Twitter: @BostonUResearch | #researchontap

RESEARCH ON TAP

Health Data Science

Wednesday, November 29, 2023

bu.edu/research/events

BOSTON UNIVERSITY

Boston University Office of Research

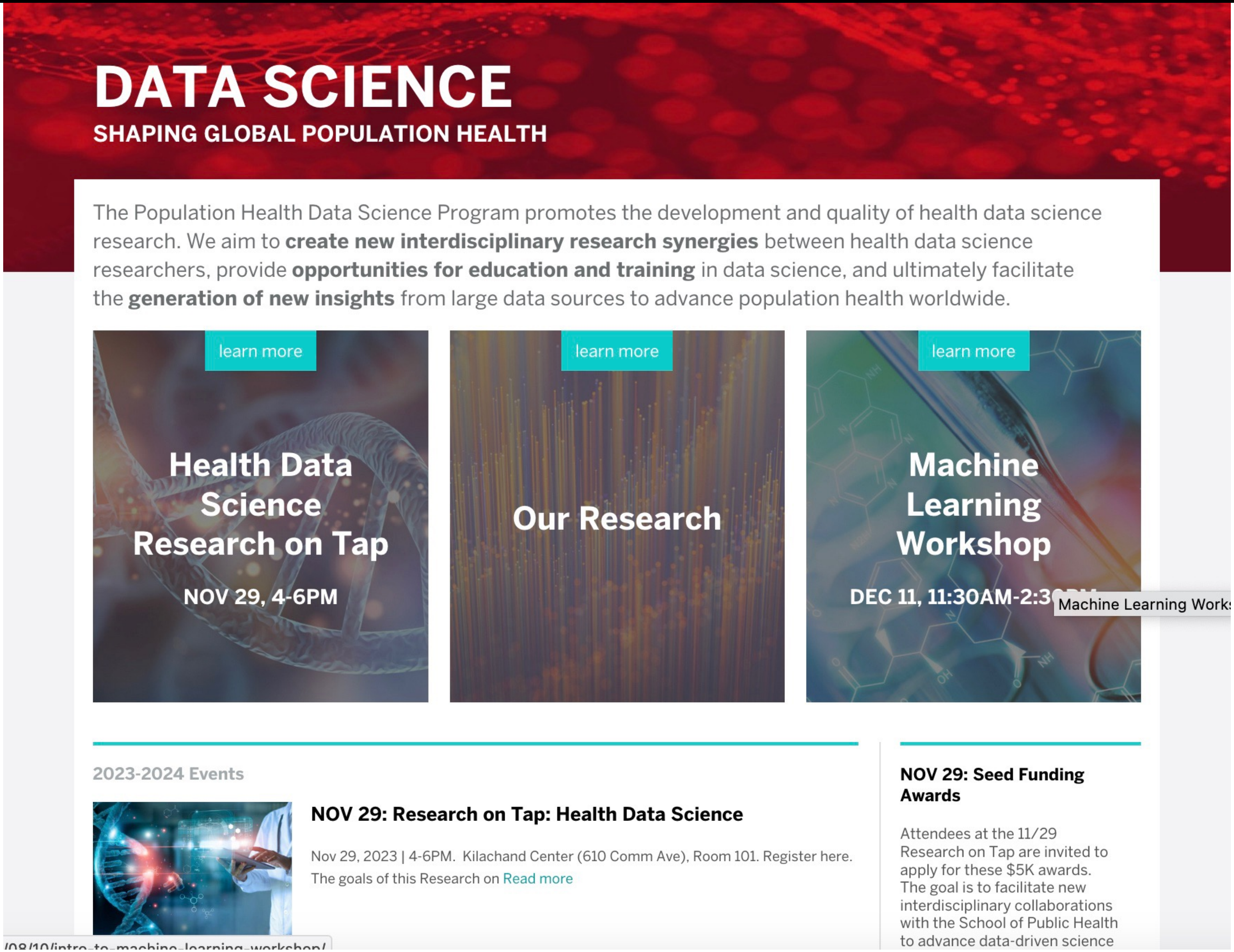
Agenda

- Welcome Remarks
- Presentations
  - Kevin Lane
  - Neha Gondal
  - Jonathan Huggins
  - Kayoko Shioda
  - Shariq Mohammed
  - Archana Venkataraman
  - Diane Joseph-McCarthy
  - Pawel Przytycki
  - Heather Hsu
  - Judith J. Lok
  - Vijaya B. Kolachalama
- Closing Remarks

Health Data Science

Debbie Cheng

Professor of Biostatistics
Director, Population Health Data Science Program
Department of Biostatistics, School of Public Health



DATA SCIENCE

SHAPING GLOBAL POPULATION HEALTH

The Population Health Data Science Program promotes the development and quality of health data science research. We aim to **create new interdisciplinary research synergies** between health data science researchers, provide **opportunities for education and training** in data science, and ultimately facilitate the **generation of new insights** from large data sources to advance population health worldwide.

Health Data Science Research on Tap

NOV 29, 4-6PM

Our Research

Machine Learning Workshop

DEC 11, 11:30AM-2:3

2023-2024 Events

NOV 29: Research on Tap: Health Data Science

Nov 29, 2023 | 4-6PM. Kilachand Center (610 Comm Ave), Room 101. Register here. The goals of this Research on Read more

NOV 29: Seed Funding Awards

Attendees at the 11/29 Research on Tap are invited to apply for these $5K awards. The goal is to facilitate new interdisciplinary collaborations with the School of Public Health to advance data-driven science

/08/10/intro-to-machine-learning-workshop/

https://sites.bu.edu/ph-datascience/

Goals for Today

- Strengthen our BU health data science community
- Engage new scholars in health data science
- Foster new collaborations across the university
- Provide seed funding opportunity to advance new research

Population Health Data Science Seed Funding Awards

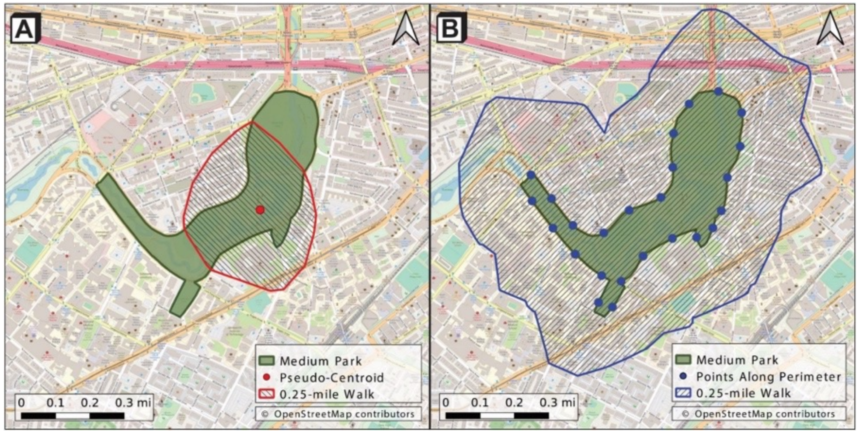
- $5000 for 1 year period
- 1-Page Proposal (background, aims, approach)
- PI ROT attendee (faculty, postdoc or student)
- Team must include SPH member
- Deadline: 12/13/23

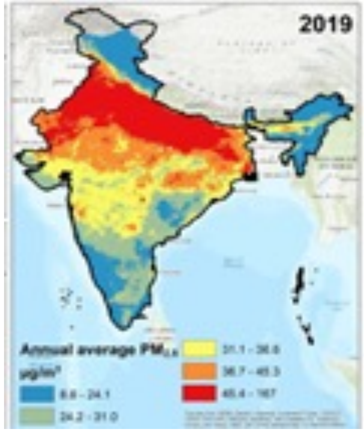
Details: https://sites.bu.edu/ph-datascience/

Cloud Processing and Machine Learning for Local, National and Global Public Health Research

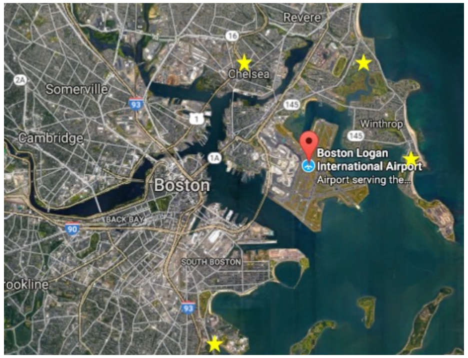
Kevin Lane, PhD MA

Assistant Professor
Chief Data Officer at BUSPH Center for Climate Health
Department of Environmental Health, Boston University School of Public Health





Community measurements of aviation-related air pollution near Logan International airport



ML Source Quantification Methods

PNC

1-sec aggregated to hourly

- Meteorology
- Aviation Activity
- Automobile Activity
- Temporal

ML Model

1. Correlated Data
2. Pre-processing
3. Circular Predictors
4. Cross-Validation
5. Missing Data
6. Sample Weighting
7. Outliers
8. ML Method
9. Hyperparameter Tuning

PNC ~ Flight + Traffic + Met + Temporal

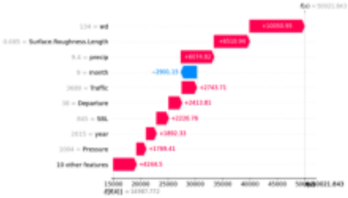
Model Equation

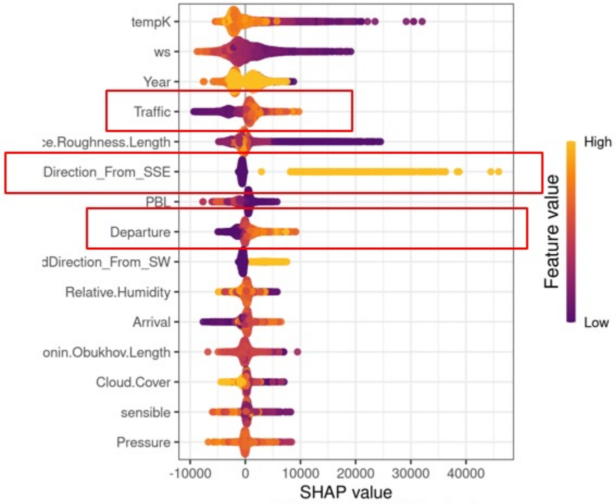
RMSE= $\sqrt{\frac{\sum_{i=1}^{N}(y(i)-\widehat{y(i)})^2}{N}}$ MAE= $\frac{\sum_{i=1}^{N}|y(i)-\widehat{y(i)}|}{N}$ R2 = $(Actual, Pred)$

Model Evaluation

Interpretation

Shapley Additive Explanations (SHAP)





XGBoost Model

RMSE = 7530 MAE = 4590 R^2 = 0.64

Sean Mueller
EH Doctoral Candidate

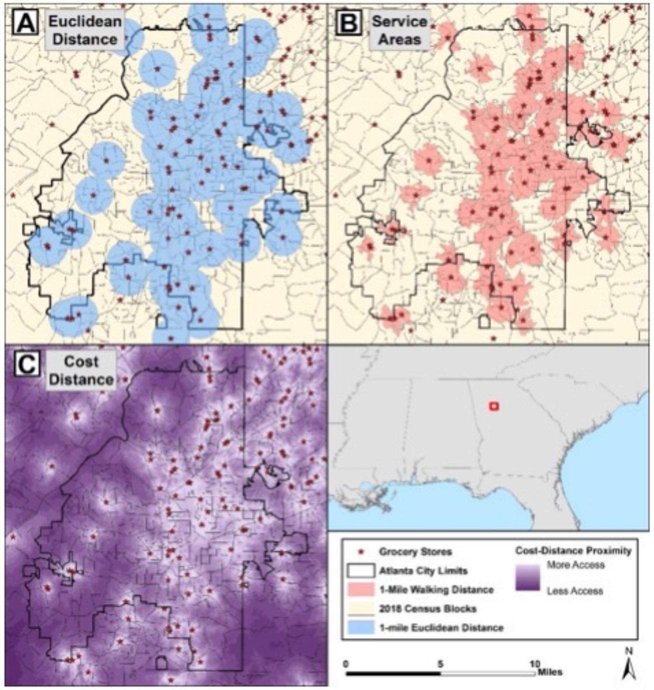
Prasad Patil PhD,
Biostatistics Assistant Professor

Community
Well-Being Index
in partnership with BU School of Public Health

National Studies of Environmental and Community Social Determinants of Health and Well-Being :Measuring Geospatial Access to Resources

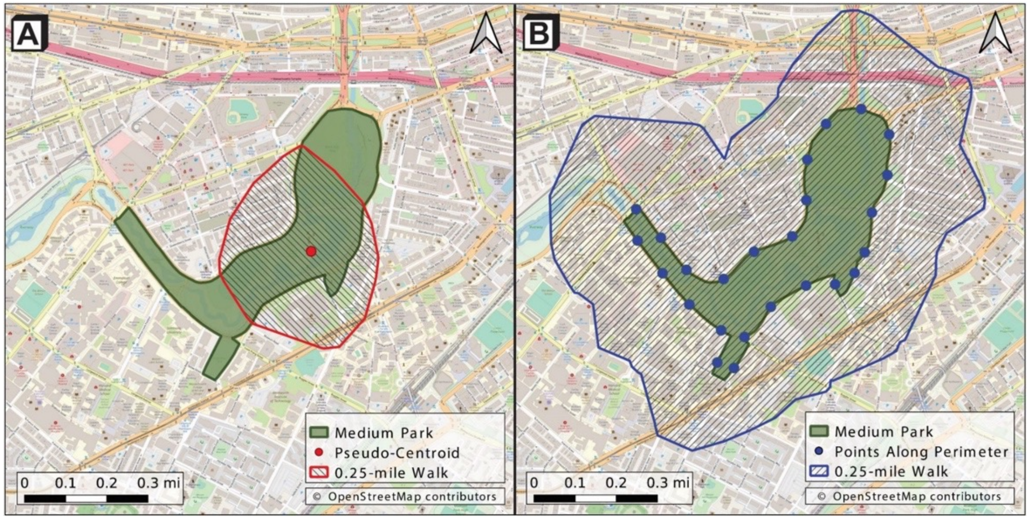
https://wellbeingindex.sharecare.com/

Figure 1: Illustration of Methods for Estimating Access to the Nearest Grocery Store



