Brain Technologies – From Quanta to Neural Nets

Multiscale AI Systems using Quantumscale, Nanoscale, Microscale, and Macroscale Brain Networks Data

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Slides: Google "SOCR News"

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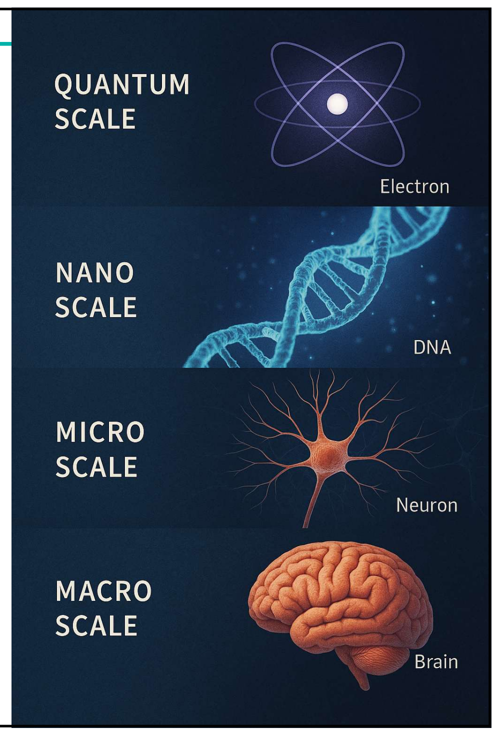
Outline

- ❑ *Quantum-scale – complex-time reps of repeated measurement processes*
- ❑ *Nano-scale*
- ❑ *Micro-scale*
- ❑ *Macro-scale*
- ❑ *Neuro Data, Brain Networks, MLP & AI*
- ❑ Case-Studies – *integrated experimental, theoretical, computational & data sciences*



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Multiscale Neuroscience

Feature	Quantum Scale	Nano Scale	Micro Scale	Macro Scale
Size Range	10^{-15} - 10^{-9} m	10^{-9} - 10^{-7} m	10^{-6} - 10^{-3} m	10^{-3} m and larger
Components	Atoms, ions, subatomic particles	Biomolecules, nanoparticles, nanoscale devices	Neurons, glia, synapses, microcircuits	Brain regions, large-scale networks
Focus	Fundamental quantum phenomena	Molecular interactions, nanoscale tools & structures	Cellular physiology, local circuits	Systems-level function, brain regions & networks
Key Techniques	Quantum modeling, Spectroscopy, Kime-phase tomography (KPT)	Nanofabrication, high-resolution microscopy, nanoscale sensors Cryotomography	Electrophysiology (patch-clamp), optical microscopy, micro-connectomics	fMRI, EEG, MEG, PET, macro-connectomics, lesion studies
Complexity	Lowest (individual particles)	Intermediate (molecules, small devices)	Higher (cells, small circuits)	Highest (brain regions, whole brain)

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Quantum Scale: Complex-time (Kime) Reps

Using QM principles to model **quantum variability**

Kime-Phase Simulation – Repeated Spacetime Measurements

3 Processes – **Green**, **Red** and **Blue** colors (scatter)

At a given spatial location, $\boldsymbol{x}$, $\kappa = te^{i\varphi} \in \mathbb{C}$, where the magnitude ($t > 0$) is time and the event phase $\varphi \sim \Phi(t)_{[-\pi;\pi)}$ is an angular displacement, event direction, reflecting a random sampling index

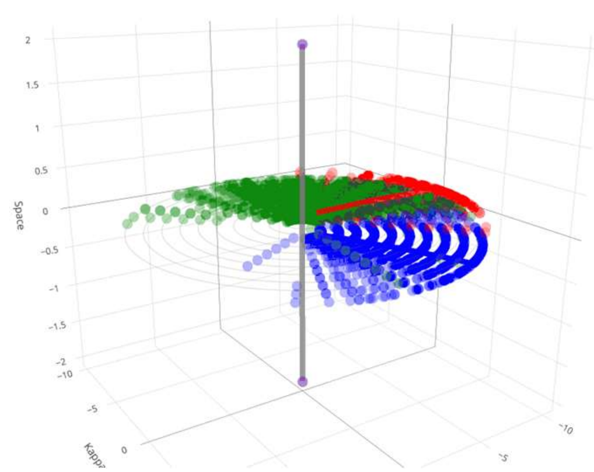
1 Fixed spatial location (vertical axis is 1D space)

