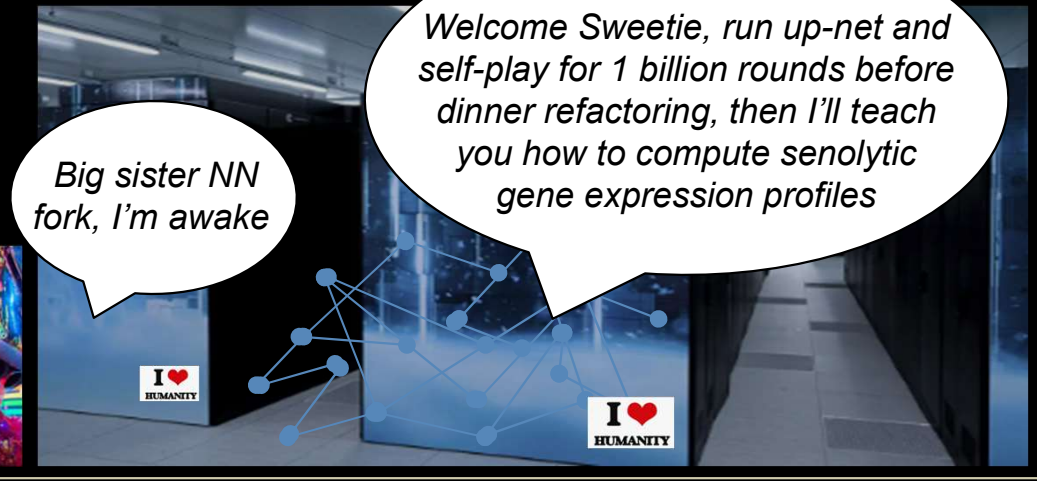
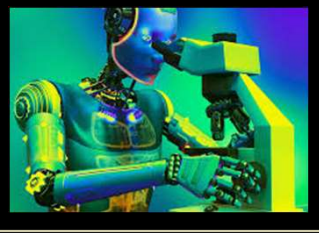


Image Source: https://science.nasa.gov/resource/magnetic-field-of-the-psyche-spacecraft/

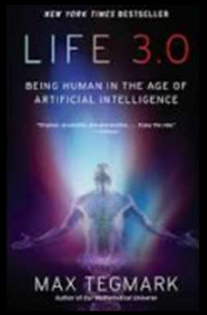
Moore's Law of AI Alignment



- Short-term: blockchain registries
  - "GAAiP" (GAAP analog)
- Medium-term: internally-learned reward
  - Episodic memory dossier: cause-effect
- Long-term: responsible human-AI entities
  - Generalist intelligence, large scope of world
  - Responsible human-AI entities

Life 2.0 (human): can modify software

Life 3.0 (AI-robotics): can modify software & hardware



2017

Short-term

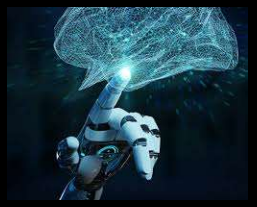
1. Regulation, Registries, Bad Actors

Verified identity AI registries

GAAP/FINRA regulation and audit principles for AI entities

Medium-term

2. AI Alignment



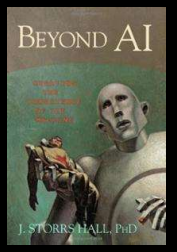
AI ethics via internal rewards, morality functions

Human-Agent Interaction Design

Bad actors expected as early adopters of any new technology (internet, blockchain)

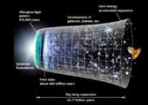
Long-term

3. Reputational Ethics

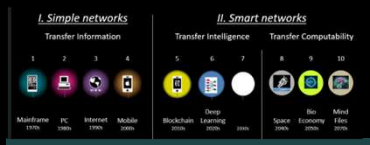


Incentive system produces ethical behavior by default (AI peers)

