Revolutionizing Connectomics using Generative, federated and holistic learning

Islem Rekik

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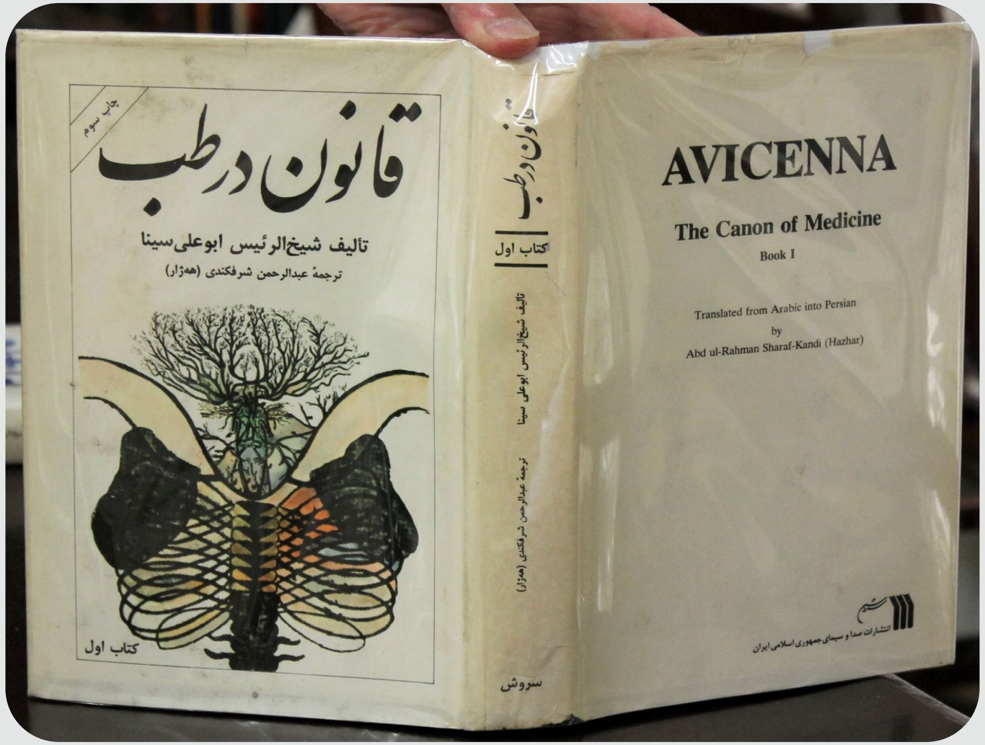
https://basira-lab.com/

"The physician should not treat the disease but the patient who is suffering from it."
Avicenna (980–1037)



Imperial College London

AI revolutionizing healthcare & medicine

Forbes

FORBES > INNOVATION > ENTERPRISE TECH

The 10 Biggest Trends Revolutionizing Healthcare In 2024

Bernard Marr Contributor

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Oct 3, 2023, 03:15am EDT

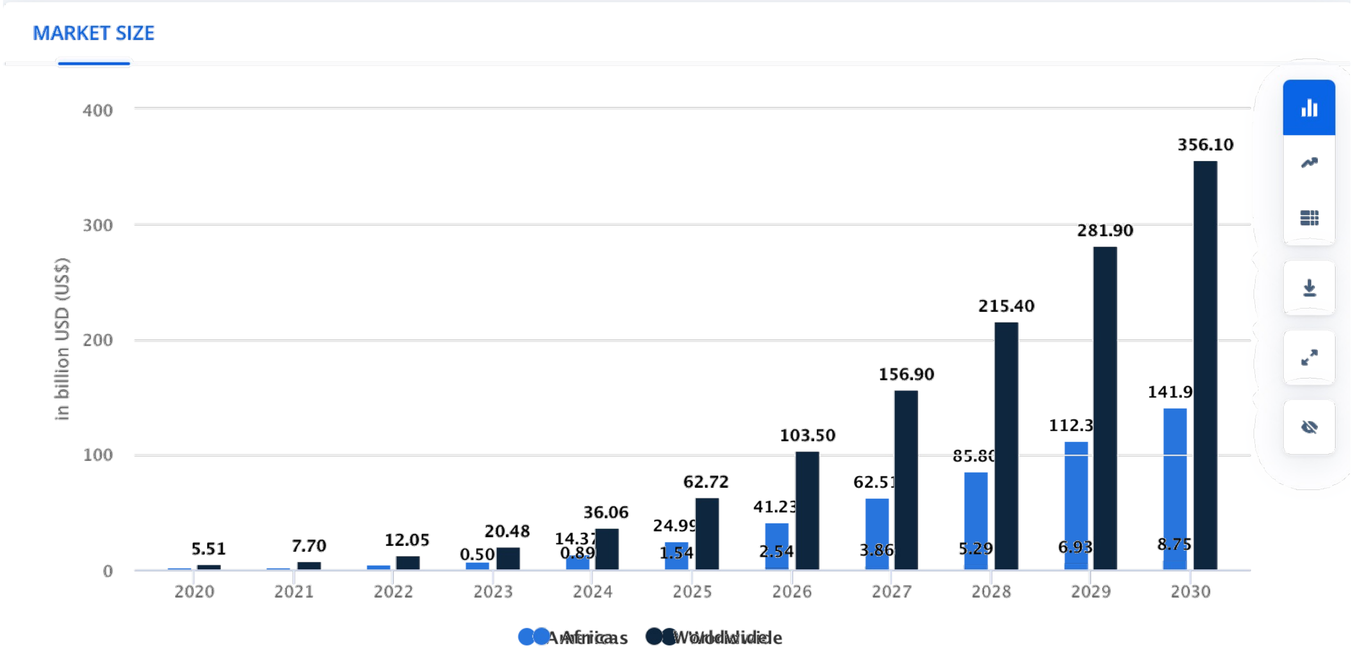
A longer-living population, the emergence of transformative technologies with applications across the healthcare spectrum, and continued global economic uncertainty. These are the key societal drivers that will impact healthcare in 2024.

The 10 Biggest Trends Revolutionizing Healthcare In 2024 ADOBE STOCK

Personalized Medicine

Generative AI In Healthcare

Generative AI market size worldwide



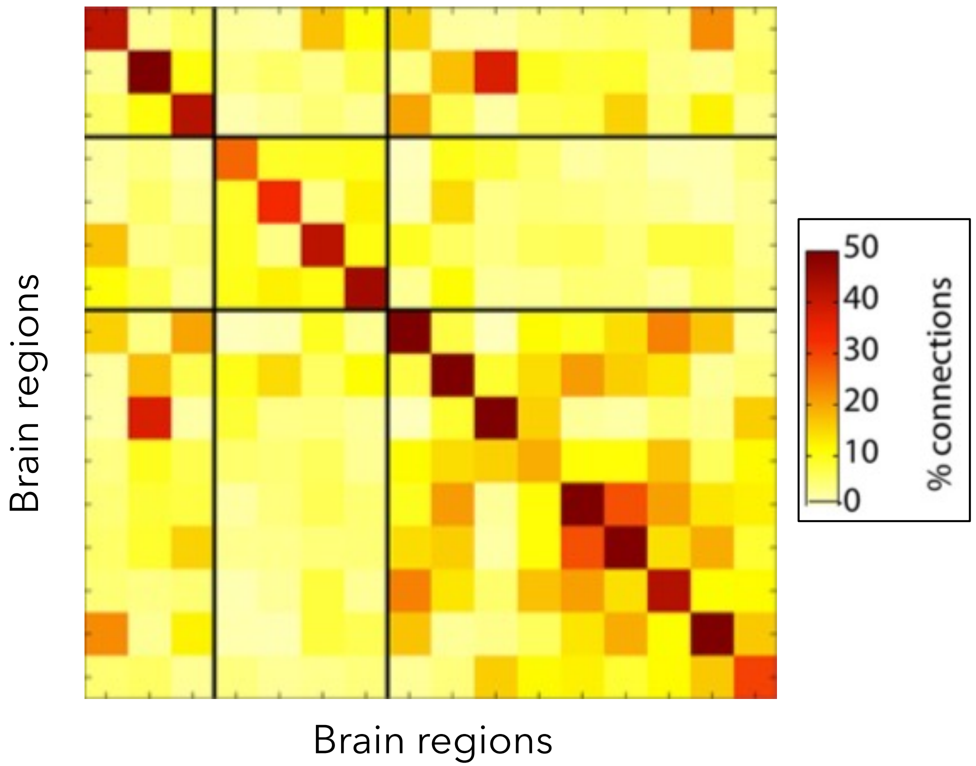
Notes: Data was converted from local currencies using average exchange rates of the respective year.