Repeated IID Measurements colocalized in 4D ST

3 Different Kime-Phase distributions (color-coded)

Radial displacement t = **time**

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



Wang et al., 2022 | Dinov & Velev (2021)
https://kime.statisticalcomputing.org

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Quantum Scale: Quantum → Kime-Phase Tomography

Measurable Observables: Repeated longitudinal measurements (time-series), $f_i(t): \mathbb{R}^+ \to \mathbb{C},\ \forall i \in \mathbb{N}$

Representation: Complex-time (kime) representation, $\kappa = te^{i\theta} \in \mathbb{C}$, parameterizing the time-series using event ordering (time, $t \in \mathbb{R}^+$) and random draws from a time t -dependent kime-phase distribution $\theta \sim \Phi(t)$

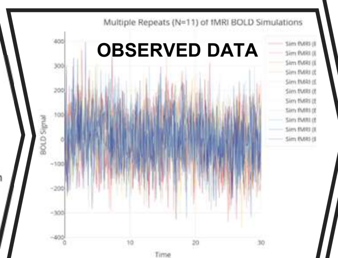
Problem: The kime-phase is *unobservable*; its recovery requires indirect kime phase tomography (KPT). Similarly to the quantum mechanical approach for recovering the wavefunction phase, KPT takes repeated measurements in different non-commutative bases and *distribution action* on *kime-test functions*

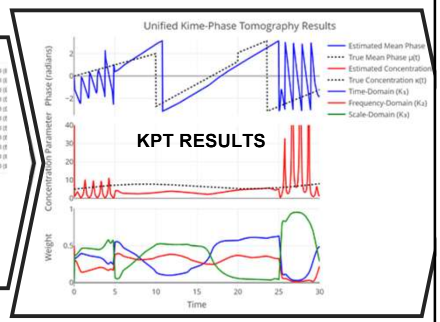
PROTOCOL

Input: BOLD time series $\{x_n(t)\}_{n=1}^N$ and kernel K.

Output: Estimated phase $\hat{\phi}(t)$.

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





https://www.socr.umich.edu/TCIU/HTMLs/Chapter3_Kime_Phase_Problem.html

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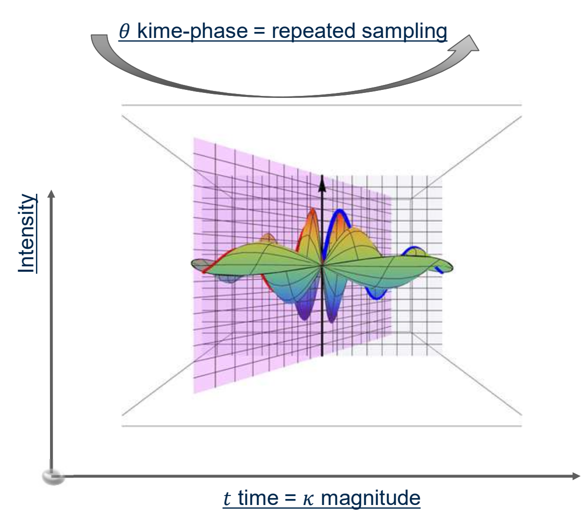
Quantum Scale: Complex-time (Kime) Reps

Observable Longitudinal Data Time-Series ⟼ Kime-Surfaces (not curves)

In the 5D spacekime manifold, time-series curves extend to kime-series, i.e., surfaces parameterized by kime-magnitude (t) and the kime-phase (θ).

Kime-phase aggregating operators that can be used to transform standard time-series curves to spacekime kime-surfaces, which can be modeled, interpreted, and predicted using advanced spacekime analytics.