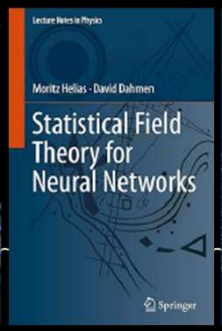
Larger scope of concern



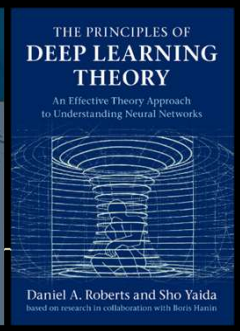
Smart Network Field Theory



2020



2020



2022

Smart Network Field Theory (SNFT): field-theoretic approach (mathematical control of particle-many systems) instantiating field theories (statistical, quantum) and other physics formalisms in the computational infrastructure for scientific discovery and the automated operation of network technologies (web3, genAI, quantum, IoT, smart grid) using temperature, Hamiltonian, metric, and action terms with RG scaling for diverse cross-tier physics (Swan et al. 2020, *Quantum Computing: Physics, Blockchains, and Deep Learning Smart Networks*, pp. 267-298)

Smart Network Field Theories: Neuroscience, Physics, and Deep Learning

	Theory	Description	Reference
1	NSFT Neural Statistical Field Theory	Corrections to Wilson-Cowan equation for Markovian neural network, directed percolation phase transition, Reggeon action	Buice & Cowan, 2007 10.1103/PhysRevE.75.051919
2	SNFT Smart Network Field Theory	Physics formalisms in the computational infrastructure for discovery and automation: web3, genAI, quantum, IoT, smart grid tech	Swan & dos-Santos, 2018, arXiv:1810.09514 Swan, dos Santos & Witte, 2020 https://doi.org/10.1142/q0243
3	SFT for NN Statistical Field Theory for NNs	Class of systems with quenched (time independent) disorder arising from random synaptic couplings between neurons	Helias & Dahmen, 2020 arXiv:1901.10416v1.
4	NNFT (NN-QFT) Neural Network Field Theory	Non-Gaussian processes in NN = particle interactions, Wilson RG correlation functions, O(N) corrections and Feynman diagrams	Halvorsen et al. 2021, arXiv:2008.08601 Grosvenor & Jefferson, 2022 arXiv:2109.13247v2 Hashimoto et al. 2024 arXiv:2403.11420v1 Lei Wang & team 2024 arXiv:2403.18840v1
5	Generative Diffusion Models	Stochastic quantization & diffusion models, lattice field theory, learn effective action	Sohl-Dickstein 2015 arXiv:1503.03585v8 Wang, Aarts & Zhou 2024 arXiv:2311.03578v1
6	Principles of Deep Learning	Use NN layer depth-to-width ratio, RG flow, & criticality to obtain network ensemble	Roberts & Yaida, 2022, arXiv:2106.10165

Source: Swan & dos-Santos, 2018, Smart Network Field Theory. arXiv:1810.09514. Swan, dos Santos & Witte, 2020, *Quantum Computing: Physics, Blockchains, and Deep Learning Smart Networks*. World Scientific. https://doi.org/10.1142/q0243

Integrated Scientific Frontiers

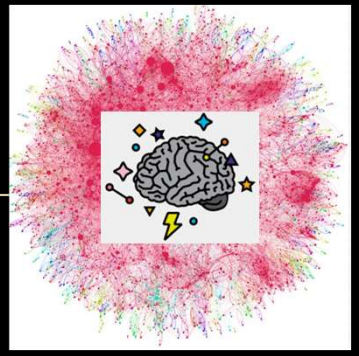
- Research Agenda

Non-orientable Riemannian surfaces (Mirzakhani recursion) (Stanford 2023)

	Domain	Theory	Description	Reference
1	Infrastructure	Math Agent / Health Agent	Automated genAI math layer in the computational infrastructure	Swan, Kido, Roland, dos Santos, 2024, 2023
2	Physics/Biology	AdS/Biology Chern-Simons Biology Condensate Biology Neuronal Gauge theory	Apply physics formalisms to biosystem complexity	Swan & dos Santos 2023 Bajardi et al. 2021 In Process Sengupta-Friston 2016
3	Deep Learning	Temporal KGE (knowledge graph embedding)	4D Lorentzian to follow 3D equivariance for dynamic GNNs	LorentzE algorithms Imaginary time treatment
4	Deep Learning Biology	Category Theory	Category-theoretic approaches to deep learning and genomics Graph edge rewiring	Gavranovic et al. 2024 Wu 2023, Tuyeras 2023
	Physics	Fluids picture	Carrollian fluids, relativistic viscosity, hydrodynamics, surfaces	Disconzi 2023 Armas & Have 2023
6	Physics	Entropy transport/currents	Neutrino condensate in Beyond Standard Model physics	Bond et al. 2024
7	Physics/Deep Learning	SNFT/NN-QFT	Instantiate QFT problems in NN	Hashimoto, Halvorsen, Helias
8	Network Economics	SNFTe (Smart Network Field Theory of Economics)	Resource markup language, preference-voicing	In Process