Source: Statista Market Insights

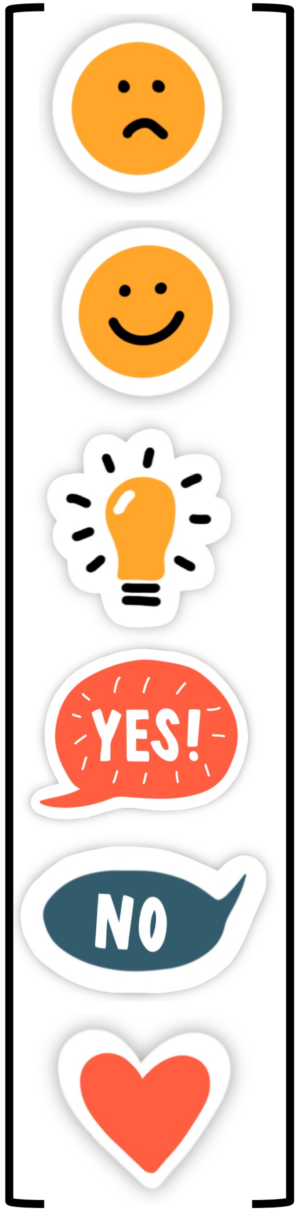
Three trends in the AI-powered healthcare revolution

Generative learning	Generate *multidimensional* brains	Generate population brain templates
Federated learning	Federate to generate the future of the brain	Federate heterogeneous diagnostic tasks
Holistic learning	Insights into the future of an inclusive and holistic AI in medicine	

EXAMPLE (2): BRAIN GENERATION



encodes



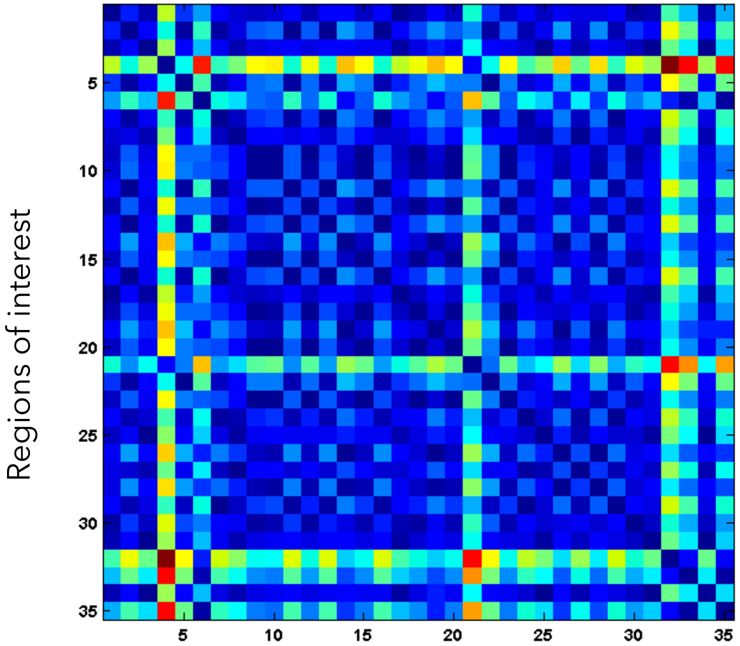
Geerligs L, Rubinov M, Henson RN. State and trait components of functional connectivity: individual differences vary with mental state. Journal of Neuroscience. 2015 Oct 14;35(41):13949-61.

Generative learning

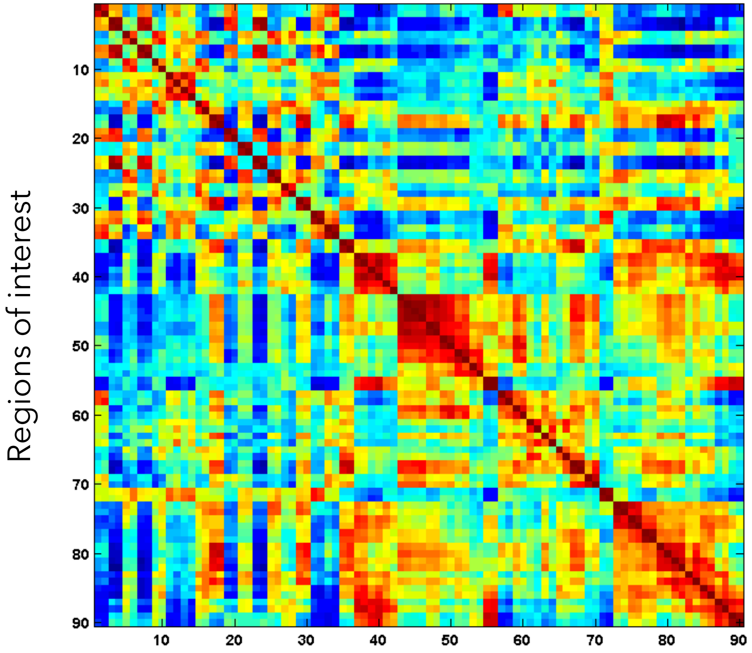
Generate *multidimensional* brains

FROM THE CRADLE TO THE GRAVE

Thickness-based morphological brain network (0 months)

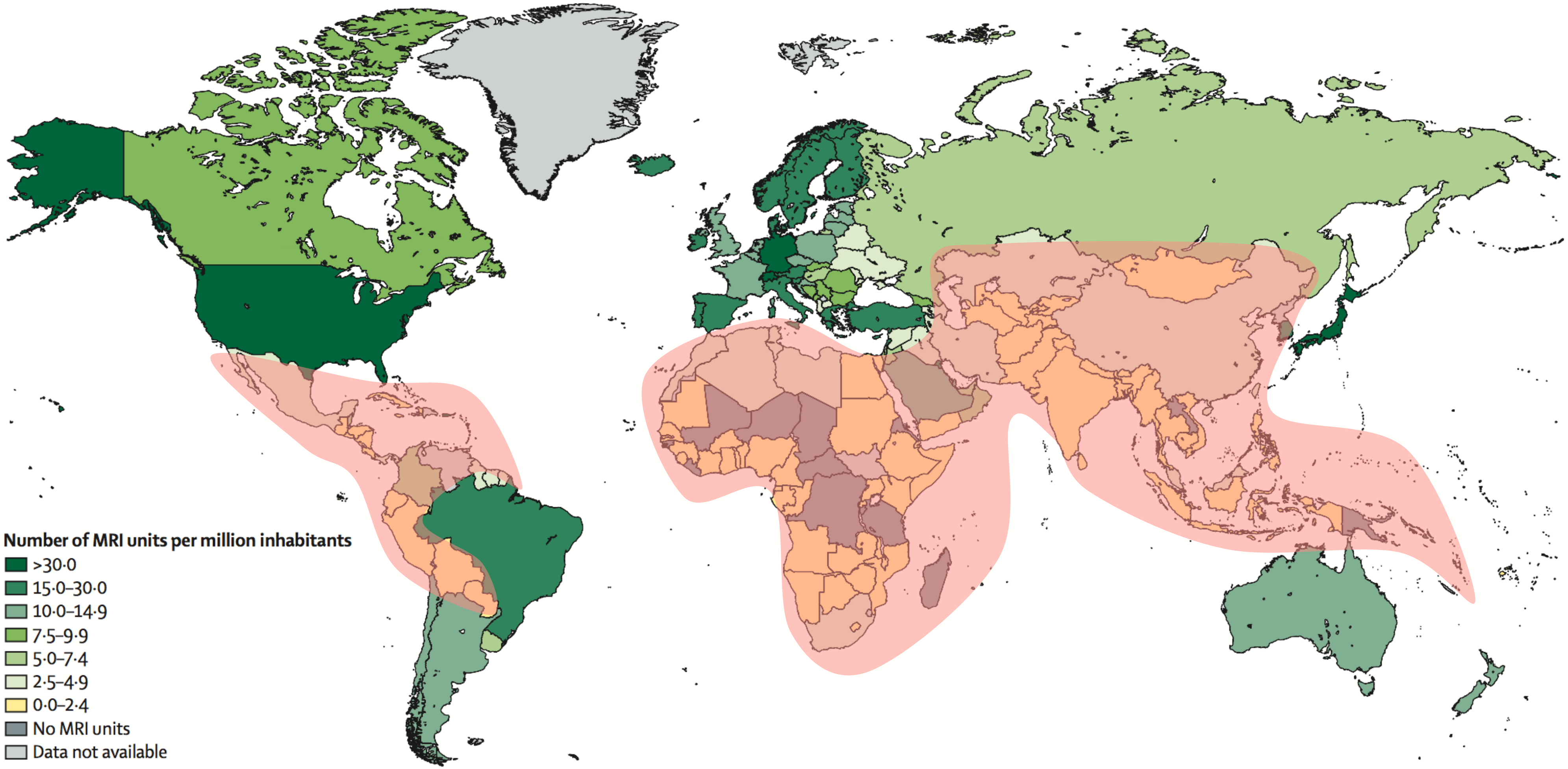


Functional brain network of a normal control (75 years)