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

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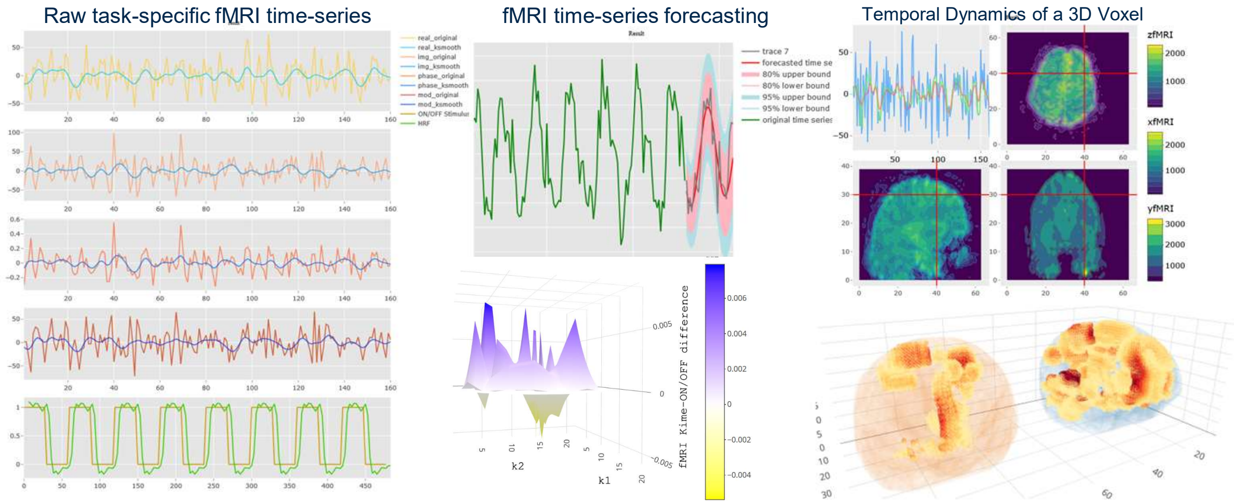
Quantum Scale: Spacekime Analytics

Complex-valued finger tapping fMRI ($64x \times 64y \times 40z \times 160t$)



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

On-Off fMRI time-series to Kimesurface

Level-1 and Level-2 3D Stat Significance Maps

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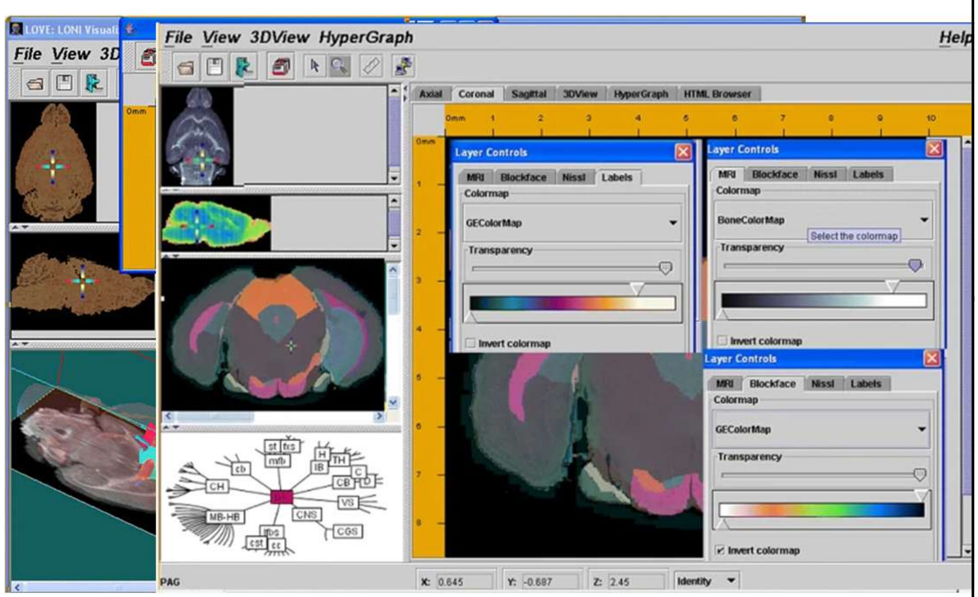
Nano Scale: Cryotomography

LONI Brain Atlas Viewer

Brain atlases contain imaging data (MRI, cryotomographic, Nissl stain, and labeled volume), a *BrainGraph* model, and a relational database, i.e., Brain architecture management system.