Potential for Measurement Error in Environmental Variables Indicating Access to Resources, by Distance Measurement Method Amruta Nori-Sarma, Keith Spangler, Nina Cesare, Biqi Wang, Kimberly Dukes, Kevin Lane

Nori-Sarma et al, JESEE 2022



Spangler et al. (2023), https://doi.org/10.1016/j.sste.2023.100606

NERC

MGHPCC

Keith Spangler, PhD
Research Scientist EH

Dennis Milechin, P.E., GISP
Scientific Programmer/Analyst IS&T

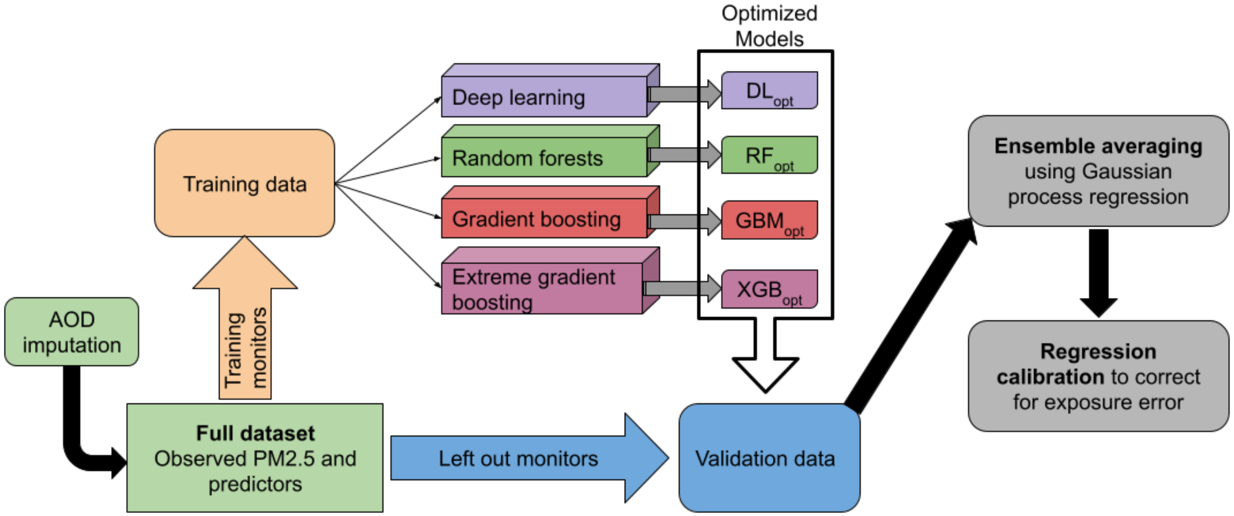
Development of Nationwide Air Pollution and Temperature Models for Health Studies in India

Consortium for Climate, Health & Air Pollution Research in India

CHAIR INDIA

CHAIR Study Goals: Develop nationwide 1 km x 1 km daily PM2.5 and Temperature models from 2008 – 2020 for all of India.

BUSPH Researchers: provide technical and structural support for researchers across the globe via SCC OnDemand



Optimized Models

Deep learning

Random forests

Gradient boosting

Extreme gradient boosting

DL_{opt}

RF_{opt}

GBM_{opt}

XGB_{opt}

Training data

Training monitors

AOD imputation

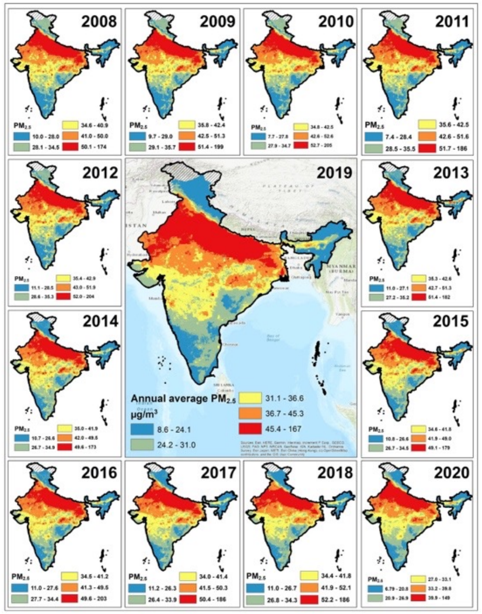
Full dataset Observed PM2.5 and predictors

Left out monitors

Validation data

Ensemble averaging using Gaussian process regression

Regression calibration to correct for exposure error



PUBLIC HEALTH FOUNDATION OF INDIA

Karolinska Institutet

Ben-Gurion University of the Negev

HARVARD T.H. CHAN SCHOOL OF PUBLIC HEALTH

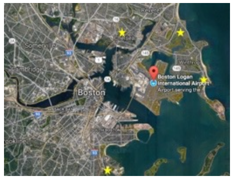
Icahn School of Medicine at Mount Sinai

BU School of Public Health Center for Climate & Health

ASCENT
AVIATION SUSTAINABILITY CENTER

ASCENT Project 18: Community Measurements of Aviation Contributions to Ambient Air Quality

Tufts UNIVERSITY | School of Engineering

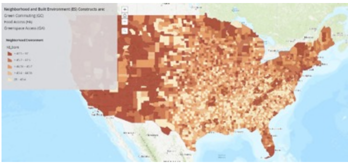

Emma Gause


Sean Mueller


Maria Bermudez


Jon Levy

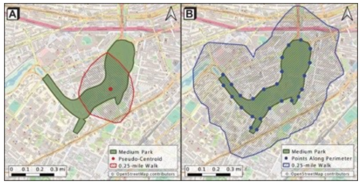

Bre Van Loenen

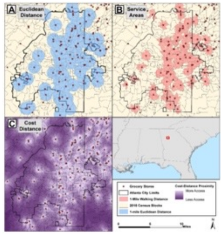



sharecare

Community Well-Being Index

in partnership with BU School of Public Health



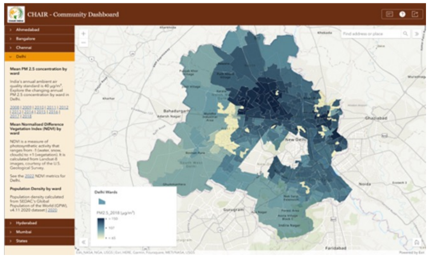


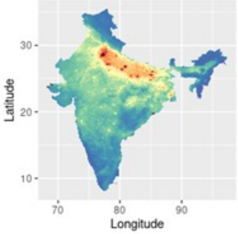

Keith Spangler

Amruta Nori-Sarma


Consortium for Climate, Health & Air Pollution Research in India

CHAIR INDIA





Muskaan Khemani


Amruta Nori-Sarma


Greg Wellenius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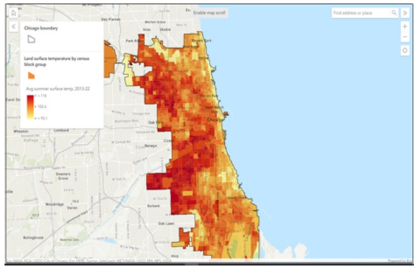
Boston University Office of Research

BU School of Public Health
Center for Climate & Health



Muskaan Khemani


Talia Feldscher


Zach Popp


Greg Wellenius


Chicago Tribune

Modeling Health Behaviors using Social Network Data

Neha Gondal

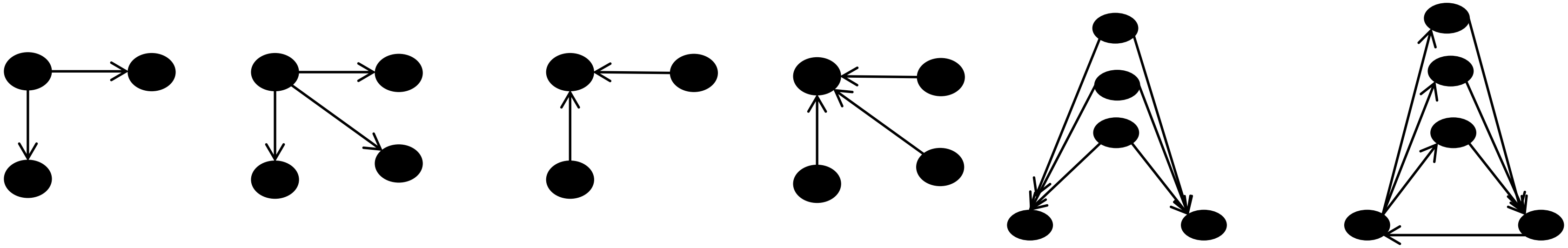
Assistant Professor
Department of Sociology and Faculty of Computing & Data Sciences

Social Networks and Health

- Health behaviors tend to cluster within social networks. E.g.,
    - Smoking and drinking (McMillan et al. 2018, Cheadle at al 2013))
    - Oral health (Heaton and Gondal 2023; Maupome et al. 2016)
    - Obesity and exercise (Centola and Rijt 2015, Shoham et al 2012)
    - Eating behavior (Fletcher et al 2011)
    - Mental health (Schaefer et al. 2011)
- Two ways to model health outcomes using social network analysis techniques.

ERGMs for Sociometric Data

- What are the micro-level structures that concatenate to produce the overall structure of the network.
- E.g., is there homophily on health behaviors like smoking?



ABMs

- Agent-based models are useful for testing theory when data are unavailable, infeasible, or unethical.
- Agents interact in social networks.
- AMBs can be used to test public health interventions(e.g., should intervention target individual or a network of connected persons) and combined with ERGMs to generate realistic models and outcomes.

Thank You!

gondal@bu.edu

More Data, More Problems?

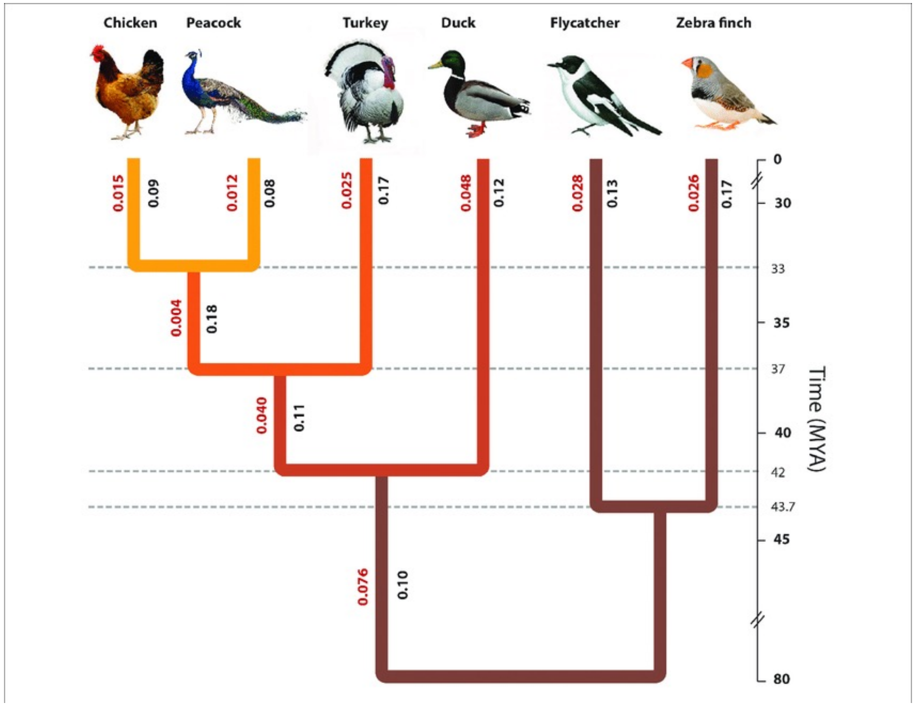
Jonathan Huggins

Assistant Professor
Department of Mathematics & Statistics, CAS
+ Faculty of Computing & Data Sciences