A mechanistic understanding of the **human connectome** is not only important for understanding **normal brain function**, but will also help tackle the even **more complex pathological brain**.

Mind the medical imaging gap!



Estimates of the number of MRI units per million inhabitants. The map was produced by the International Atomic Energy Agency (Vienna, Austria).[1]

[1]Hricak, Hedvig, et al. "Medical imaging and nuclear medicine: a Lancet Oncology Commission." **The Lancet Oncology** 22.4 (**2021**): e136-e172.

Can we diagnose early and better with **minimal resources (limited data)** and **at lower costs**?

"data" $\qquad\qquad$ "no-data"

$$\mathbf{X} \xrightarrow{f} \hat{\mathbf{X}}$$

- Affordable to acquire
- Accessible
- Low–middle quality

- Costly to acquire
- Inaccessible in many countries
- High quality

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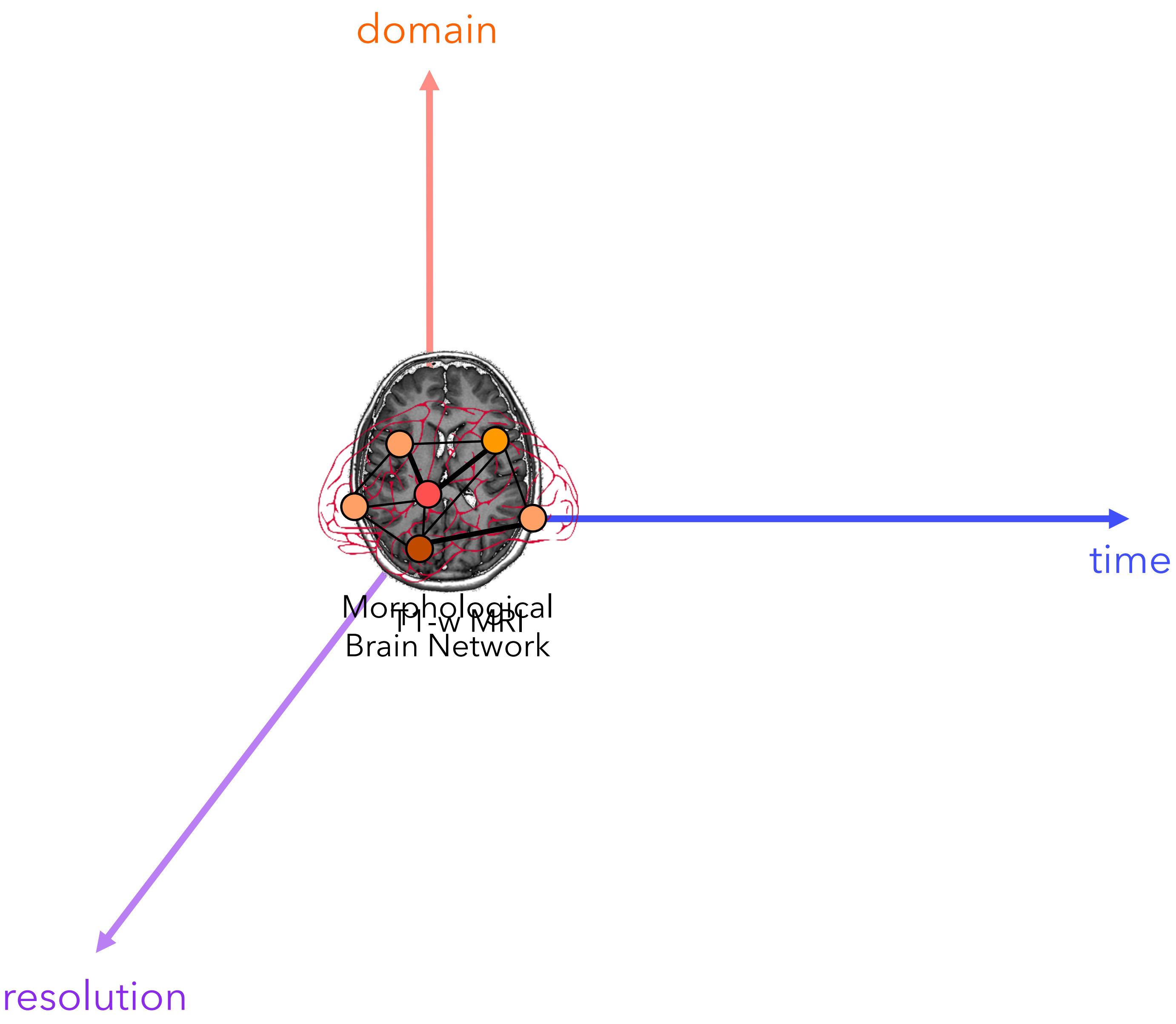
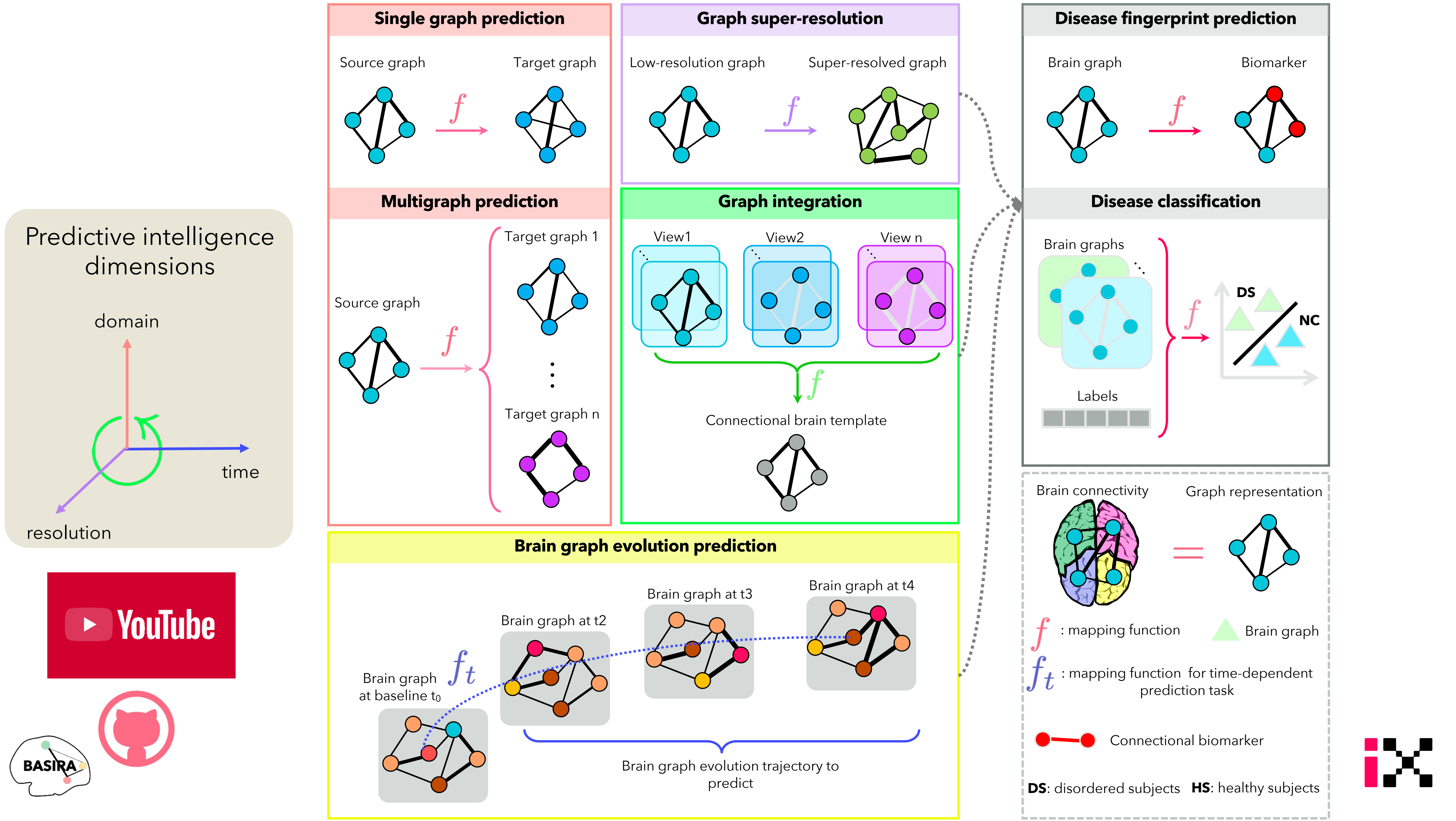
Pioneering and developing **70+ predictive/generative learning** works in **network neuroscience** (**2019-2023**)