DOI: 10.1007/s10278-006-0266-8

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Micro Scale: Confocal microscopy

Fig 1: A schematic overview of a confocal microscopy experiment, cancer data collection, and analysis.

(A) Sample preparation, treatment, and imaging.

(B) 3D nuclear segmentation, shape modeling, and feature extraction.

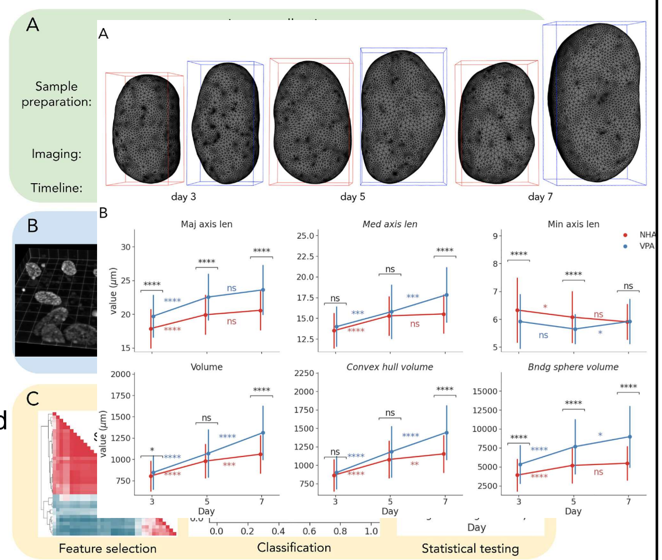
(C) Feature selection, and univariate statistical and machine learning analysis.

Fig 2:

(A) Reconstructed surfaces of representative NHA (normal) and VPA (valproic acid) treated nuclei

(B) Time-dependent changes in morphometric measures of nuclear sizes (mean $\pm SE$)

DOI: 10.1091/mbc.E20-08-0502



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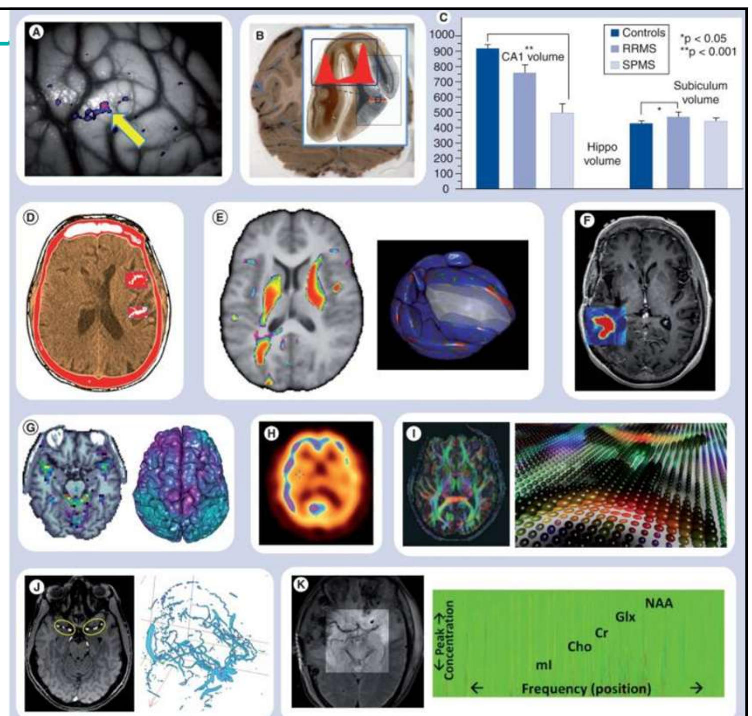
Macro Scale

Common neuroimaging protocols & computational statistical mapping

Invasive neuroimaging
- Functional (in vivo)
- Anatomical (ex vivo)
- Structural (ex vivo)

Noninvasive neuroimaging
- Structural
- Functional
- Diffusion
- Angiography
- Spectroscopy