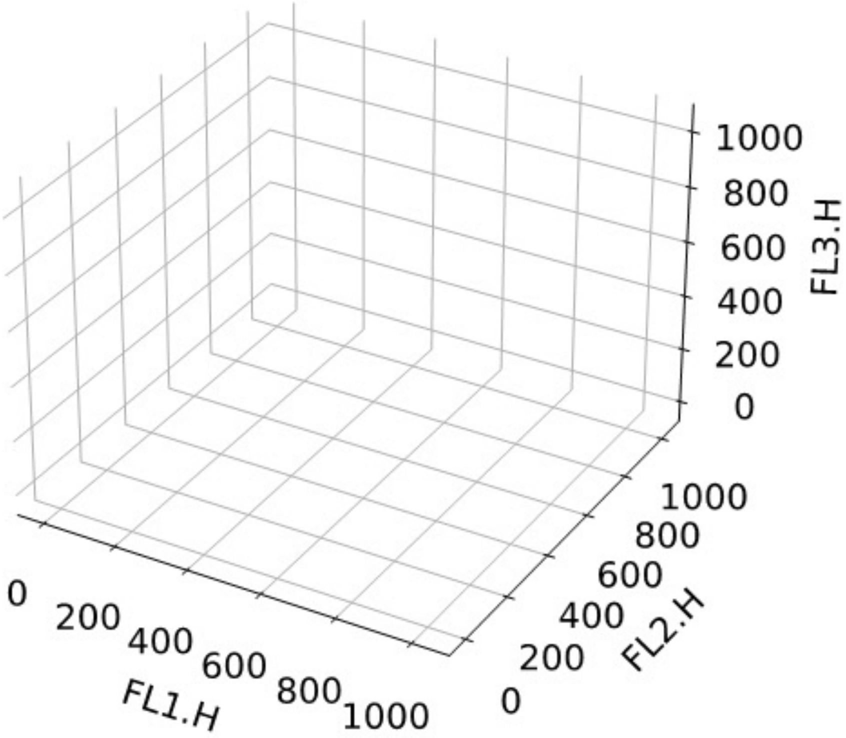
Models: turning data into knowledge

Model = family of possible data-generating processes

- Designed based on scientific / other prior knowledge
- Interpretable



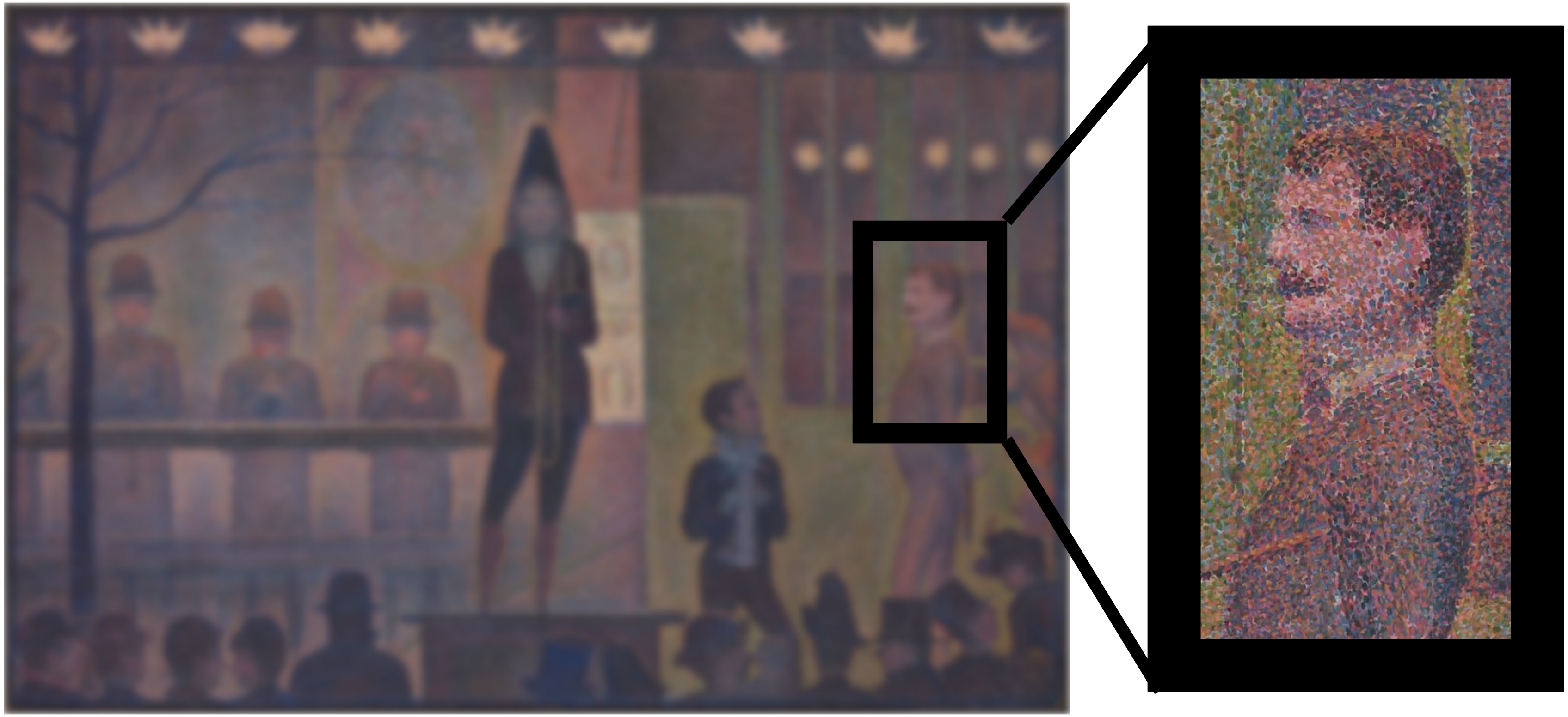
https://www.researchgate.net/figure/Phylogenetic-position-of-peacock-with-respect-to-other-bird-genomes-The-phylogenetic_fig2_327750618



More data, more problems

Models **approximate reality**

- With only a little data, can’t tell that model is wrong
- More data = more detail

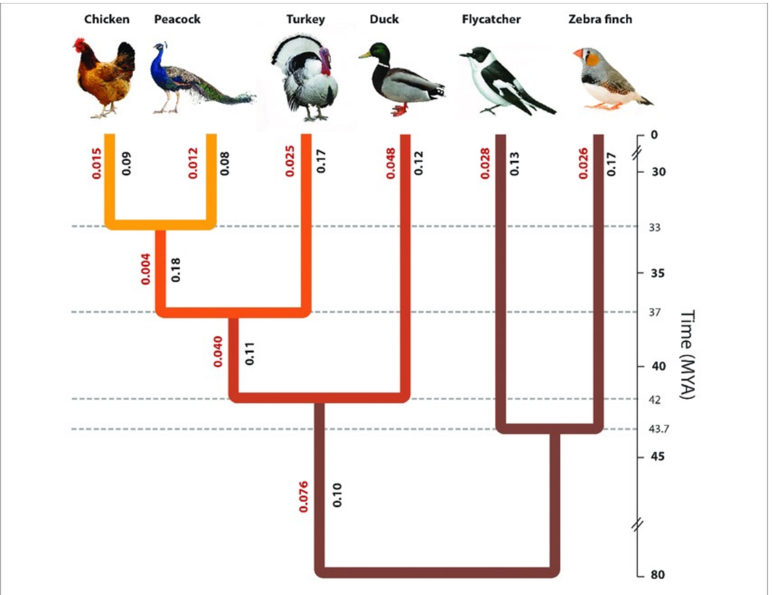


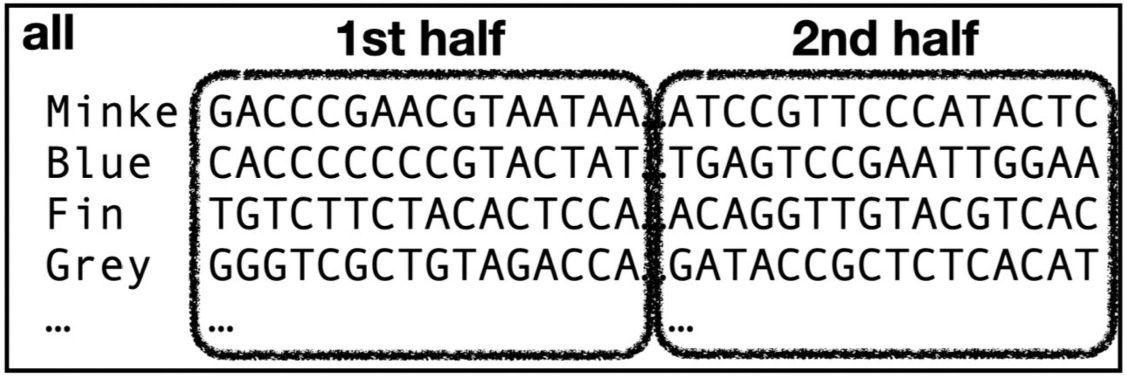
Georges Seurat, Parade de cirque (1889)

Example 1: Phylogenetic tree inference

Problem: If two trees are equally good, then standard methods declares one of them is best

- We show: **bagged posterior** resolves the issue
- Example: infer phylogeny of 13 whale species
    - ➢ **Standard method:** ✗ 0 trees the same
    - ➢ **Bagged posterior:** ✓ 22 trees the same





```
all      1st half          2nd half
Minke  GACCCGAACGTAATAA  ATCCGTTCCCATACTC
Blue   CACCCCCCCGTACTAT  TGAGTCCGAATTGGAA
Fin    TGTCTTCTACACTCCA  ACAGGTTGTACGTCAC
Grey   GGGTCGCTGTAGACCA  GATACCGCTCTCACAT
...    ...               ...
```

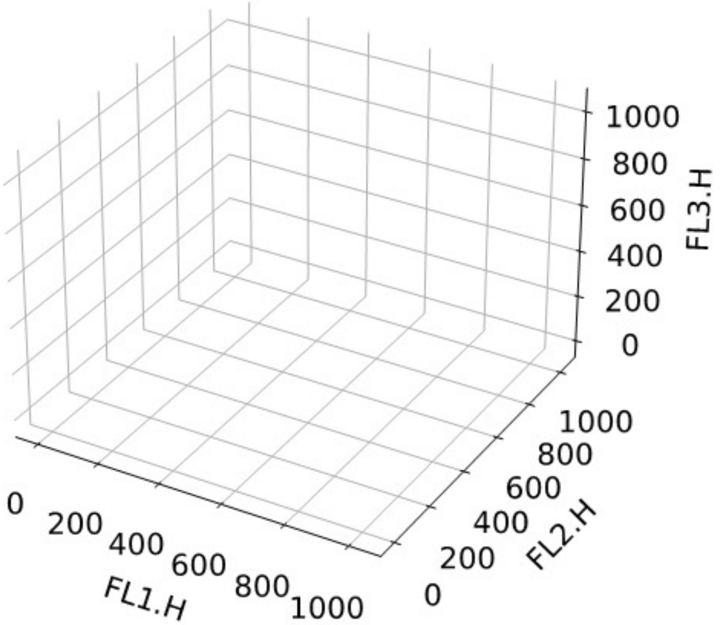
Example 2: Cell type discovery

Problem: model imperfect + using standard methods: more data ⇒ more cell types spuriously “discovered”

- Solution we developed <u>provably</u> solves spurious discovery problem

Clustering accuracy (F-measure)

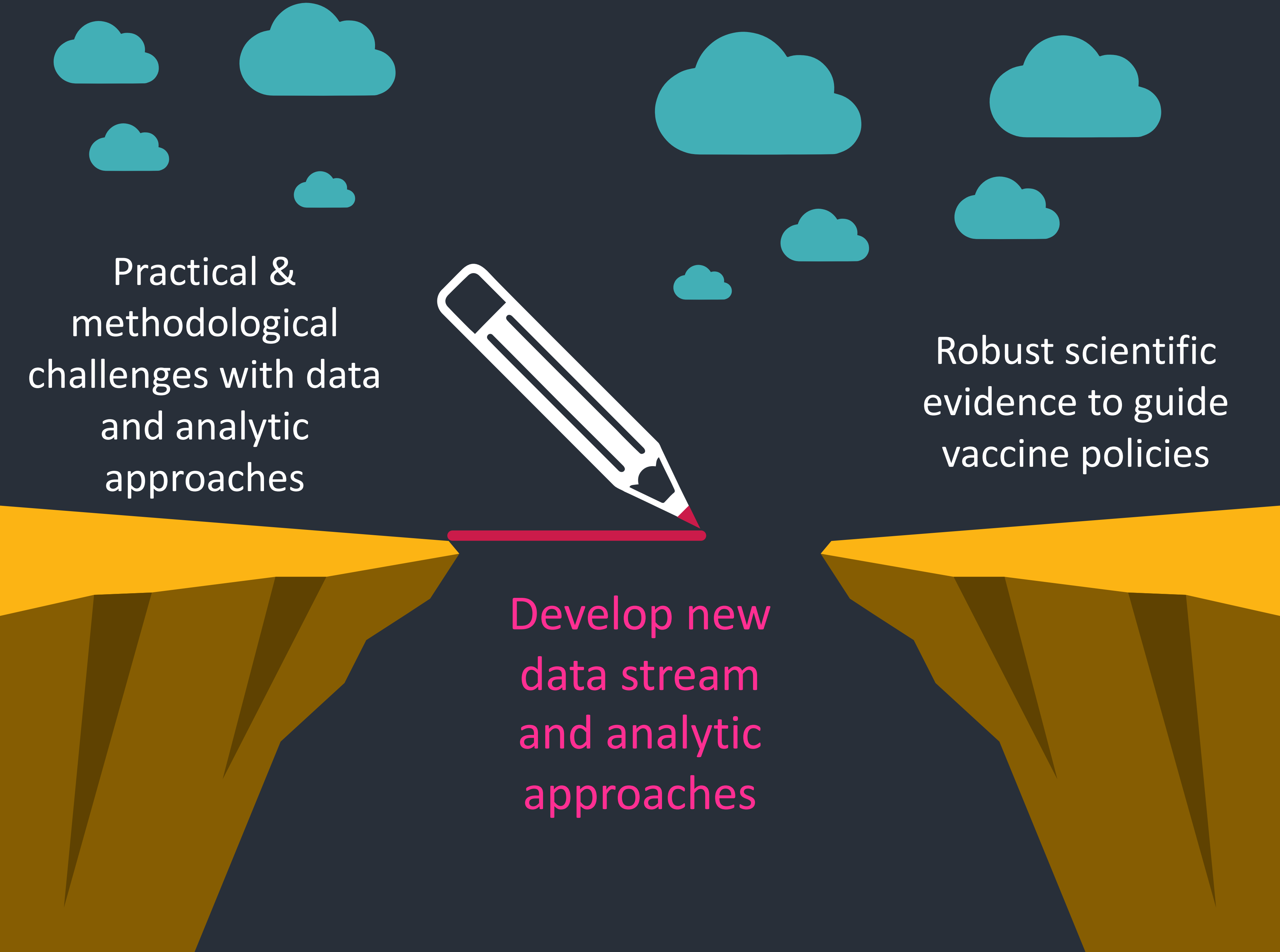
Dataset	**7**	**8**	**9**	**10**	**11**	**12**
standard approach	0.53	0.48	0.62	0.45	0.54	0.59
our solution	0.63	**0.92**	**0.94**	**0.99**	**0.99**	**0.98**
alternative solution	**0.67**	0.88	**0.93**	**0.99**	**0.99**	**0.99**



Data Science to Guide Vaccine Policies & One Health Approach

Kayoko Shioda

Assistant Professor
Global Health, School of Public Health



Practical & methodological challenges with data and analytic approaches

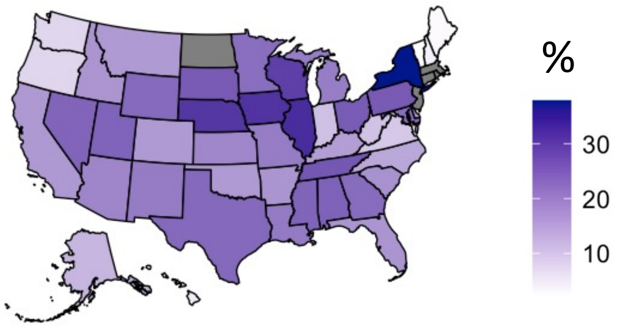
Robust scientific evidence to guide vaccine policies

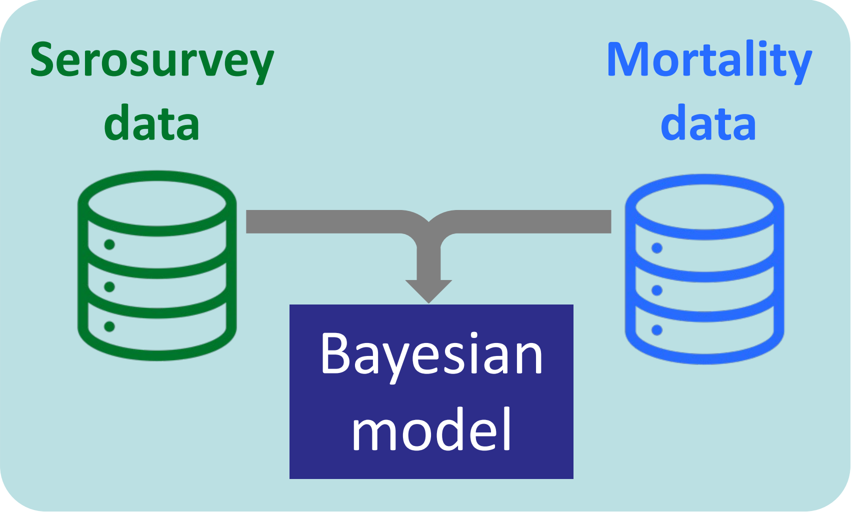
Develop new data stream and analytic approaches

Estimating the cumulative incidence of SARS-CoV-2 based on seroprevalence, accounting for antibody waning

How many people have been infected by SARS-CoV-2?