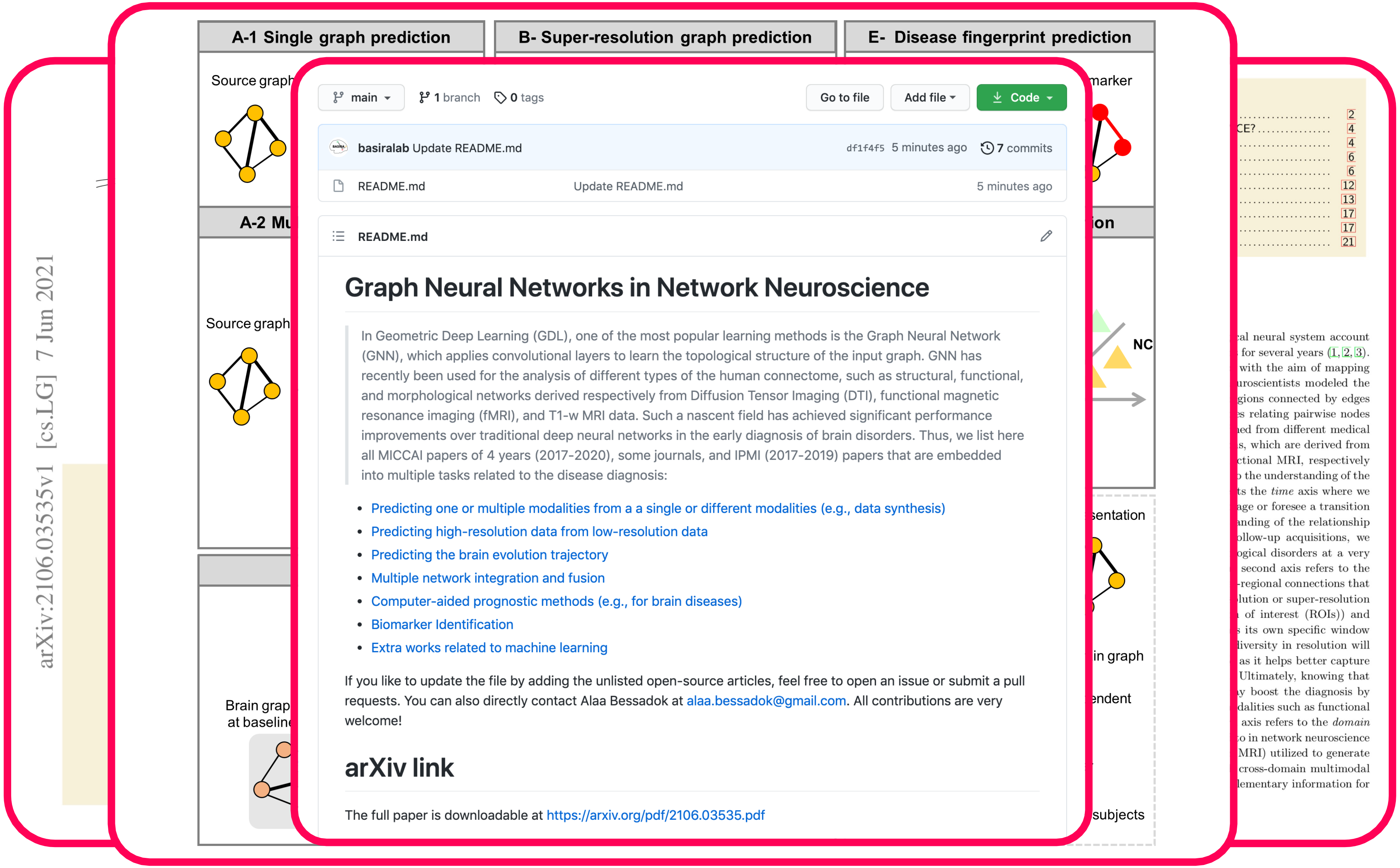




Predictive intelligence dimensions
domain
time
resolution
YouTube
BASIRA
Single graph prediction
Source graph
Target graph
f
Graph super-resolution
Low-resolution graph
Super-resolved graph
f
Disease fingerprint prediction
Brain graph
Biomarker
f
Multigraph prediction
Source graph
f
Target graph 1
Target graph n
Graph integration
View1
View2
View n
f
Connectional brain template
Disease classification
Brain graphs
Labels
f
DS
NC
Brain graph evolution prediction
Brain graph at baseline t0
f_t
Brain graph at t2
Brain graph at t3
Brain graph at t4
Brain graph evolution trajectory to predict
Brain connectivity
Graph representation
=
f : mapping function
Brain graph
f_t : mapping function for time-dependent prediction task
Connectional biomarker
DS: disordered subjects
HS: healthy subjects