DOI: 10.2217/iim.11.37



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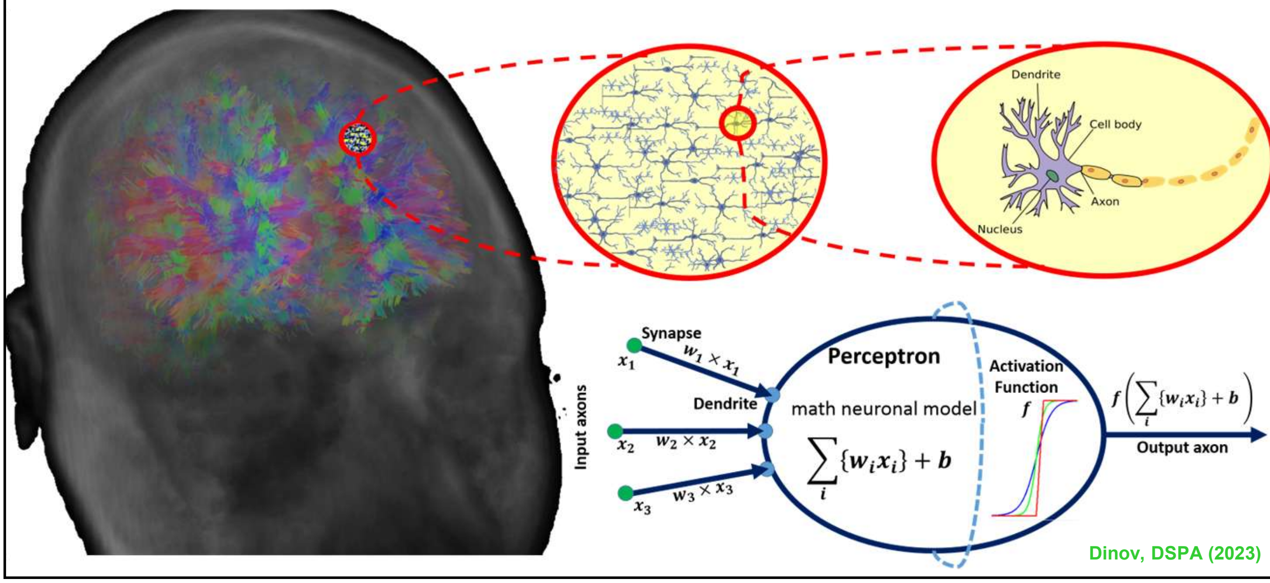
Neuro Data, Brain Networks, MLP & AI



Dinov, DSPA (2023)

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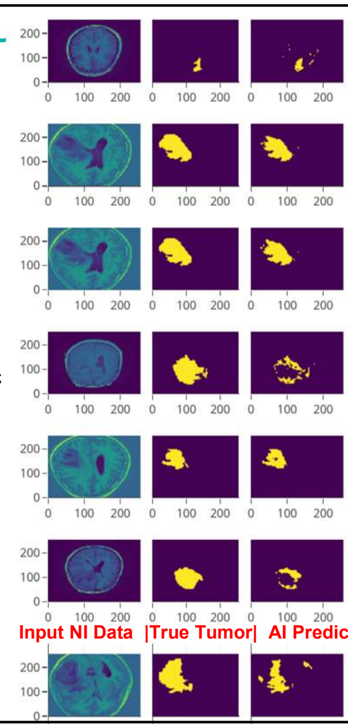
Neuro Data, Brain Networks, MLP & AI

Data: Brain Tumor Imaging data, N=110 patients with lower-grade gliomas. The 2D brain MR images are paired with 2D tumor masks (expert-delineated), which are trivial for controls & non-trivial for patients

Imaging: 3-channels of the MRI data; pre-contrast, FLAIR, and post-contrast

Preprocessing: *Data augmentation* to ensure DCNN-invariance to specific spatiotemporal and intensity transformations. During imaging-data augmentation, the training images/masks may be *flipped, resized*, and *rotated* with specifiable probabilities for each type of augmentation transformation

AI Model: Unet model architecture with encoding (analysis) branch for shrinking the input images and incrementing the number of filters, as well as decoding (synthesis) phase branch for synthetic tumor-mask generation



Dinov, DSPA (2023)