Estimated % population ever infected



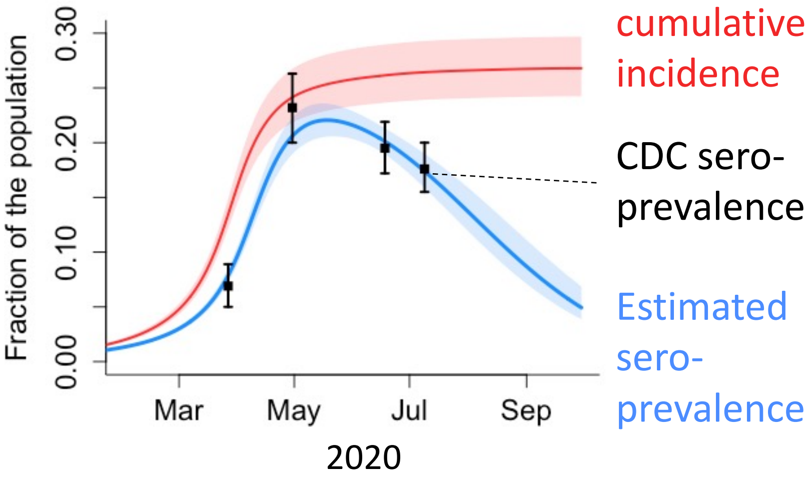


Serosurvey data

Mortality data

Bayesian model

New York City



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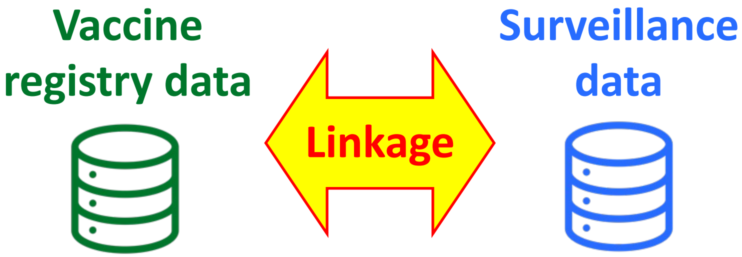
(Shioda, *et al. Epidemiology* 2021; Shioda, *et al. JID* 2022)

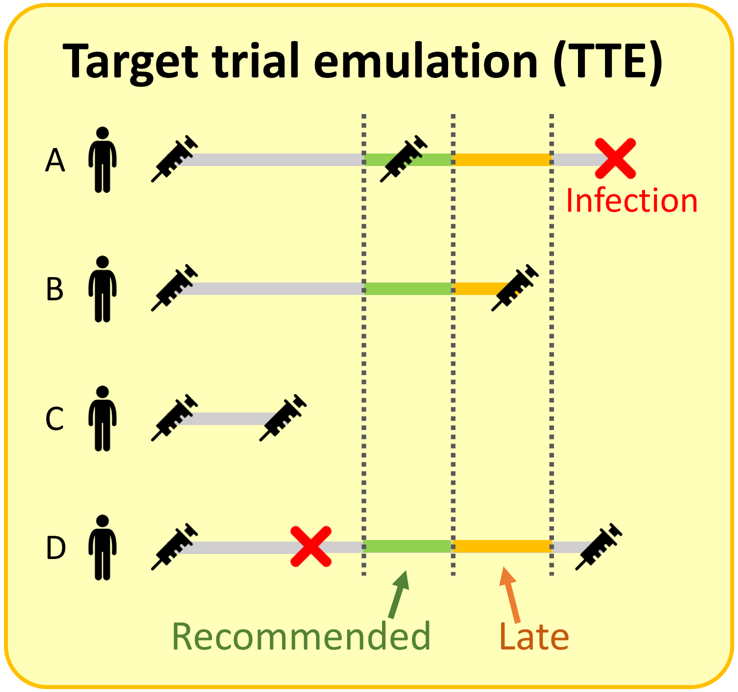
What is the **optimal timing** to administer the 2^{nd} dose of mRNA COVID-19 vaccines?



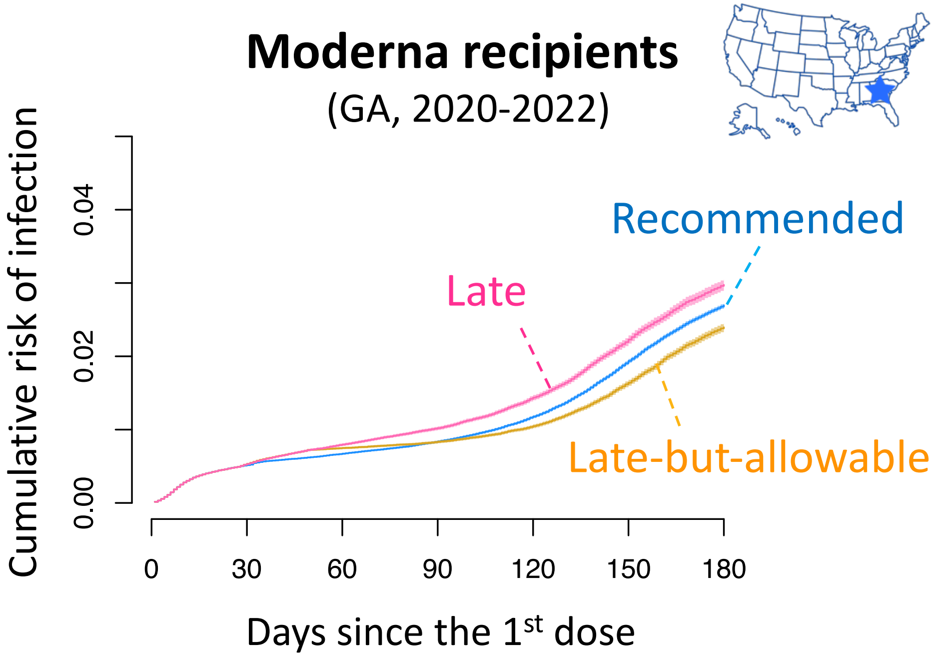
Vaccine registry data

Linkage

Surveillance data



Target trial emulation (TTE)



Moderna recipients

(GA, 2020-2022)

Findings:

- Delaying the 2^{nd} dose by **~10 days** would provide **stronger long-term** protection
- But longer delay would increase the risk

Plans: PCV, rotavirus vaccines

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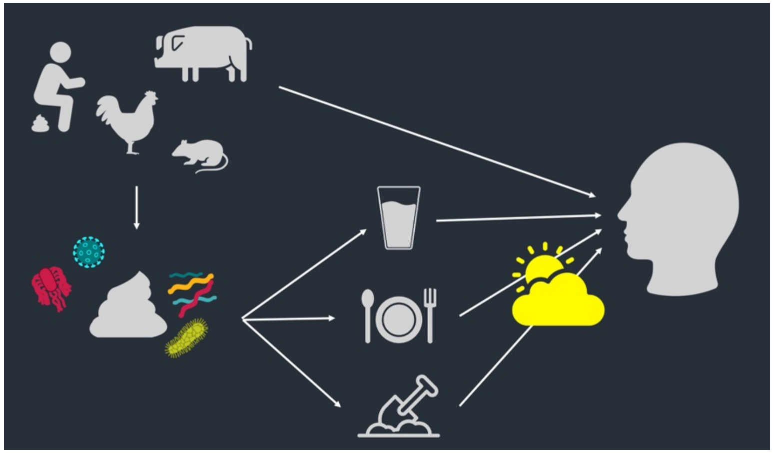
(Shioda, *et al. medRxiv* 2023)

Zoonotic pathogens spread via water, food, soil and animal contacts. How many infections are coming from each pathway?



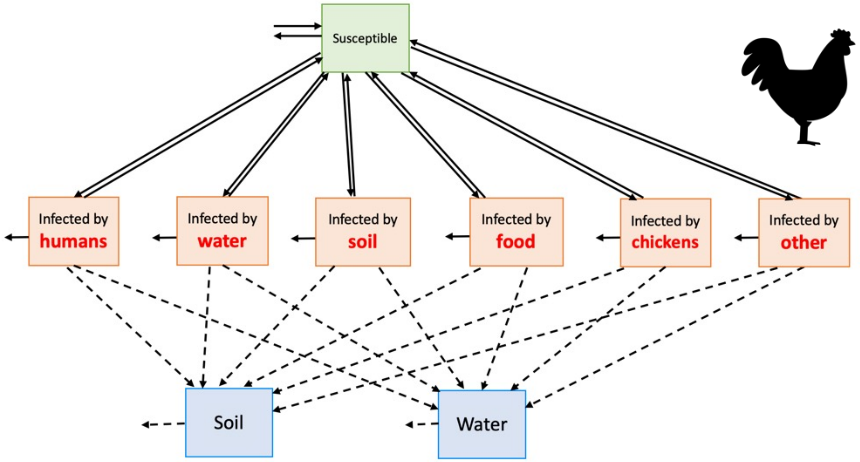
Human infection data

Linkage

Exposure source data

Climate data

Transmission dynamic modeling



Findings:

If the **foodborne** pathway is reduced by **50%**, the total *Campylobacter* infection would decrease by **30%** (95% CrI: 24-36%)

Future Plans:

How does this change by weather & climate?
What's the optimal climate-resilient control measure?

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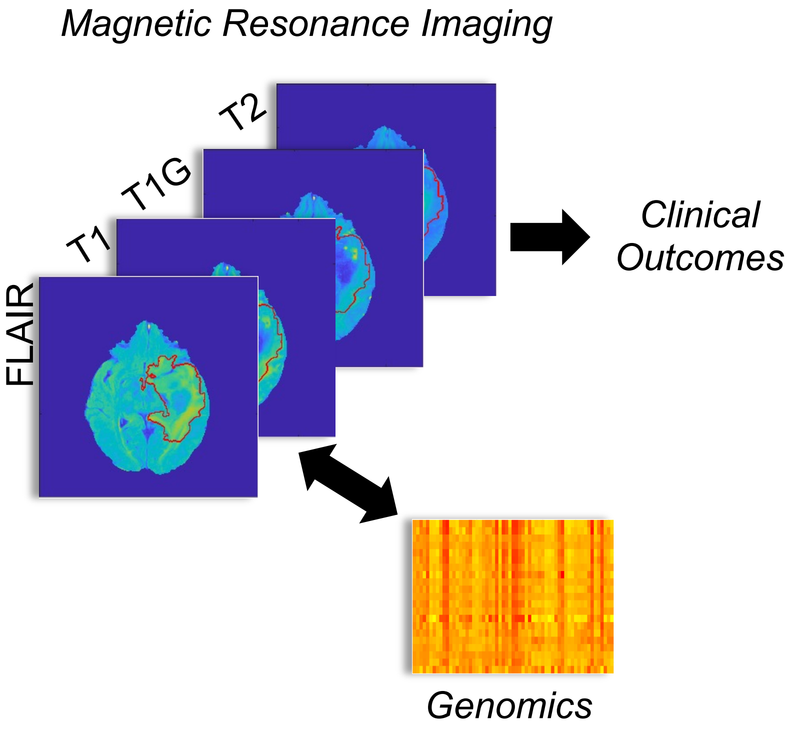
(Shioda, *et al. EHP* 2023)

Statistical Methods for Complex Health Data

Shariq Mohammed

Assistant Professor, Department of Biostatistics
Rafik B. Hariri Junior Faculty Fellow
shariqm@bu.edu

Imaging-genomic associations in gliomas



- Detect imaging markers of tumor heterogeneity associated with molecular characteristics
- Using imaging markers to predict clinical outcomes

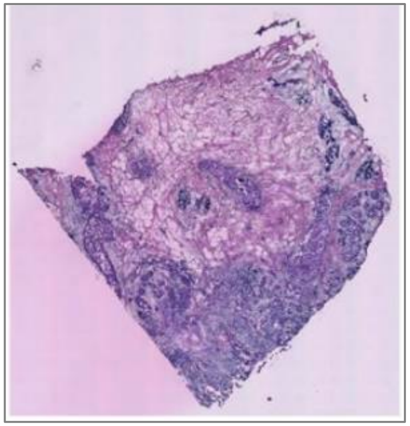
Statistical methods

- Bayesian modeling
- Variable selection
- Functional data analysis

Mohammed et. al. (2023), Med Image Anal
Mohammed et. al. (2022), Am J Neuroradiol
Mohammed et. al. (2021), Ann Appl Stat

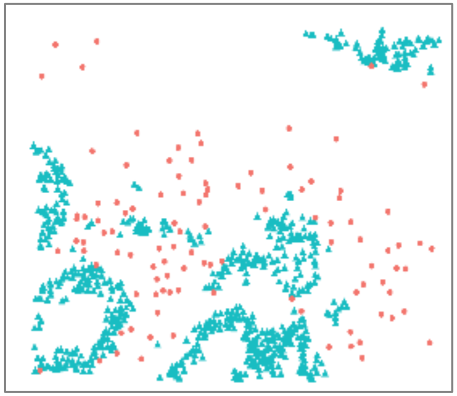
U. Michigan Precision Health Scholar Award