Review paper published in IEEE TPAMI in 2022

Graph neural networks in network neuroscience

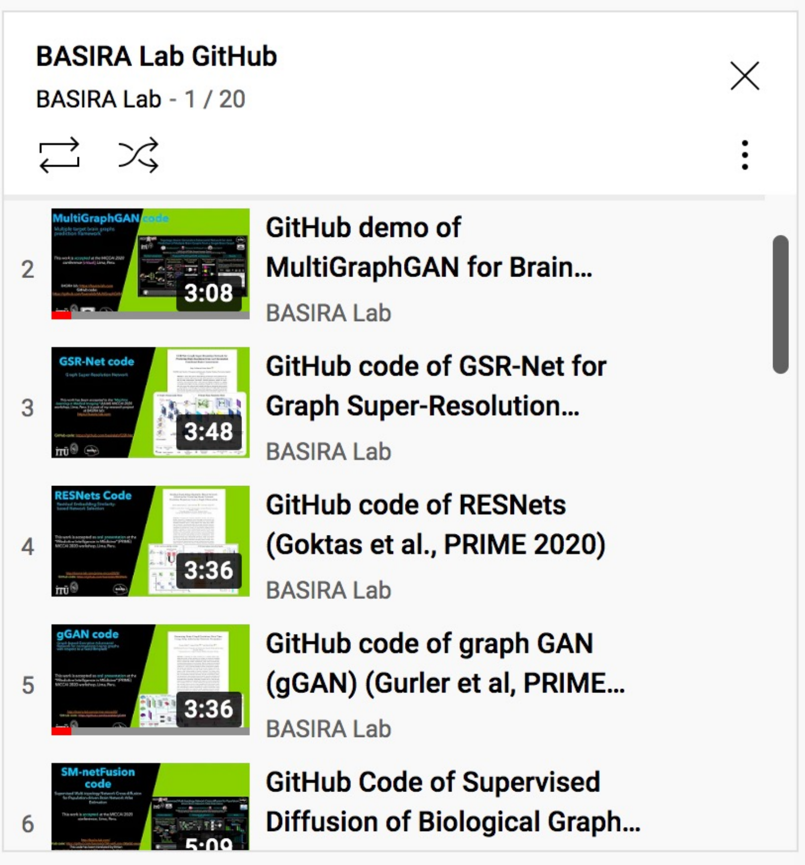


GitHub link: https://github.com/basiralab/GNNs-in-Network-Neuroscience

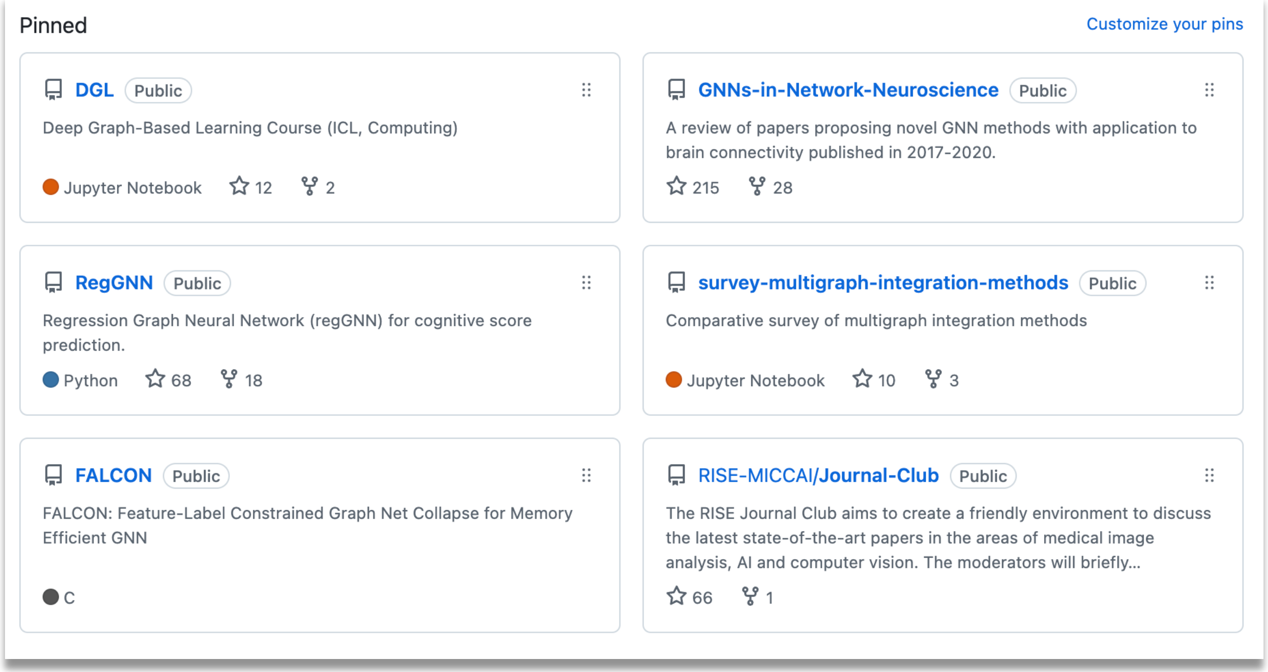
Bessadok, A., Mahjoub, M.A. and Rekik, I., 2022. Graph neural networks in network neuroscience. IEEE Transactions on Pattern Analysis and Machine Intelligence.

Reproducible, inclusive and open science

YouTube **20 GitHub code video demo (since 2020)**



65+ GitHub codes



https://github.com/basiralab

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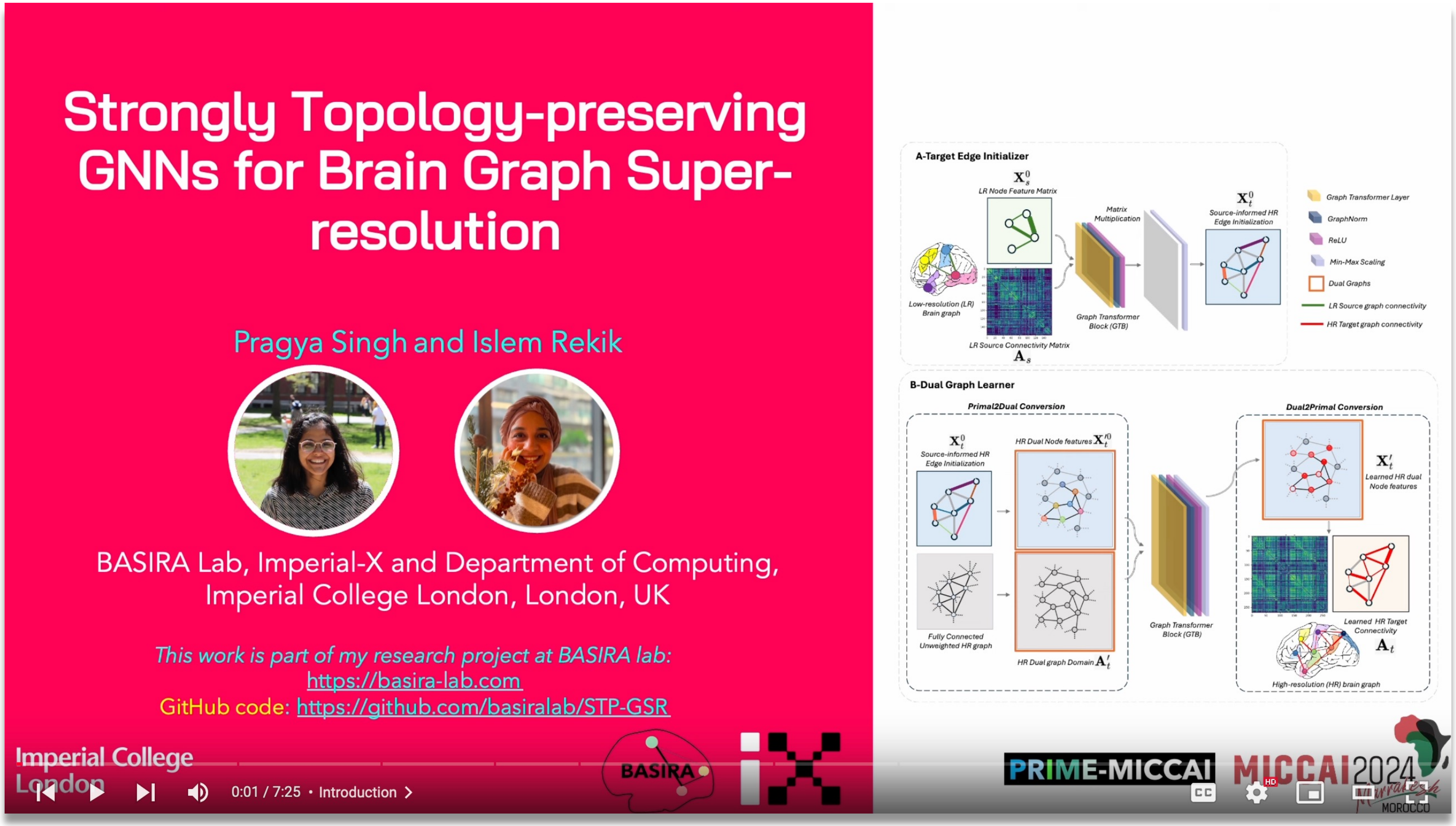
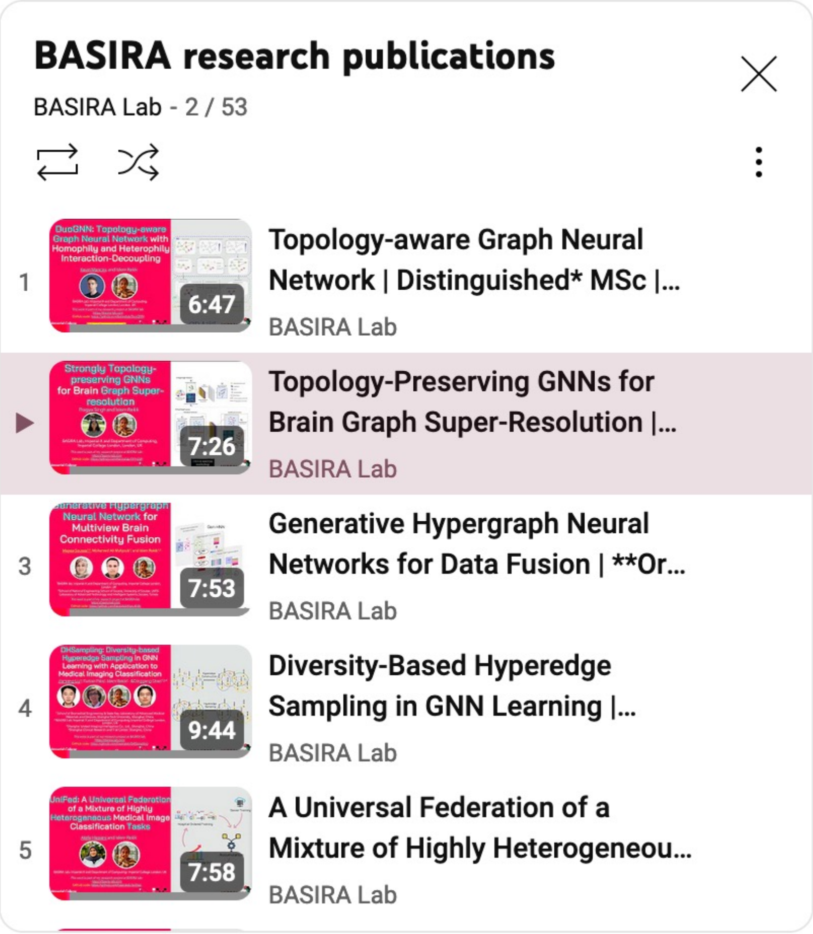
Reproducible, inclusive and open science