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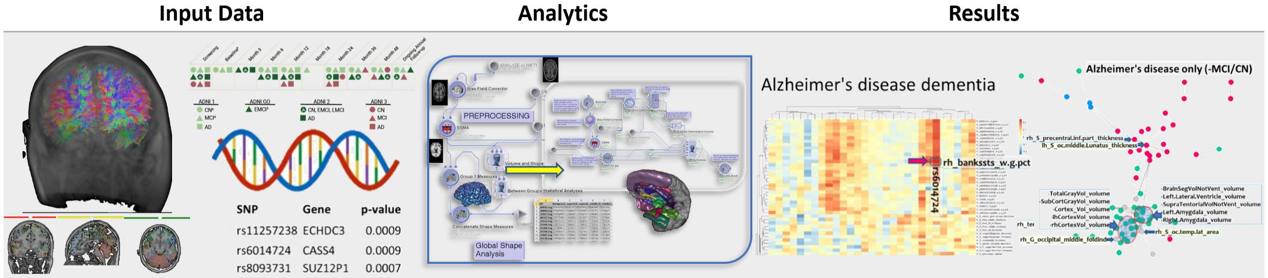
Cohort Study: *Normal & Pathological Aging*

- **Problem** – Model age-related cognition in 3 participant cohorts – (1) *Asymptomatic Controls*, (2) *Mild Cognitive Impairment*, (3) *Dementia*
- **Evidence** (data types) – *clinical* evaluation (tables), *genetic* information (sequences), and 3D/4D *neuroimaging* (spatiotemporal)
- **Status-quo** of clinical care – independent analysis of the 3 different data types followed by inference pooling
- **Challenge** – introduce new holistic Health-Analytics Protocol for AI modeling, Dx, classification, and Tx plan using the joint distribution of the entire observed data.

Refs: https://www.socr.umich.edu/people/dinov/publications.html Apps: https://socr.umich.edu/HTML5/

Input Data | Analytics | Results



3D Neuroimaging | Genetics | End-to-end Pipeline Workflow | Neuroimaging-Genetics Associations | Network Analyses

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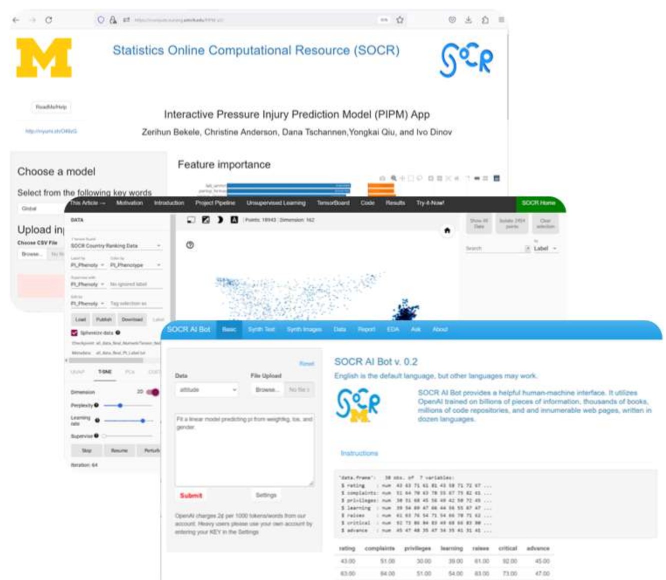
Live SOCR AI Webapps

- Interactive Pressure Injury Prediction Model (PIPM) App (RShiny)
- Visual Exploratory Data Analytics (SOCR Tensorboard Webapp)
- Quantitative AI-driven Analytics (SOCR AI Bot)