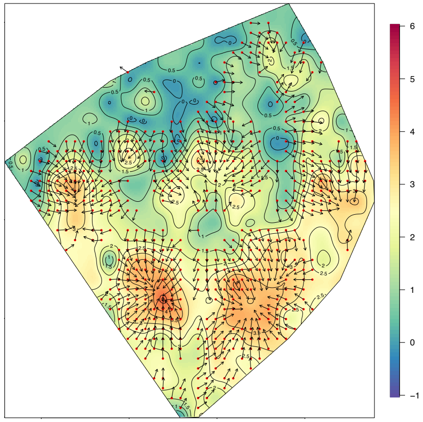
Understanding tumor micro-environment



Tissue slice

Cell types





Gene expression change

- Offer localized insights on gene expression changes across the tissue
- Quantify interaction between cell types to predict response to treatment

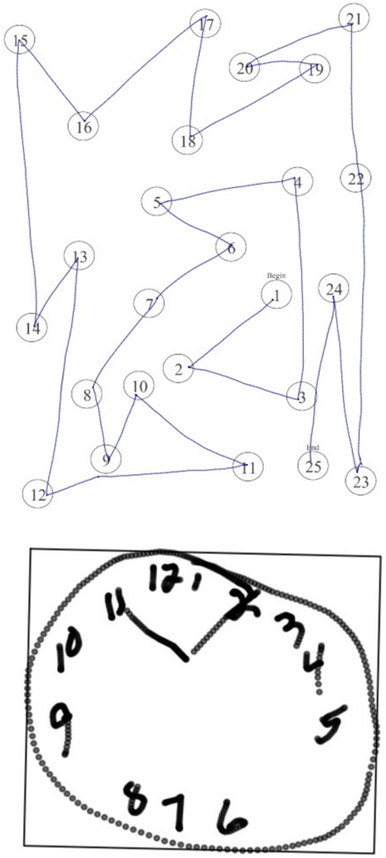
Statistical methods

  - Bayesian modeling
  - Spatial statistics
  - Differential geometry

Krishnan, Mohammed et. al. (2022), Sci Rep

BU SPH Early Career Catalyst Award

Cognitive assessment using digital neuropsychological tests



Digital pen data

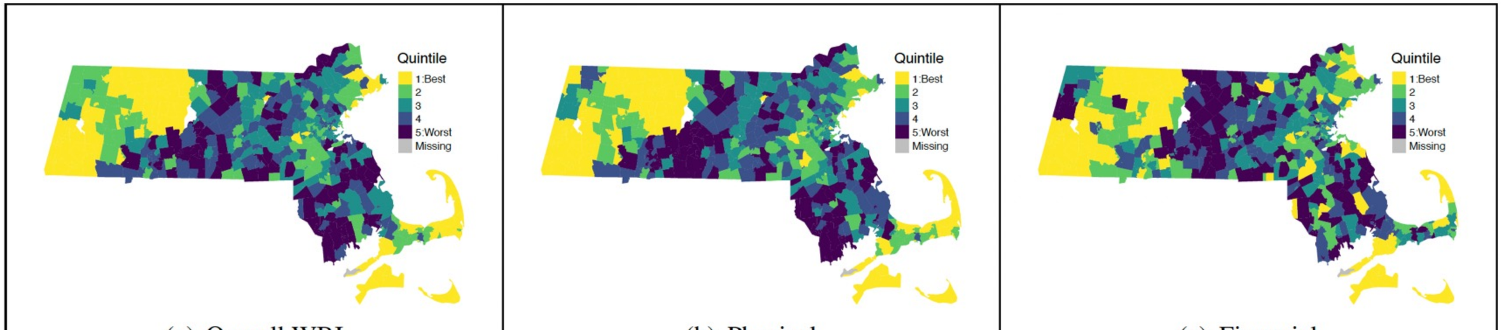
- Quantify performance on digital tests – high frequency pen movement data
- Distinguish participant profiles based on novel performance measures
- Potential non-invasive diagnostic tools for early detection

Statistical methods

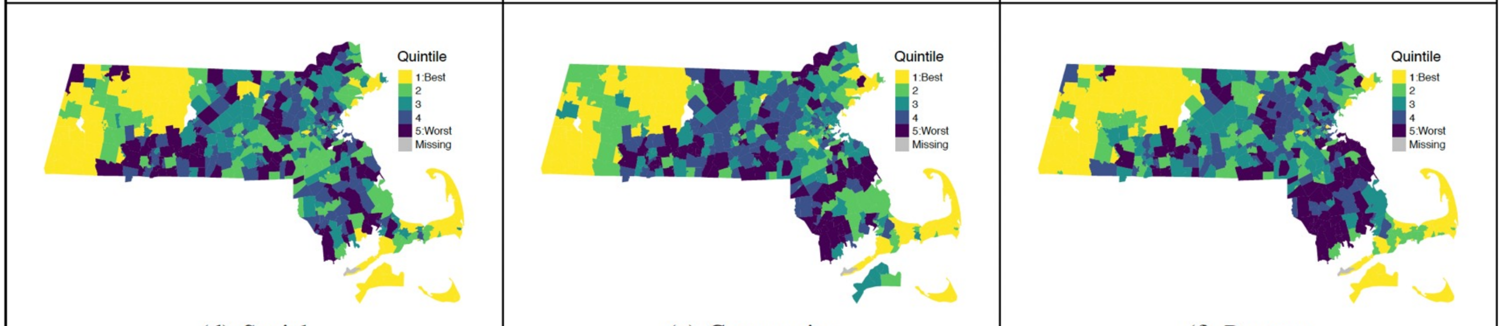
  - Functional data analysis
  - Prediction models

Framingham Heart Study
Brain Aging Program Pilot Award

Community well-being indices



(a) Overall WBI (b) Physical (c) Financial



(d) Social (e) Community (f) Purpose

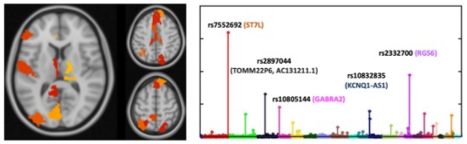
- Rank zip-codes for overall well-being and its subscales using individual-level survey data
    - Zip-code neighborhood using driving times

Engineering Solutions to Brain Dysfunction

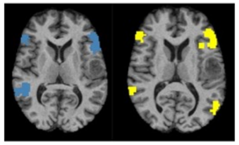
Archana Venkataraman

Associate Professor
Department of Electrical & Computer Engineering
College of Engineering

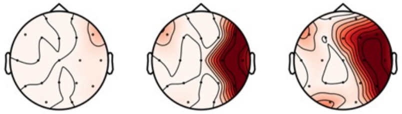
Bringing AI into Clinical Neuroscience



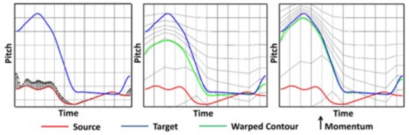
Biomarker Discovery via Imaging-Genetics



Presurgical Eloquent Cortex Mapping using rs-fMRI

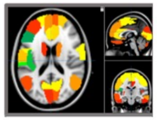


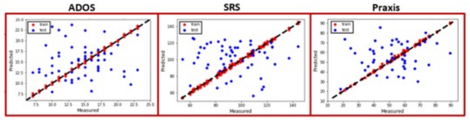
Seizure Detection and Localization from EEG



Manipulating Emotional Cues in Human Speech

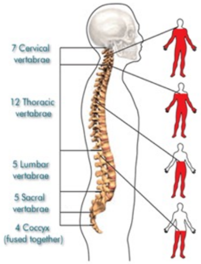
Foundational **Translational** **Exploratory**

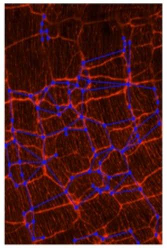




Multidimensional Clinical Phenotyping via Connectomics

Predicting SCI Rehabilitation Outcomes



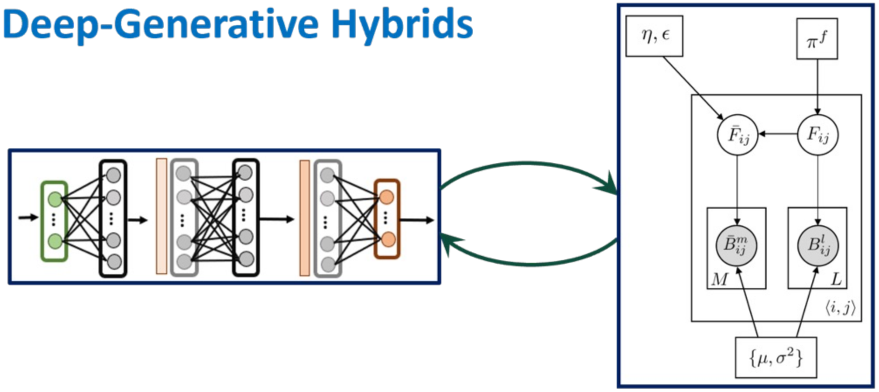


Mapping the ENS: Towards a Brain-Body Connection

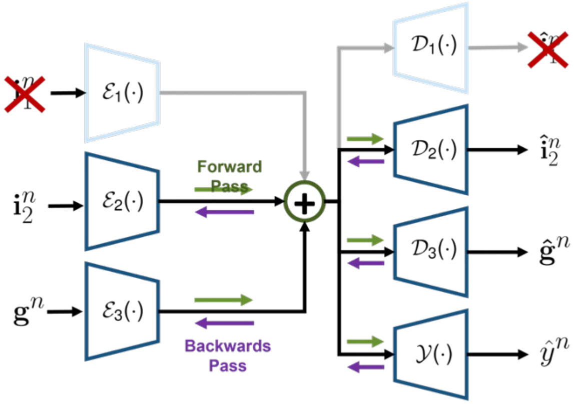
Challenges:
- **Small Datasets – $N \sim O(10)$ or $N \sim O(100)$**
- **Patient Heterogeneity**
- **Interpretability is Paramount**
- **Noisy/Missing/Inadequate Training Labels**