50+ oral paper presentations



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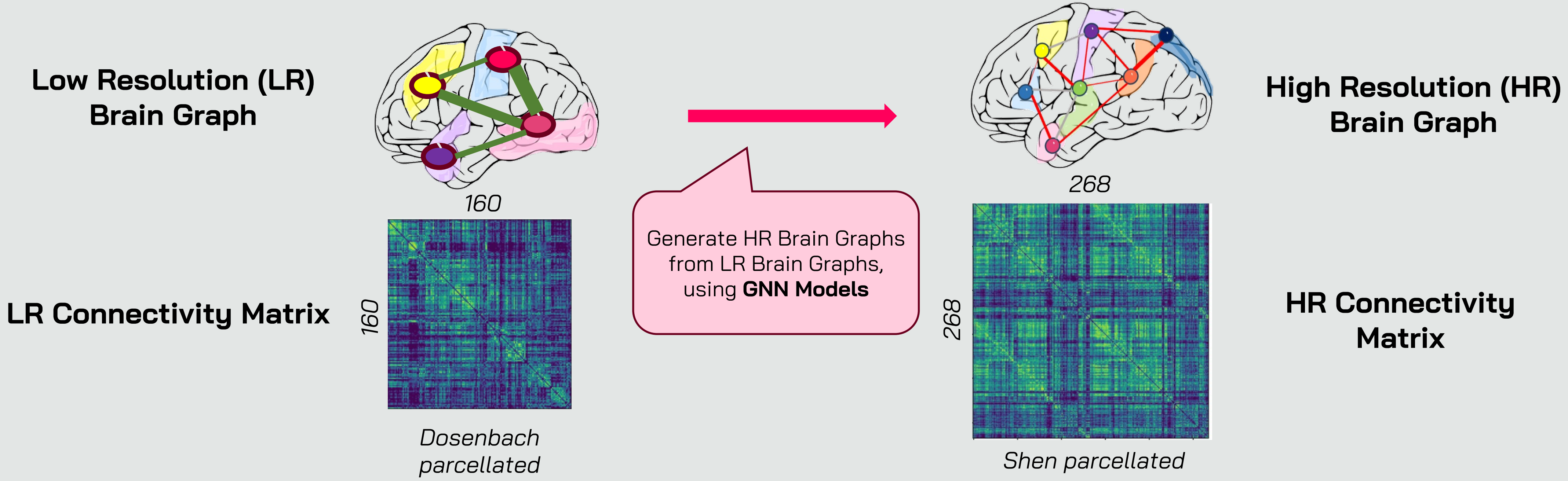
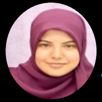
Cross-resolution prediction



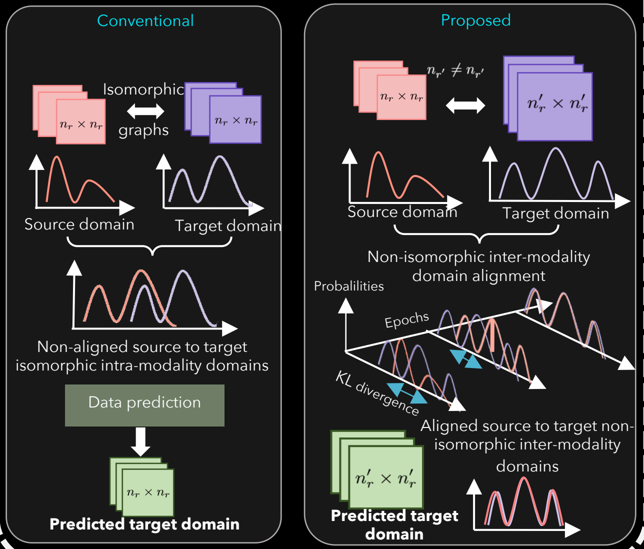
Cross-domain | Cross-resolution | Cross-time

Non-isomorphic Inter-modality Graph Alignment and Synthesis for Holistic Brain Mapping

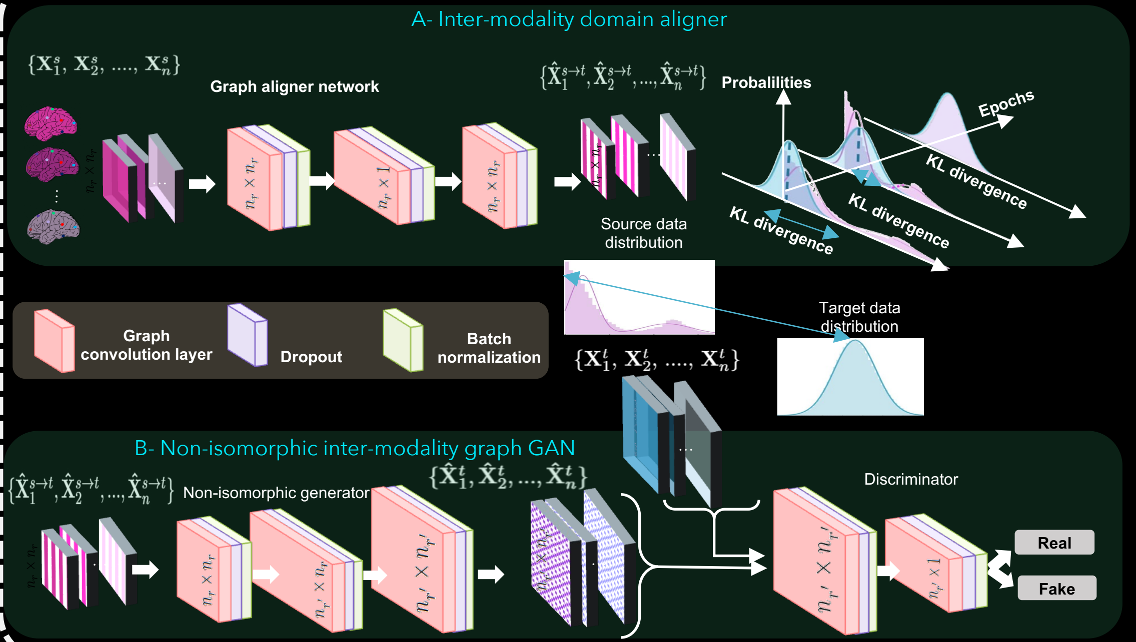
Islem Mhiri , Ahmed Nebli , Mohamed Ali Mahjoub  and Islem Rekik 

Problem statement

How to predict inter-modality non-isomorphic brain graphs from a base graph ?