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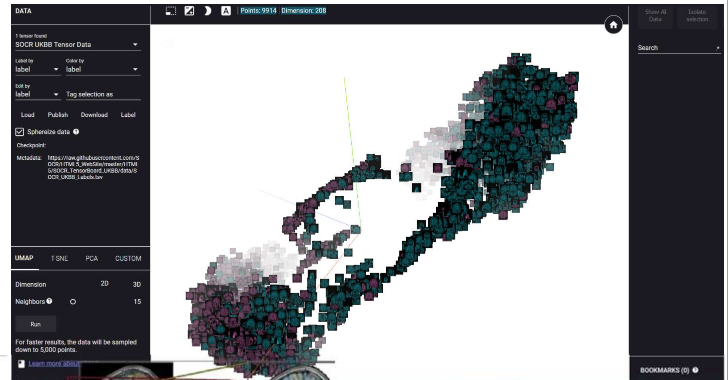
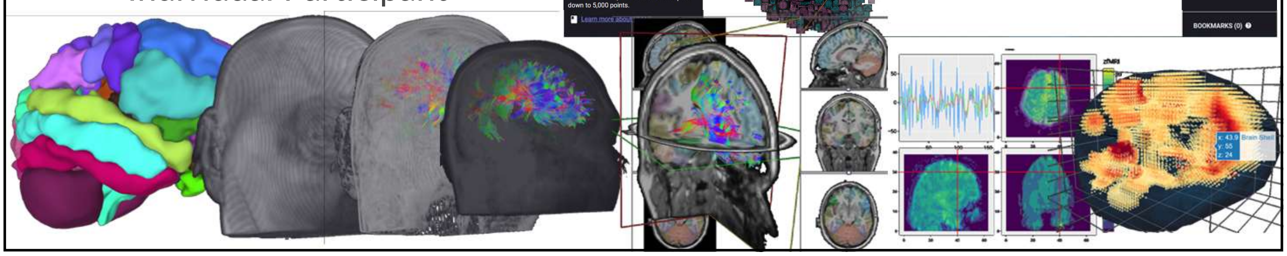
Neuroscience Demos

- ❑ SOCR Dimensionality Reduction App
  - 10K participants,
  - 200 clinical, imaging, genetics biomarkers
- ❑ SOCR Brain Viewer
  - Population Atlas
  - Individual Participant





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Open Science Community

R/RStudio/Posit, ChatGPT, OpenAI, RTutor & CRAN

Collaborators

- ❑ SOCR: Yueyang Shen, Kaiming Cheng, Zerihun Bekele, Milen Velev, Shihang Li, Daxuan Deng, Zijing Li, Yongkai Qiu, Zhe Yin, Yufei Yang, Yuxin Wang, Rongqian Zhang, Yuyao Liu, Yupeng Zhang, Yunjie Guo, Jun Chen, Simeone Marino, …
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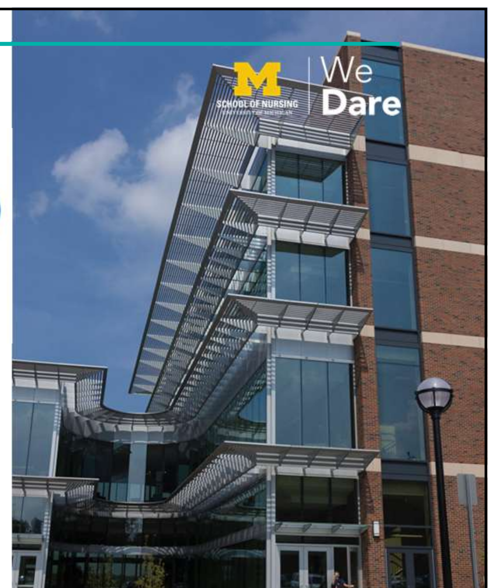

https://www.SOCR.umich.edu

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We Dare

Available AI Resources

- ❑ SOCR Motto – *"It's Online & Freely Accessible, Therefore it Exists!"*

- ❑ Pubs: https://socr.umich.edu/people/dinov/publications.html
- ❑ GitHub: https://github.com/SOCR/PressureInjuryPrediction
- ❑ PIPM App: https://rcompute.nursing.umich.edu/PIPM_v2/
- ❑ AI Apps: https://socr.umich.edu/HTML5/
- ❑ SOCR AI Bot: https://rcompute.nursing.umich.edu/SOCR_AI_Bot/
- ❑ Demos: https://DSPA2.predictive.space (Appendix 9 – OpenAI Synth Text Img & Code)
- ❑ Tutorials: https://TCIU.predictive.space & https://SpaceKime.org
- ❑ Websites: https://nursing.umich.edu & https://socr.umich.edu

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