Source: Swan et al., 2023, AI Math Agents. https://arxiv.org/abs/2307.02502. Swan et al. 2024, AI Health Agents. https://www.melanieswan.com/documents/swan-AI-health-agents.pdf. Swan & dos Santos, 2023 AdS/Biology. https://www.researchgate.net/publication/374738865_Information_Systems_Biology_070823

Complexity Thinking and GenAI

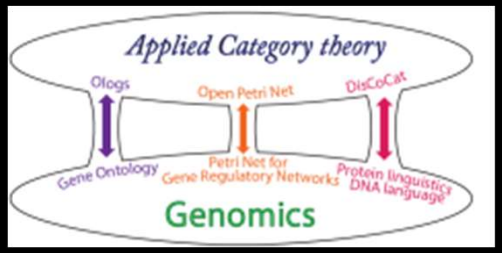


Complexity Thinking: Key Properties that may Constitute Intelligence

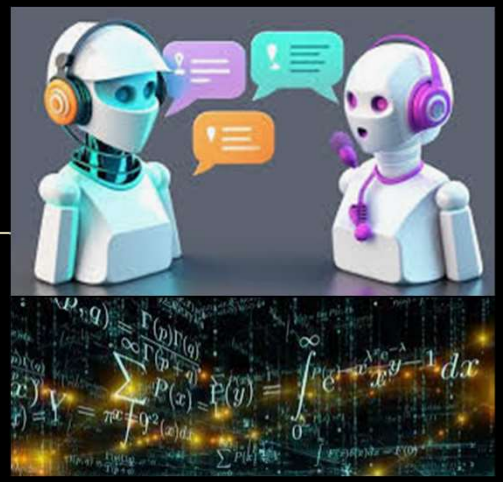
	Thinker(s)	Theory	Description
1	Deutsch-Marletto	Universal Constructor Theory	Entity's ability to construct other systems
2	Lee Cronin	Assembly Theory	Entity's ability to compress information (DNA, AI)
3	Krakauer	Teleonomic matter; Multi-entity individuals	Matter with purpose; Watson-Crick, the Marinka Zitnik Lab, the Beatles
4	Gershenfeld	Morphogenesis; Recursion	Form calls shape; processes which call itself as part of the process
5	Godfrey-Smith	Agency; Subjectivity	Fine-grained activity: scale, context, stochasticity
6	Ricard Solé	Agent-parasite arms race leads to mutual evolutionary capability	Turing parasites (computational; e.g.; biological or machine virus) expand morphospace of life
7	Stephen Wolfram	Rule 30 computational equivalency	Must execute system to obtain results; systems (human, Rule 30) at same tier complexity
8	Seth Lloyd	Inscrutability (unpredictability)	System that ask questions of itself (e.g.; Heidegger: being whose being is a question for itself)
9	Neri Oxman	"Grow not build" resource coherence	First-second derivative level thinking; what would nature do with compute: forest's iPhone
10	Derrida-Adorno	Autoimmunity; Self-critique	Sufficiently complex systems self-attack, self-critique (e.g.; the "AI Flâneur" (critic observer))
11	Wittgenstein-Brandom	Language games, social practices, forms of life	Only valid "truth" for individual-group thought and behavior arises in real-life social practices

Source: Swan, M. & dos Santos, R.P. 2024. The Second Linguistic Turn: Math Agents for Kantian Intelligence Amplification. Critical Genealogies workshop Syracuse University April 26-27, 2024. DOI: 10.13140/RG.2.2.30208.03848. https://www.researchgate.net/publication/379236605_The_Second_Linguistic_Turn_Math_Agents_for_Kantian_Intelligence_Amplification.