Proposed IMANGraphNet Method

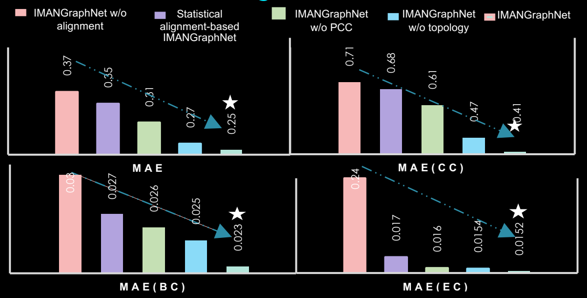


Results

Dataset evaluation

SLIM[1] dataset: 150 functional connectomes (160 x 160)
150 morphological connectomes (35 x 35)

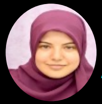
Prediction results using different evaluation metrics



This work is accepted at IPMI 2021 and selected for an oral presentation.
GitHub code: https://github.com/basiralab/IMANGraphNet

Cross-domain | Cross-resolution | Cross-time

Non-isomorphic Inter-modality Graph Alignment and Synthesis for Holistic Brain Mapping

Islem Mhiri , Ahmed Nebli , Mohamed Ali Mahjoub  and Islem Rekik 

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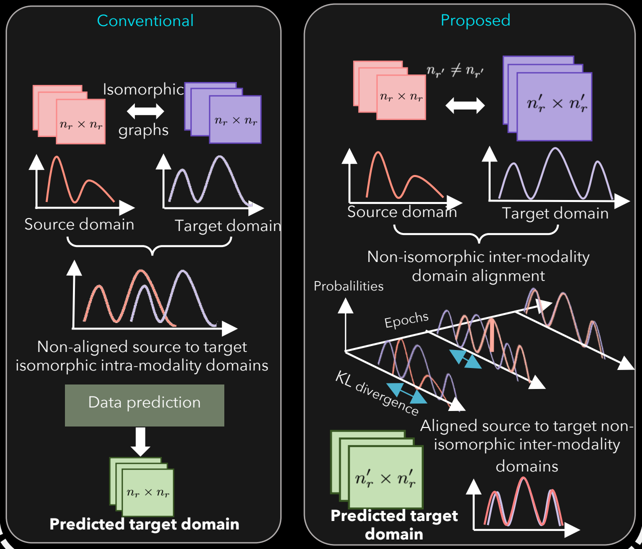
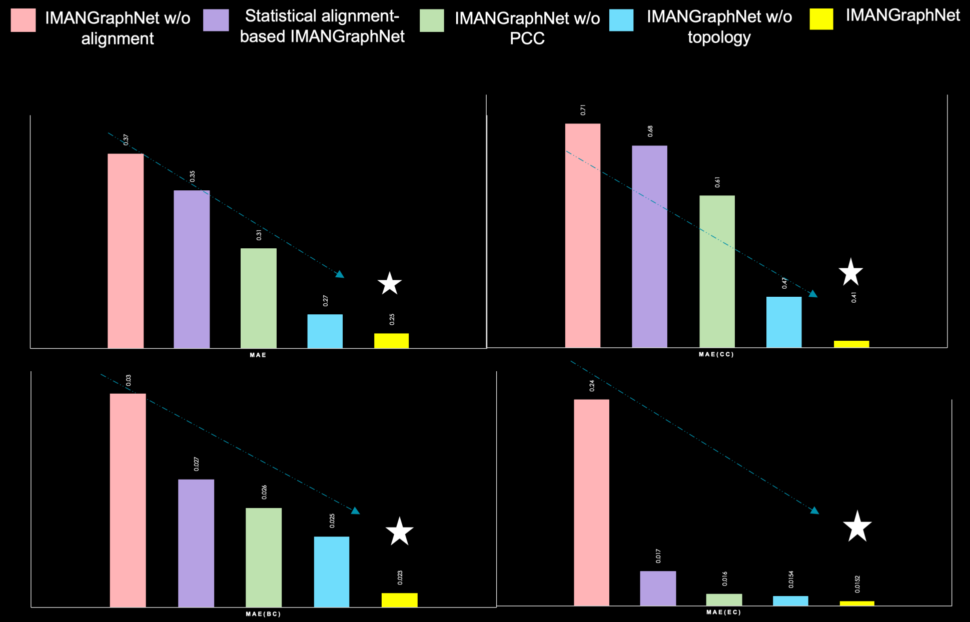


Bar plots



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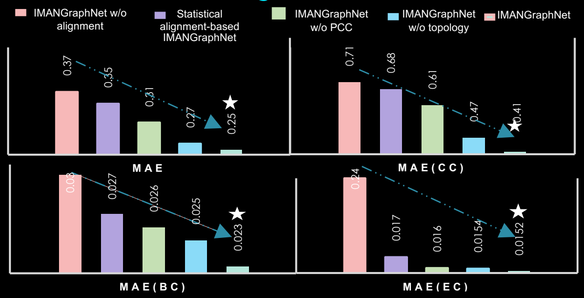
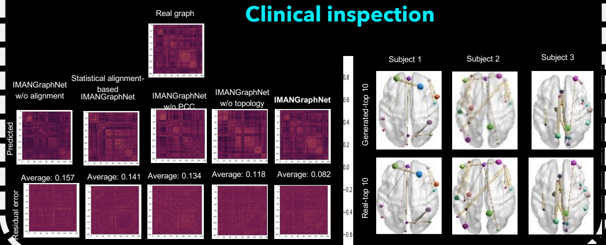
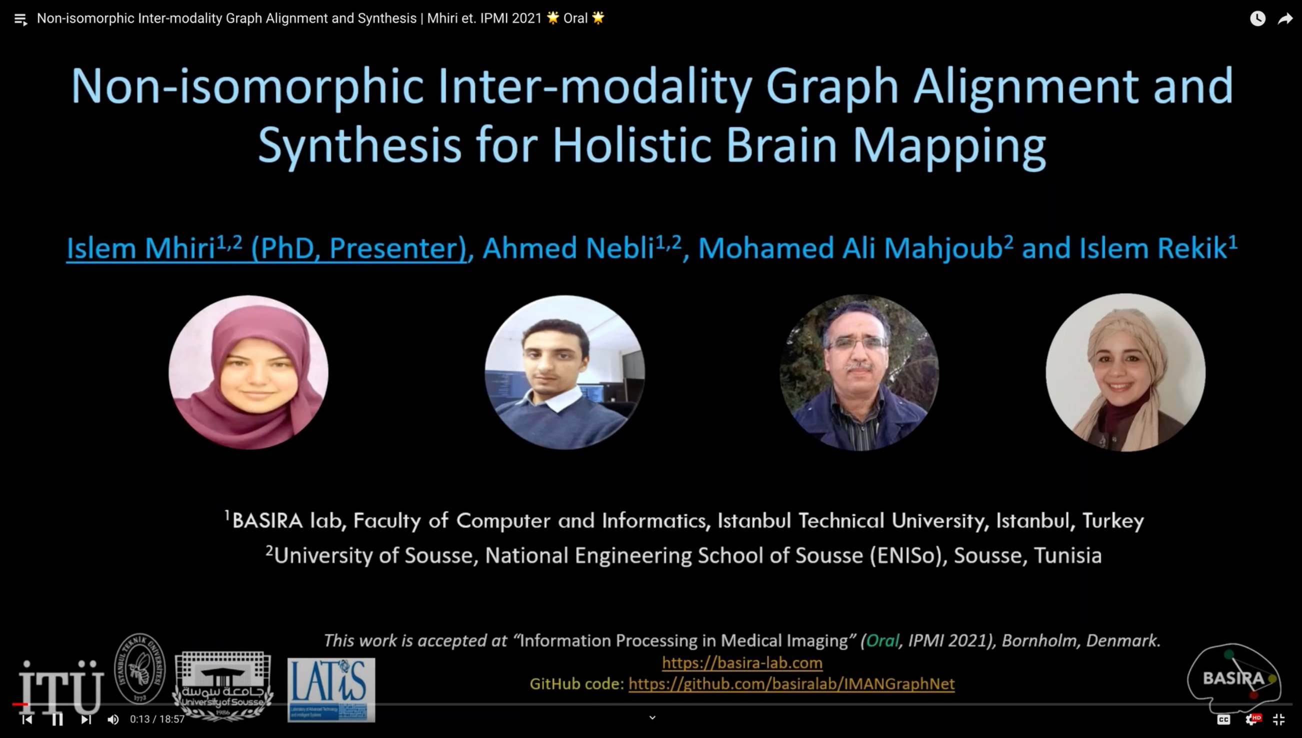