Addressing the Technical (and Data) Challenges

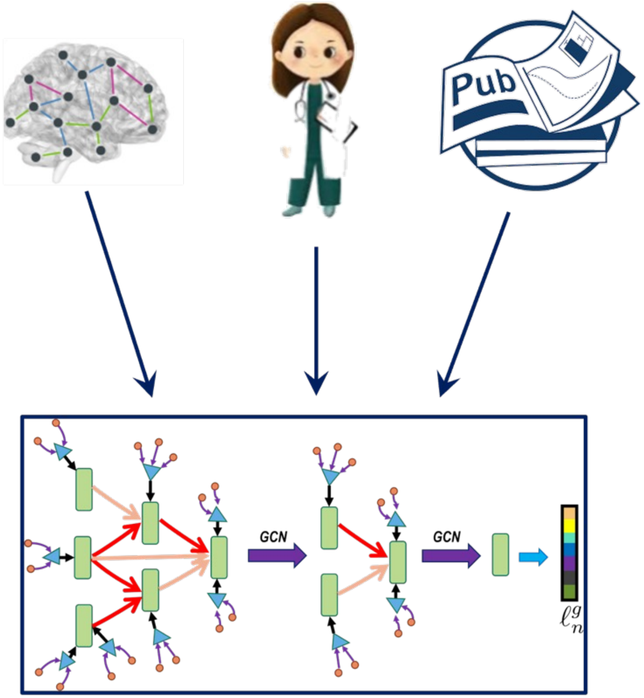
Deep-Generative Hybrids



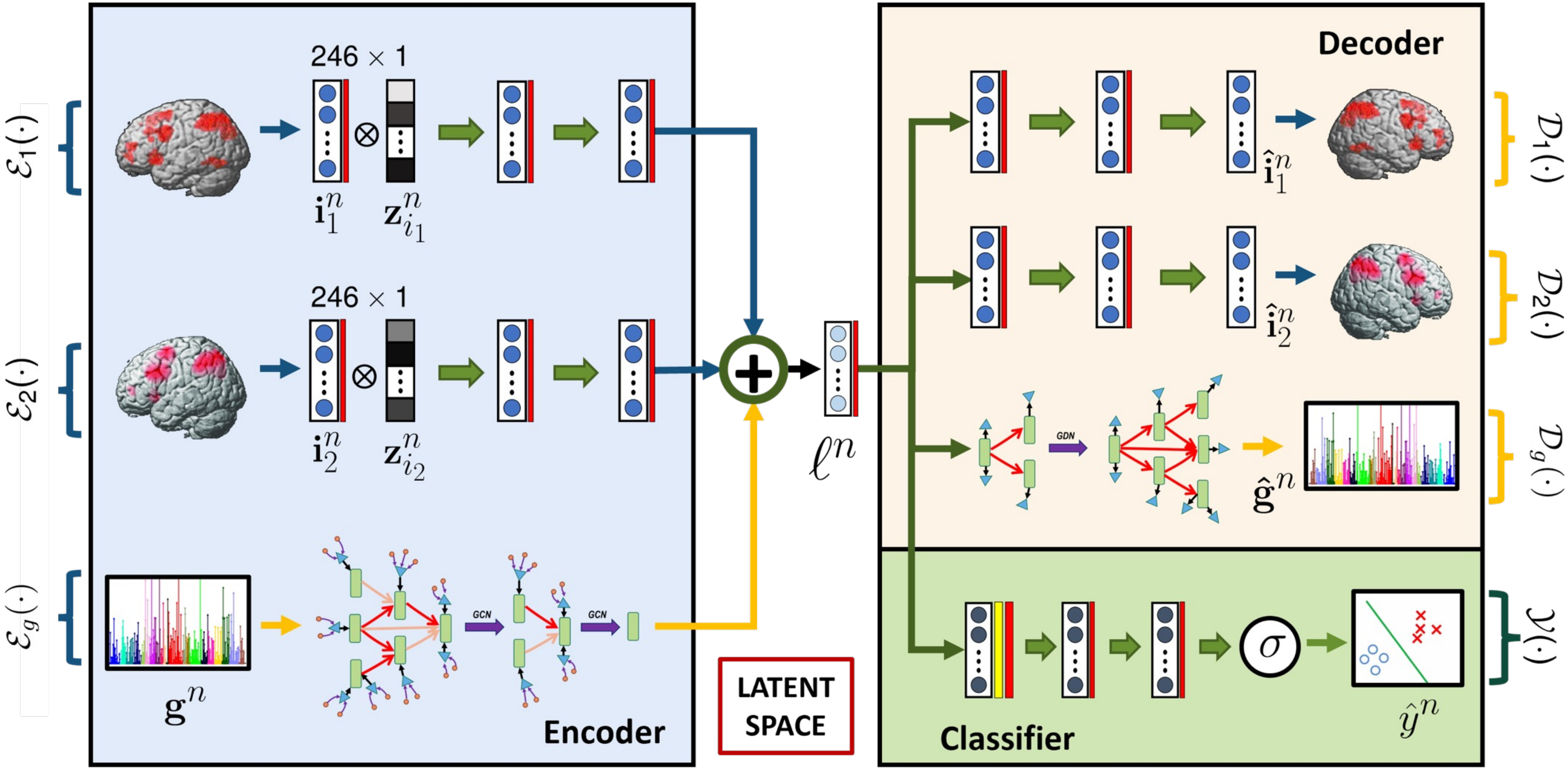
Robust and Adaptable Optimization



Biologically-Informed Models



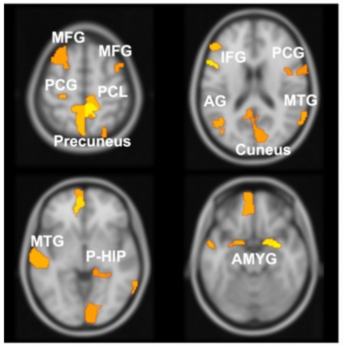
Deep Imaging-Genetics for Mental Health



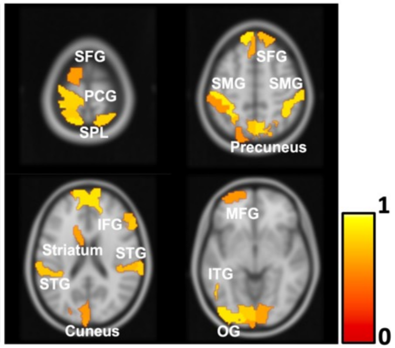
BOSTON UNIVERSITY

Ghosal et al., NeuroImage 2021, SPIE 2021, ICLR, 2022

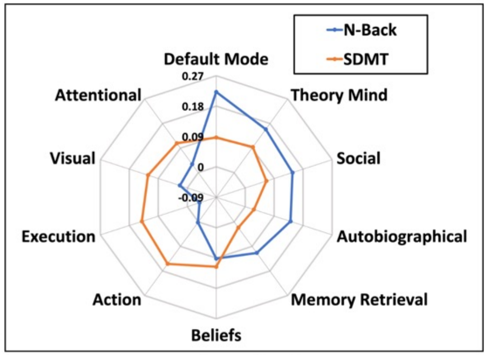
Multimodal Influences of Schizophrenia



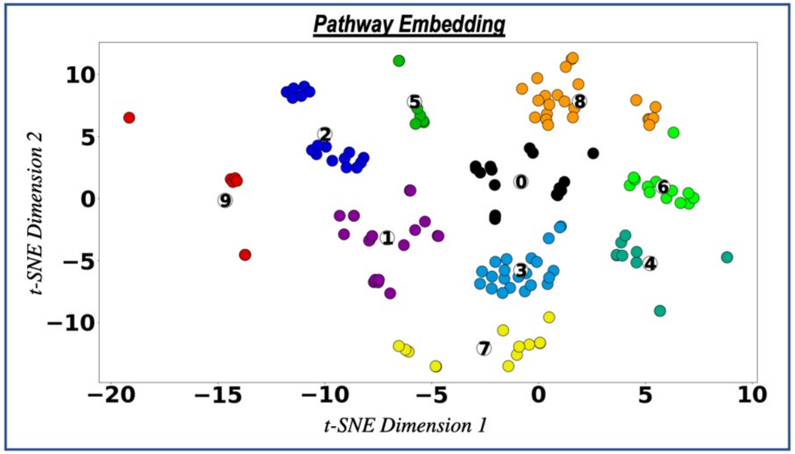
Nback



SDMT



NeuroSynth



⓪ Neuronal Action Potential, Extracellular Matrix Secretion

① Immunological Synapse, Macrophage Derived Foam Cell Differentiation

② Epithelial to Mesenchymal Transition, Cardiac Septum/Atrium Morphogenesis

③ Calcium Ion Transport, Calcium Ion into Cytosol

④ Histone Methylation, Meiotic Cell Cycle

⑤ Suppression by Virus of Host STAT/Molecular Activity

⑥ Lipid Storage, Sequestering of Triglyceride

⑦ Endoplasmic Reticulum Stress Induces Dephosphorylation

⑧ Cholesterol/Sterol Biosynthetic Process

⑨ Stimulus Involved in Sensory Perception, Pseudouridine Synthesis

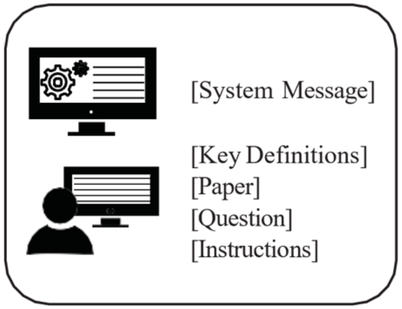
Pandemic Mitigation and Response Strategies

Diane Joseph-McCarthy

Executive Director, Bioengineering Technology & Entrepreneurship Center
Professor of the Practice
Department of Biomedical Engineering, College of Engineering

Map of current readiness with respect to targets, therapeutics, and vaccines

- Enhanced literature review using Large Language Models (LLMs) to reduce timelines
- Novel automated pipeline using prompt engineering strategies to identify drug targets
    - GPT-4 LLM by OpenAI with Zero-Shot-CoT prompting and ensembling top performer
- Applied to SARS-CoV-2 and Nipah Virus
    - Accuracy/F1-score/sensitivity/specificity:
      92.87%/88.43%/83.38%/97.82% for SARS-CoV-2
      87.40%/73.90%/74.72%/91.36% for Nipah



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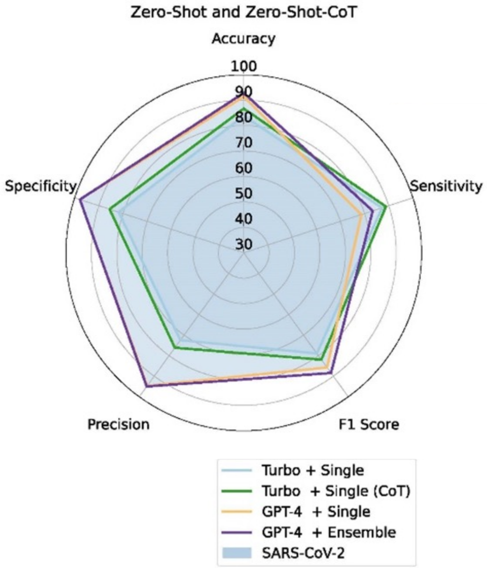
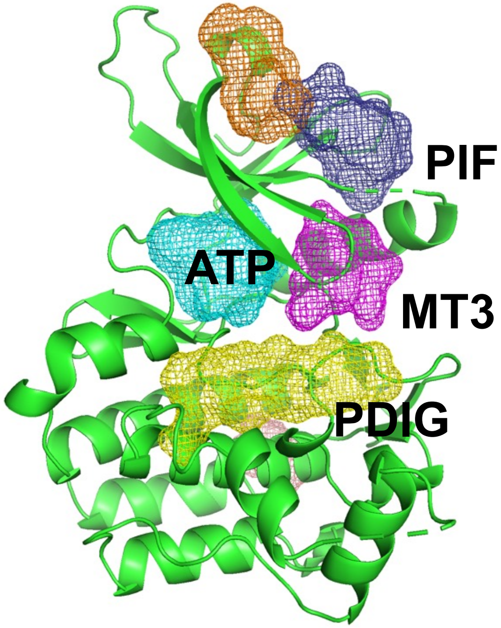


J. Yang, K.C. Walker, A. Bekar-Cesaretli, B. Hao, N. Bhadelia, D. Joseph-McCarthy, I. Ch. Paschalidis

Identify druggable sites on therapeutic target proteins from structures or homology models

- 10 SARS-CoV-2 targets
- FTMove to assess druggable sites rapidly
- Develop ranking scheme for druggable sites including allosteric/cryptic sites
- AlphaFold for proteins without structure
- Future drug repurposing efforts

Druggable Sites



FTMove: M. Egbert, M. et al. (2022) *J. Mol. Biol.* **434**:167587.
FTMap: D. Kozakov et al. (2015) *Nature Protocols* **10**:733.
Kinase Atlas: C. Yueh et al. (2019) *J. Med. Chem.* **62**:6512.
AlphaFold: J. Jumper et al. (2021). *Nature* **596**:583.

M. Lazou, A. Bekar-Cesaretli, D. Kozakov, S. Vajda, D. Joseph-McCarthy

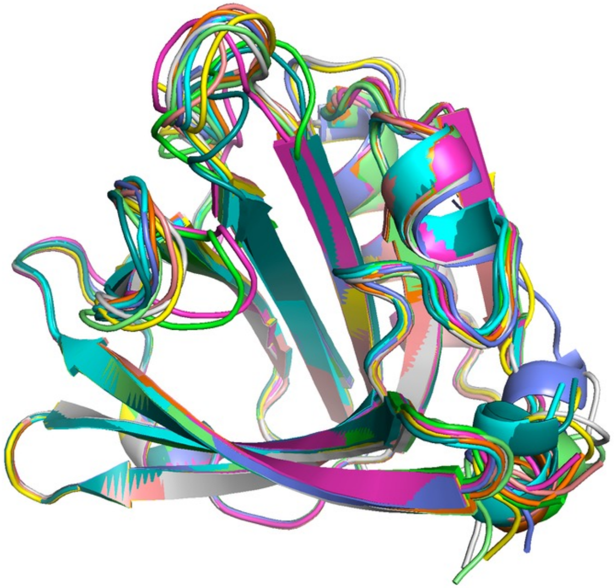
AlphaFold Models Sufficient for Hot Spot Mapping

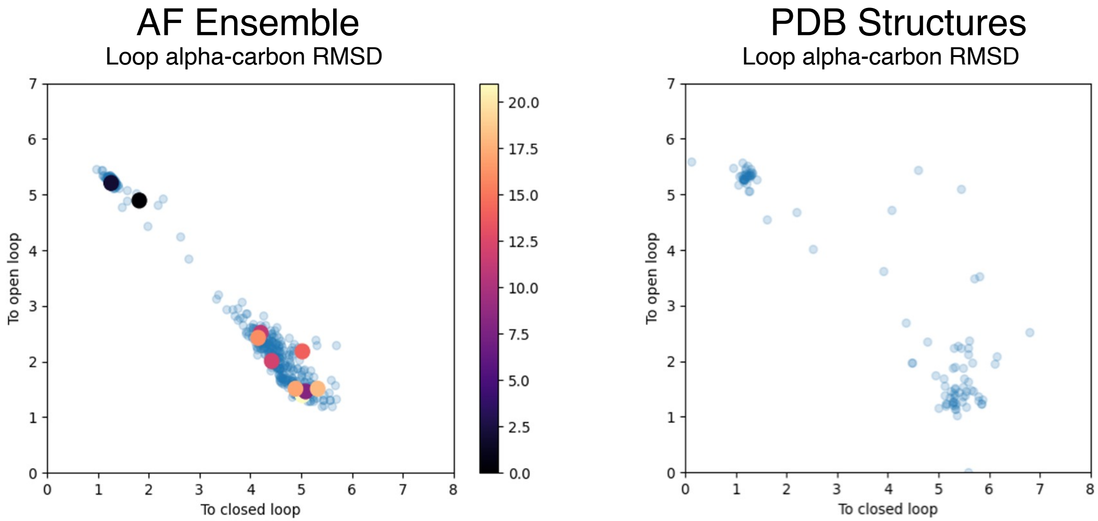
			Any hot spot, %			Top hot spot, %		
		N	13+, 50%	13+, 80%	16+, 50%	13+, 50%	13+, 80%	16+, 50%
AlphaFold		62	79.0	66.1	66.1	58.1	46.8	54.8
X-ray structure	Bound	62	77.4	69.3	70.9	56.5	50	56.5
	Unbound	48	77.1	62.5	62.5	56.3	43.7	56.3

Percentages of proteins with any hot spot or top hot spot with 13+ or 16+ probe clusters and at least 50% or 80% overlap with known fragment binder

A. Bekar-Cesaretli, O. Kahn, N. Thu, D. Kozakov, D. Joseph-McCarthy, S. Vajda, submitted to JCIM

Beta-Lactoglobulin – AlphaFold Generated Ensemble





* Colorbar indicates druggability (# of probe clusters) of binding site

- Creating a publicly available resource

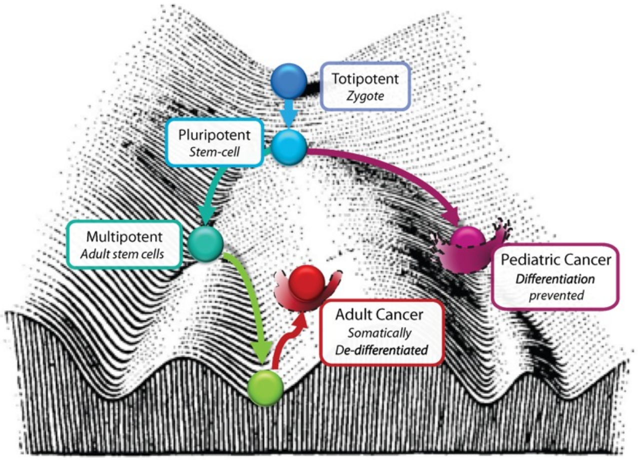
M. Lazou, A. Bekar-Cesaretli, D. Kozakov, D. Joseph-McCarthy, S. Vajda