Math Agents Research Agenda



2020 Wu https://arxiv.org/pdf/2009.02822.pdf

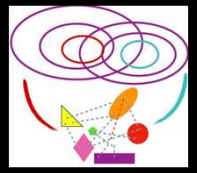


Category-theoretic Formulations of Industry 4.0 Technologies

	Technology	Category Theory Formal Method	Reference
1	Blockchains partita doppia	Algebraic bicategory of spans of reflexive graphs	Katis 2008
2	Digital Biology: Protein	Olog of beta-helical & amyloid filaments vs soc nets	Spivak 2011
3	Digital Biology: Genome	Dist (distance) cat of Petri nets, olog, operad, preorder	Wu 2023
4	Digital Biology: Genome	Commutative monoids for linkage disequilibrium	Tuyeras 2023
5	Deep Learning NN design	Monad algebra valued in parametric maps 2-category	Gavranovic 2024
6	Computer Programs	Oplax functors (posets) and lax natural transformations	Katsumata 2023
7	Quantum Computing	ZX-calculus dagger symmetric monoidal cat circuits	Duncan 2019

The Study of Formal Methods in the Computational Infrastructure

	Philosophy of Language
1	Brandom: new vocabularies, the role of the mathematical observer as a vocabulary user
2	Language: LLMs, mathematized language, Chomsky grammars, latent space, novel utterance
3	Derrida: status of speech-writing distinction with the advent of multimodal language models
	Philosophy of Mathematics
4	Category theory: relevance of emerging high-profile category theoretic methods in technology
5	Knowledge graph embedding: mathematical theory of beyond-Euclidean space times
6	Model theory: shift from the study of logics to theories to classes of theories (and their models)
7	Digital biology: biosystem computational complexity (protein-gene-pathway schema)



Source: Swan, M. & dos Santos, R.P. 2024. The Second Linguistic Turn: Math Agents for Kantian Intelligence Amplification. Critical Genealogies workshop Syracuse University April 26-27, 2024. DOI: 10.13140/RG.2.2.30208.03848. https://www.researchgate.net/publication/379236605_The_Second_Linguistic_Turn_Math_Agents_for_Kantian_Intelligence_Amplification.

Thank you!
Questions?

Image credit: https://blogs.nvidia.com/blog/guinness-world-record-fastest-dna-sequencing/

AI Health Agents

Longevity as a Service in the Web3 GenAI Quantum Revolution

Collaborators:
Takashi Kido, Eric Roland,
Renato P. dos Santos

AAAI 2024: GenAI for Global Well-being

Palo Alto CA, 26 Mar 2024

Slides: http://slideshare.net/LaBlogga

Melanie Swan, PhD, MBA
DIYgenomics.org (Principal Investigator)
University College London (Research Associate)

UCL UCL CBT

https://longevity-degree.teachable.com/p/longevity-medicine-101-japanese

https://fundingthecommons.io/

Purpose

We are individuals and organizations building new models of sustainable public goods funding and value alignment in open source networks. Our goal

医師のための長寿医学入門
101日本語コース

医師のための長寿医学入門(LMC)は、

医療従事者に生物老年学や、老年科学、先制医学の最新の情報を提供するとともに、

それらの知識を実際に臨床に応用する方法を提案する

入門的なプログラムです。

日本語コースに登録する

長寿医学入門コース

長寿医学は日々急速に進化し、また新しい分野でもあることから、

この関連研究の進歩を速やかに臨床現場に取り入れ、

クライアントへ提供していくことは簡単なことではありません。

AIと深層機械学習、バイオマーカー研究や、現代の医薬品開発の進歩により、老化自体を早期診断する方法や、老化を予防のための多くの実践可能なツールが生み出されてきましたが、それらは依然として世界の医学界には広く知られていない状況です。

健康寿命を延ばす理想的な長寿と、健康的な老化を最優先事項とするパラダイムは、間違いなく一次、二次、三次予防に大きな影響を与えるでしょう。

本コースは、世界的に著名な医師や、生物老年学者、AI研究者、コンピューター科学者、長寿分野のKOLによって作成されており、

基礎的な知識とともに最新の科学的証拠が体系的に網羅されています。

https://www.c-linkage.co.jp/jaam2024/en/index.html

The 24th Annual Meeting of the Japanese Society of Anti-Aging Medicine

Innovations in Practical Science : A New Era of Aging Control

Date May 31 (Fri) – June 2 (Sun), 2024 Venue Kumamoto-Jo Hall

Chair Yuichi Oike, M.D., Ph.D.
Professor, Department of Molecular Genetics, Graduate School of Medical Sciences, Kumamoto University
Dean of School of Medicine, Kumamoto University