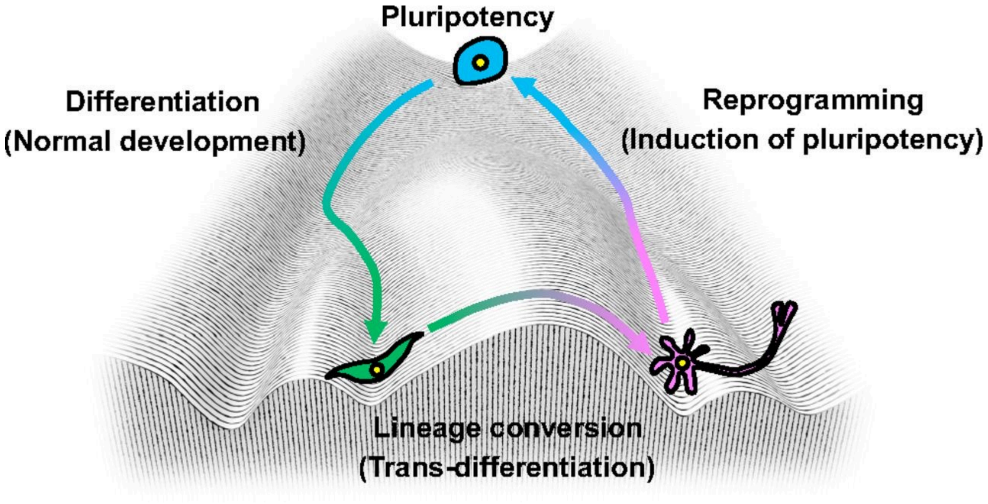
Deciphering the Role of Cell Types (and States) in Disease

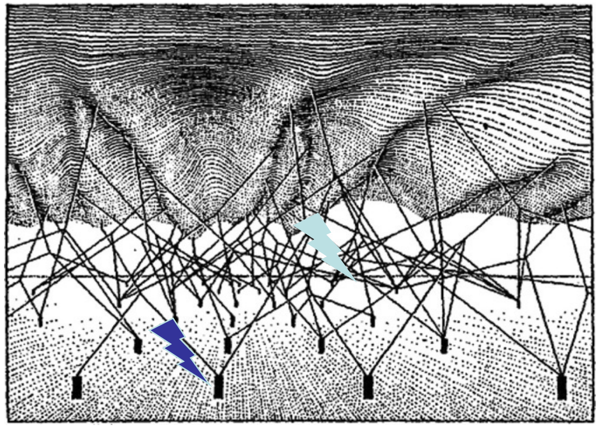
Pawel Przytycki

Assistant Professor
Faculty of Computing & Data Sciences

Waddington's Epigenetic Landscape



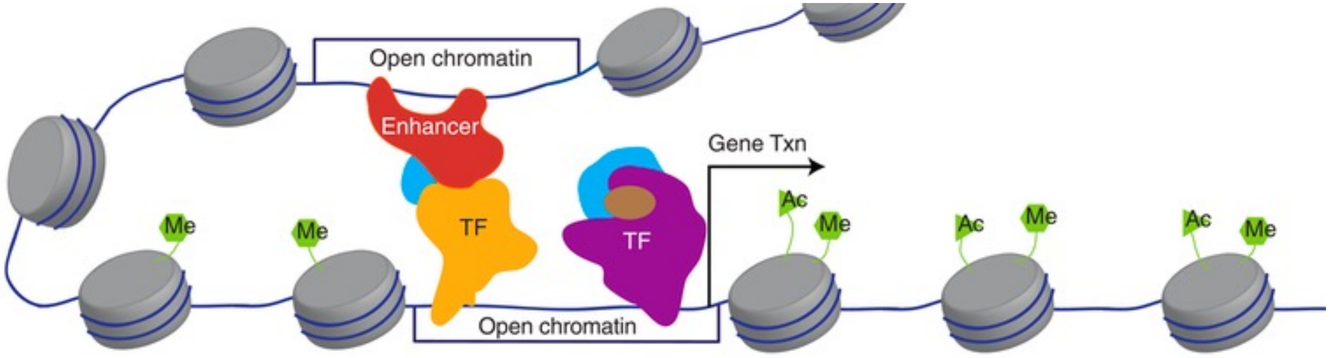




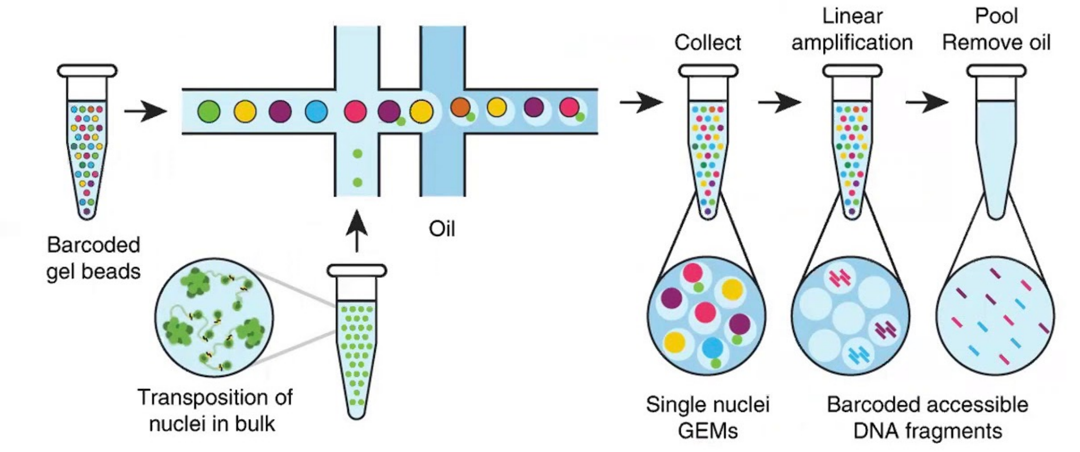
Coding Mutation

Noncoding Mutation

Multi-modal data

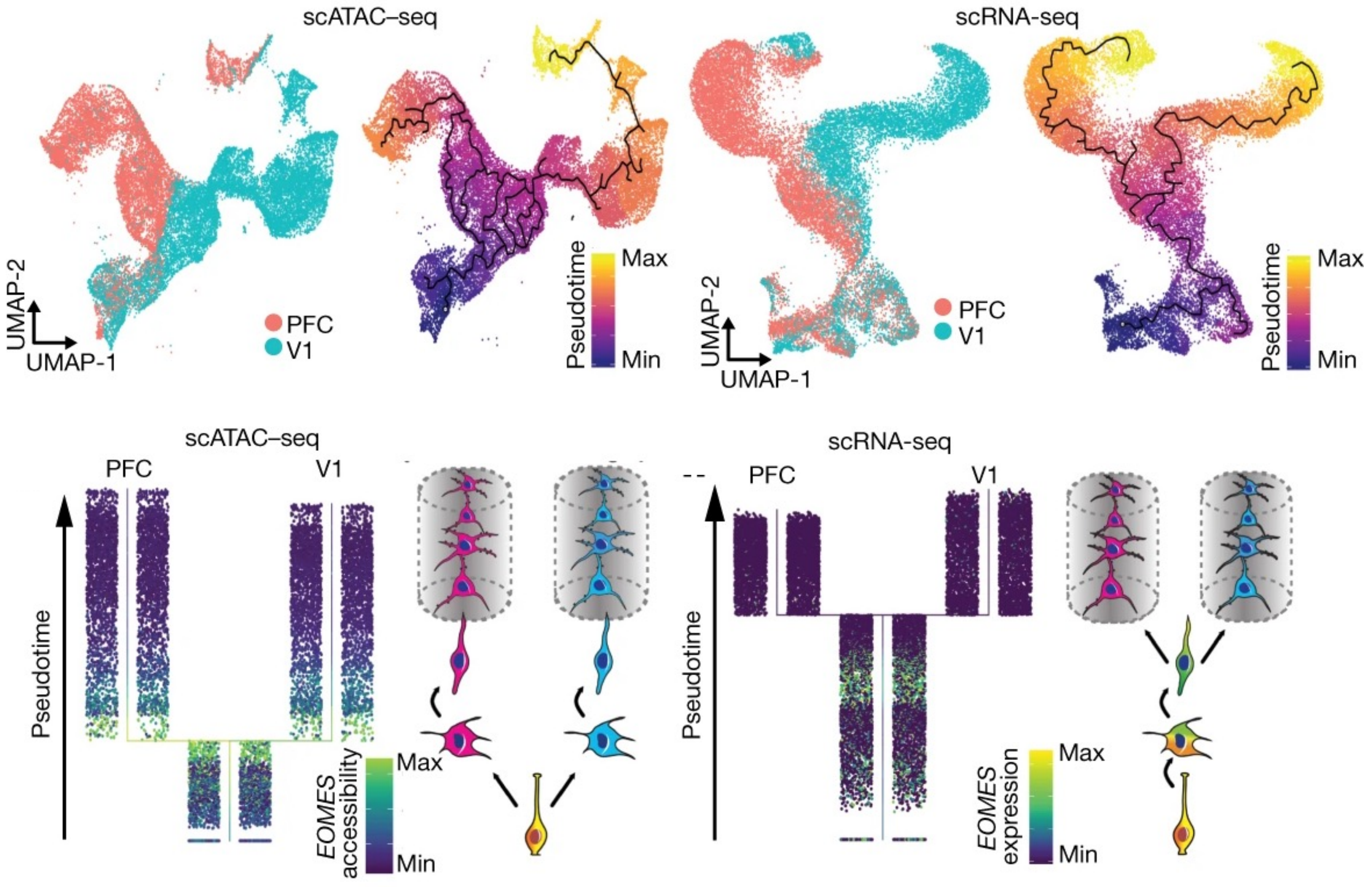


In individual cells…



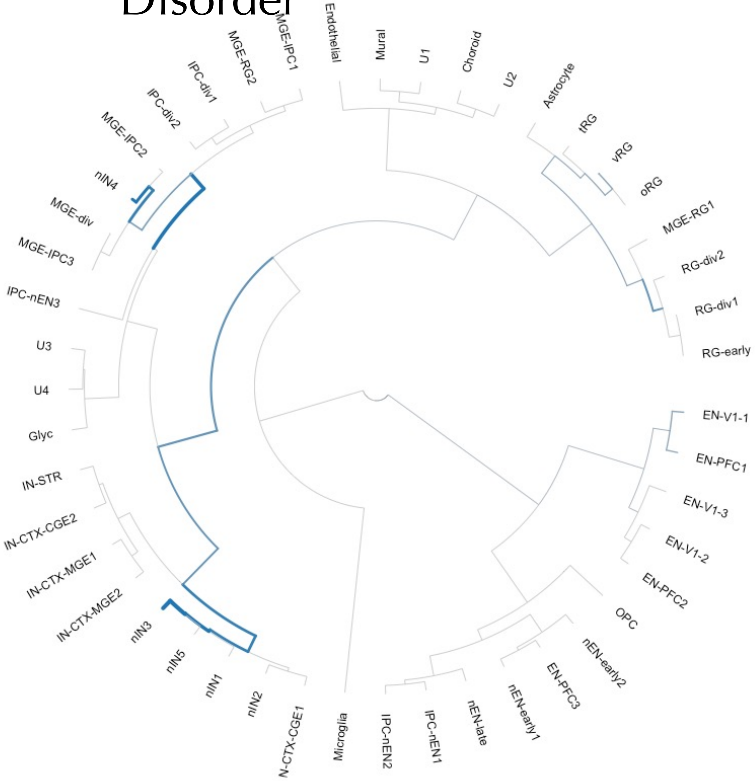
Satpathy et al, Nat Biotech 2019

Capturing dynamic changes in cell type

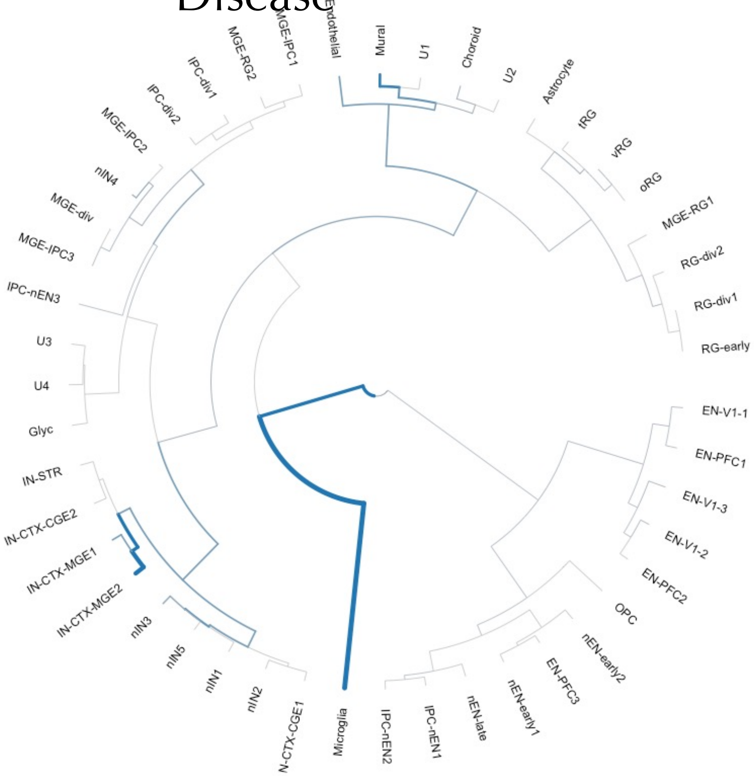


Interpreting Genetic Variants

Autism Spectrum Disorder



Alzheimer's Disease



Optimizing Value-Based Care for Health Equity

Heather Hsu, MD MPH

Assistant Professor
Department of Pediatrics, Chobanian & Avedisian School of Medicine

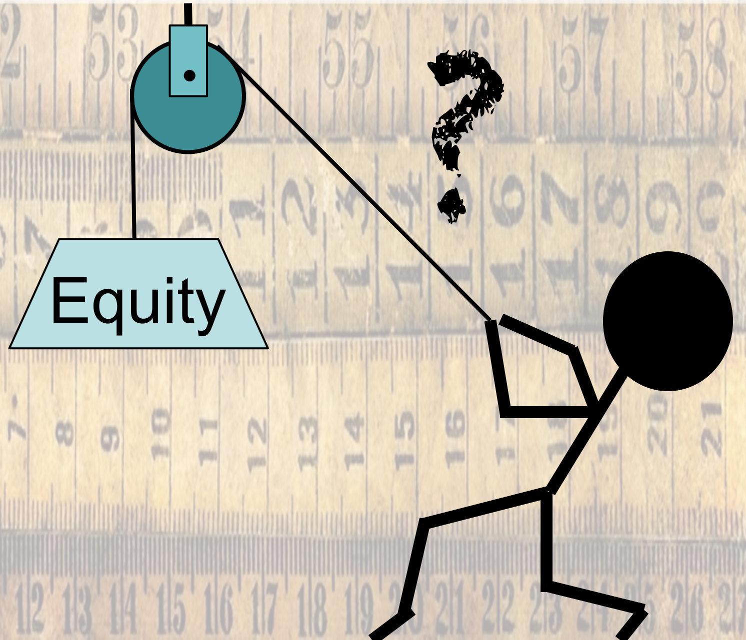
Value-Based Care

Aims to improve healthcare value by linking provider reimbursement to measures of healthcare quality

You can't fix what you don't measure

MEASUREMENT

is a cornerstone of value-based care

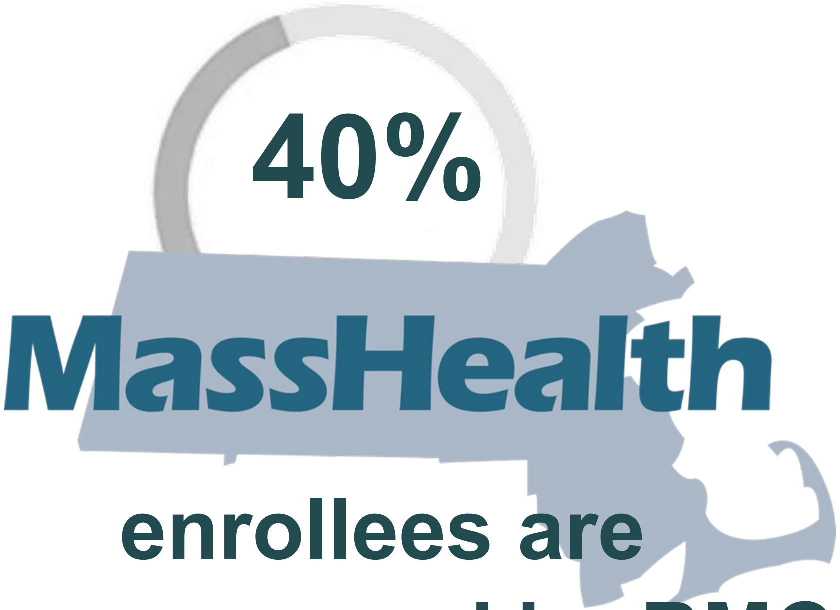


MassHealth Value-Based Care Transformation

- ✓ Medical complexity
- ✓ Social complexity

BMC Health System & the MassHealth Value-Based Care Transformation

- Assess impact on quality of care & adequacy of payment
- Identify opportunities for payment model improvement
- Address potential measurement bias



40%

enrollees are managed by BMC's WellSense Plan

Opportunities for Value-Based Care Optimization

To improve population health & healthcare equity, we must reverse the trend of

↓ Bonus payments
↑ Financial penalties

for the healthcare safety-net

Causal Mediation Analysis and the Promise of a Potential COVID-19 Treatment

Judith J. Lok

Associate Professor, Mathematics and Statistics
jjlok@bu.edu
Harvard's Radcliffe Institute for Advanced Studies 2023-2024

Collaborators:
Victoria Herrera, Nicholas Bosch, Nelson Ruiz-Opazo, Allan Walkey
Boston University Chobanian and Avedisian School of Medicine

Motivation: direct and indirect effects

Direct and indirect effects decompose the effect of a treatment A on outcome Y into:

- Part that is mediated through covariate M (indirect effect).
- Part that is not (direct effect).

Example:

A: blood pressure lowering medication, Outcome Y : heart attack.

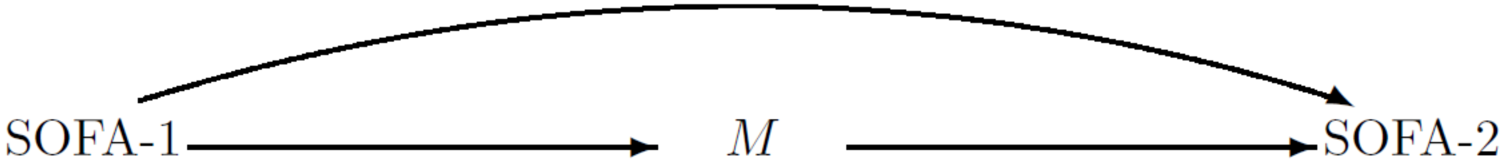
How much of the effect of the blood pressure lowering medication A is mediated by the effect of A on blood pressure M, and how much (if any) works through other pathways?

Example:

In COVID patients admitted to the ICU: What is the indirect effect of a treatment A eliminating Despr+ neutrophil nets M on the final SOFA score Y ?

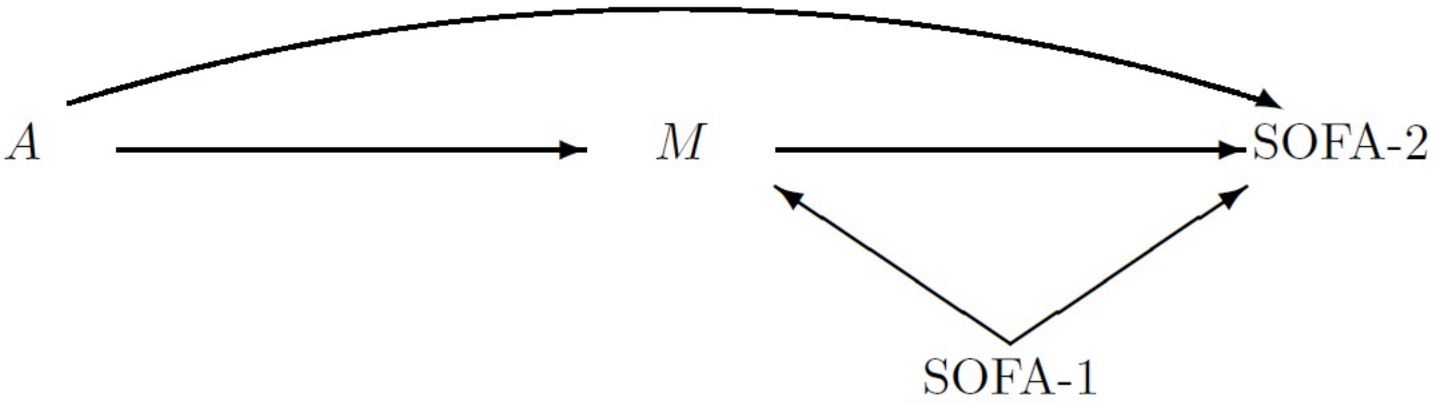
SOFA score: describes the degree of multi-organ failure.

Causal diagram: ICU COVID data; exposure: SOFA-1.



M: Despr+ neutrophil nets.
SOFA-1: SOFA score at time 1, close to ICU admission.
SOFA-2: SOFA score at time 2, the day before ICU-discharge or death.

Causal diagram: ICU COVID data



M: Despr+ neutrophil nets.

Putative exposure A: eliminates Despr+ neutrophil nets.

SOFA-1: SOFA score at time 1, close to ICU admission.

SOFA-2: SOFA score at time 2, the day before ICU-discharge or death.

The organic indirect effect of A that eliminates Despr+ neutrophil nets equals $\int_c E\left[Y|M=0, C=c, A=0\right] f_C(c)dc - EY^{(0)}$, where C is SOFA-1. We can estimate this by

$$\frac{1}{n}\sum_{i=1}^{n}\hat{E}\left[Y_i|M_i=0, C_i=c_i, A_i=0\right]-\frac{1}{n}\sum_{i=1}^{n}Y_i:$$

the average expected outcome Y had all M_i been equal to 0 (if no direct effect), minus the average expected outcome without any treatment/intervention.

No on-treatment outcome data needed for organic indirect effect/pure indirect effect.

Indirect effect estimate: a decrease in time 2 SOFA score of 0.71.

ICU doctors are mostly interested in decreasing the SOFA score of patients with a somewhat high SOFA score at ICU admission (SOFA-1$\geq$ 2). In those patients, the estimated indirect effect was more promising: 0.98 (95% CI: 0.27-2.13).

Screening Tools for Dementia

Vijaya B. Kolachalama, PhD, FAHA

Associate Professor
Department of Medicine
Department of Computer Science
Faculty of Computing & Data Sciences

Global burden of dementia

- More than 55 million people have dementia worldwide
- Every year, there are nearly 10 million new cases
- In 2019, dementia cost economies globally 1.3 trillion US dollars
- Multiple forms of dementia
  - Alzheimer’s disease (60-70% cases)
  - Lewy body dementia
  - Vascular dementia
  - Frontotemporal degeneration
  - Many more…

Global action plan on the public health response to dementia 2017-2025

World Health Organization

1. Dementia as a public health priority
2. Dementia awareness and friendliness
3. Dementia risk reduction
4. Dementia diagnosis, treatment, care and support
5. Support for dementia carers
6. Information systems for dementia
7. Dementia research and innovation

Some hope…

The New York Times

Alzheimer's Drug May Benefit Some Patients, New Data Shows

The drug, lecanemab, made by Eisai and Biogen, also carried risks of brain swelling and bleeding and should be studied further, a report of the findings said.

BBC

Home News Sport Business Innovation Culture Travel Earth Video Live

Alzheimer's drug lecanemab hailed as momentous breakthrough

The New York Times

New Federal Decisions Make Alzheimer's Drug Leqembi Widely Accessible

The F.D.A. gave full approval to the drug, but added a black-box warning about safety risks. Medicare said it would cover most of the high cost.

Our research

- Using routinely collected clinical data, we are developing AI-based methods that can perform differential diagnosis of dementia
- Such tools can assist neurologists and drug trials
- We are performing pilot studies to evaluate our tools

nature COMMUNICATIONS

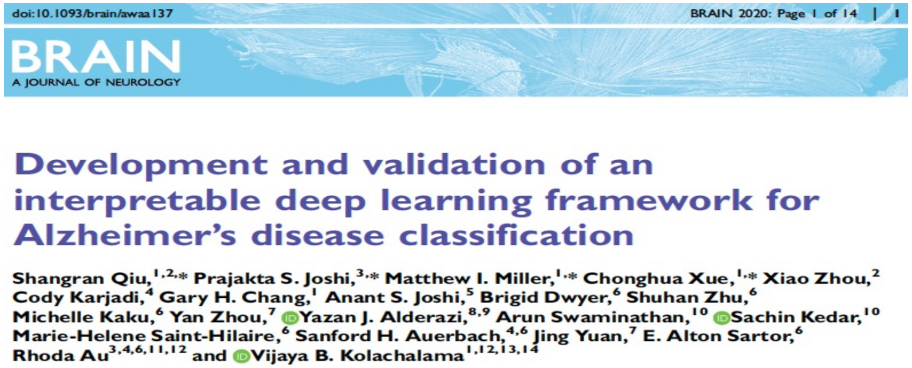
ARTICLE

Check for updates

https://doi.org/10.1038/s41467-022-31037-5 OPEN

Multimodal deep learning for Alzheimer's disease dementia assessment

Shangran Qiu[1,2,24], Matthew I. Miller[1,24], Prajakta S. Joshi[3,4,5], Joyce C. Lee[1], Chonghua Xue[1,3], Yunruo Ni[1], Yuwei Wang[1], Ileana De Anda-Duran[6], Phillip H. Hwang[3], Justin A. Cramer[7], Brigid C. Dwyer[8], Honglin Hao[9], Michelle C. Kaku[8], Sachin Kedar[10,11,12], Peter H. Lee[13], Asim Z. Mian[14], Daniel L. Murman[10], Sarah O'Shea[8], Aaron B. Paul[13], Marie-Helene Saint-Hilaire[8], E. Alton Sartor[8], Aneeta R. Saxena[8], Ludy C. Shih[8], Juan E. Small[13], Maximilian J. Smith[13], Arun Swaminathan[10], Courtney E. Takahashi[8], Olga Taraschenko[10], Hui You[15], Jing Yuan[9], Yan Zhou[9], Shuhan Zhu[8], Michael L. Alosco[8,16], Jesse Mez[5,8,16], Thor D. Stein[16,17,18,19], Kathleen L. Poston[20], Rhoda Au[3,5,8,16,21] & Vijaya B. Kolachalama[1,16,22,23]✉



doi:10.1093/brain/awaa137 BRAIN 2020: Page 1 of 14 | 1

BRAIN
A JOURNAL OF NEUROLOGY

Development and validation of an interpretable deep learning framework for Alzheimer's disease classification

Shangran Qiu,[1,2,*] Prajakta S. Joshi,[3,*] Matthew I. Miller,[1,*] Chonghua Xue,[1,*] Xiao Zhou,[2] Cody Karjadi,[4] Gary H. Chang,[1] Anant S. Joshi,[5] Brigid Dwyer,[6] Shuhan Zhu,[6] Michelle Kaku,[6] Yan Zhou,[7] Yazan J. Alderazi,[8,9] Arun Swaminathan,[10] Sachin Kedar,[10] Marie-Helene Saint-Hilaire,[6] Sanford H. Auerbach,[4,6] Jing Yuan,[7] E. Alton Sartor,[6] Rhoda Au[3,4,6,11,12] and Vijaya B. Kolachalama[1,12,13,14]

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KAREN TOFFLER CHARITABLE TRUST

Alzheimer's Drug Discovery Foundation

NIH National Heart, Lung, and Blood Institute

NIH National Institute of Diabetes and Digestive and Kidney Diseases

NIH National Institute on Aging

Gates Ventures

American Heart Association® life is why™

Johnson & Johnson

NIH NATIONAL CANCER INSTITUTE