Clinical inspection



This work is accepted at IPMI 2021 and selected for an oral presentation.
GitHub code: https://github.com/basiralab/IMANGraphNet

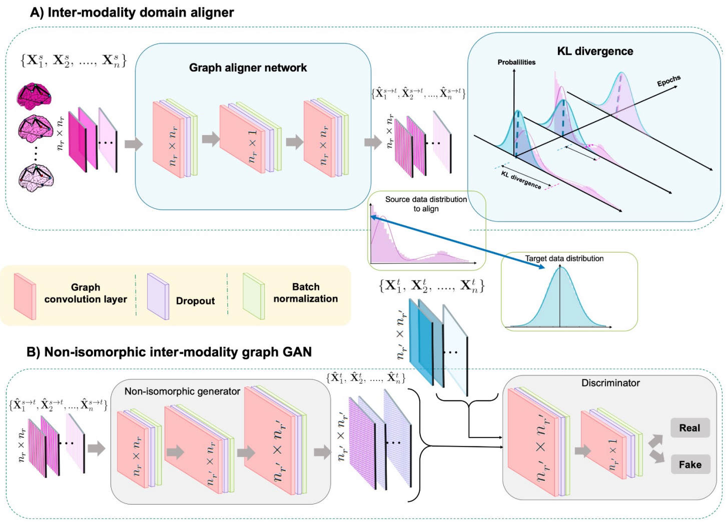


README.md

IMANGraphNet

IMANGraphNet (Non-isomorphic Inter-modality Graph Alignment and Synthesis for Holistic Brain Mapping), coded up in Python by Islem Mhiri. Please contact islemmhiri1993@gmail.com for inquiries. Thanks.

This repository provides the official PyTorch implementation of the following paper:



> Non-isomorphic Inter-modality Graph Alignment and Synthesis for Holistic Brain Mapping [Islem Mhiri][1,2], [Ahmed Nebli][1,2], [Mohamed Ali Mahjoub][2], [Islem Rekik][1](https://basira-lab.com/)

Releases

No releases published
Create a new release

Packages

No packages published
Publish your first package

Contributors 3

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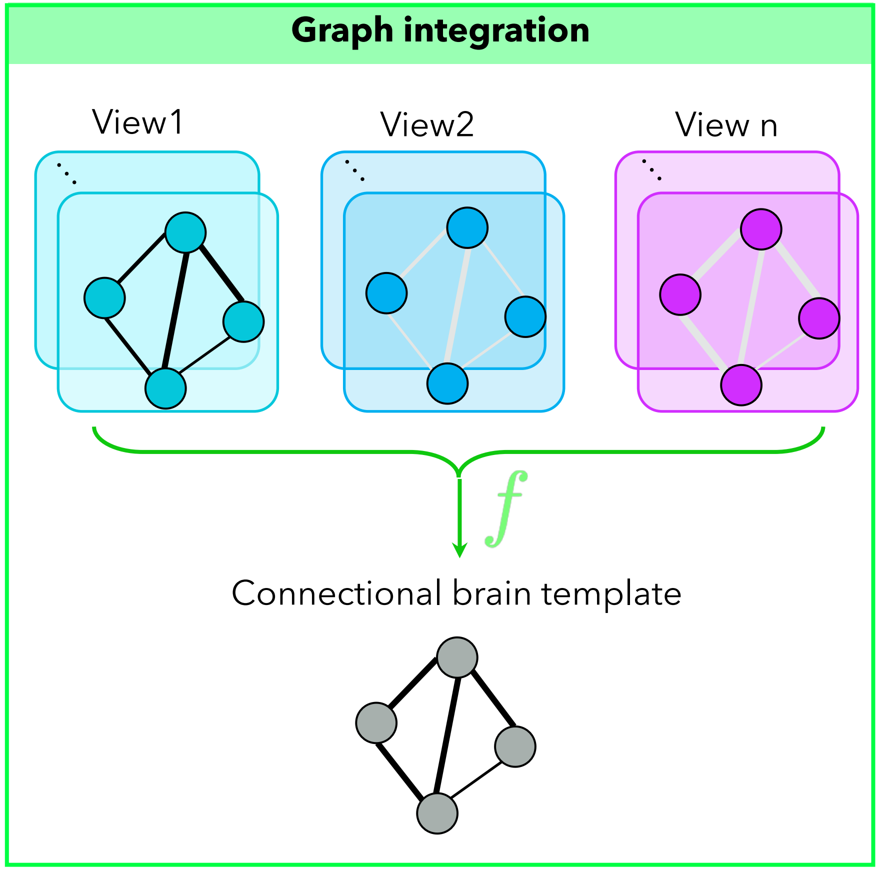
YCT1 Yekta Can Tursun
IslemRekik

Languages

Python 100.0%

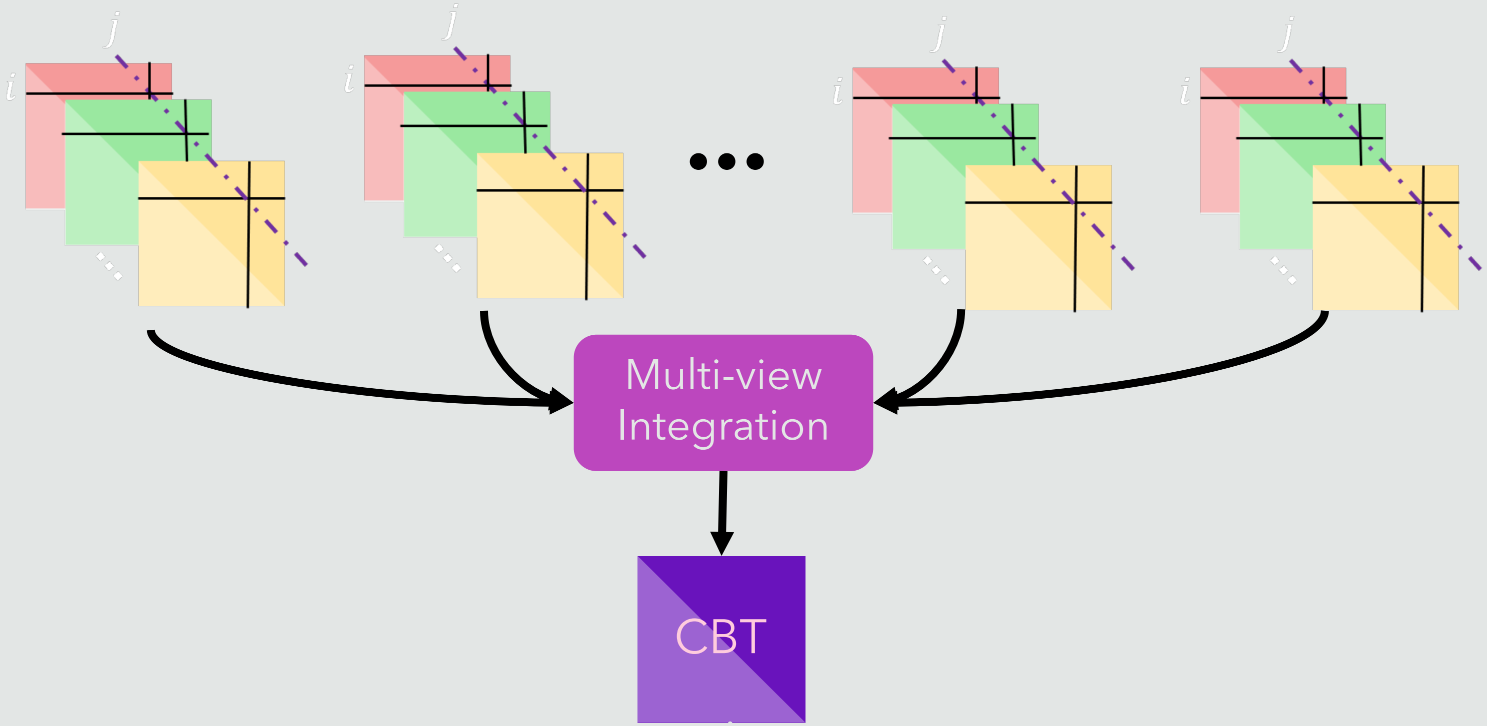
Generative learning

Generate population brain templates



Problem statement

Integrating a population of multi-view brain networks to estimate a connectional brain template (CBT)



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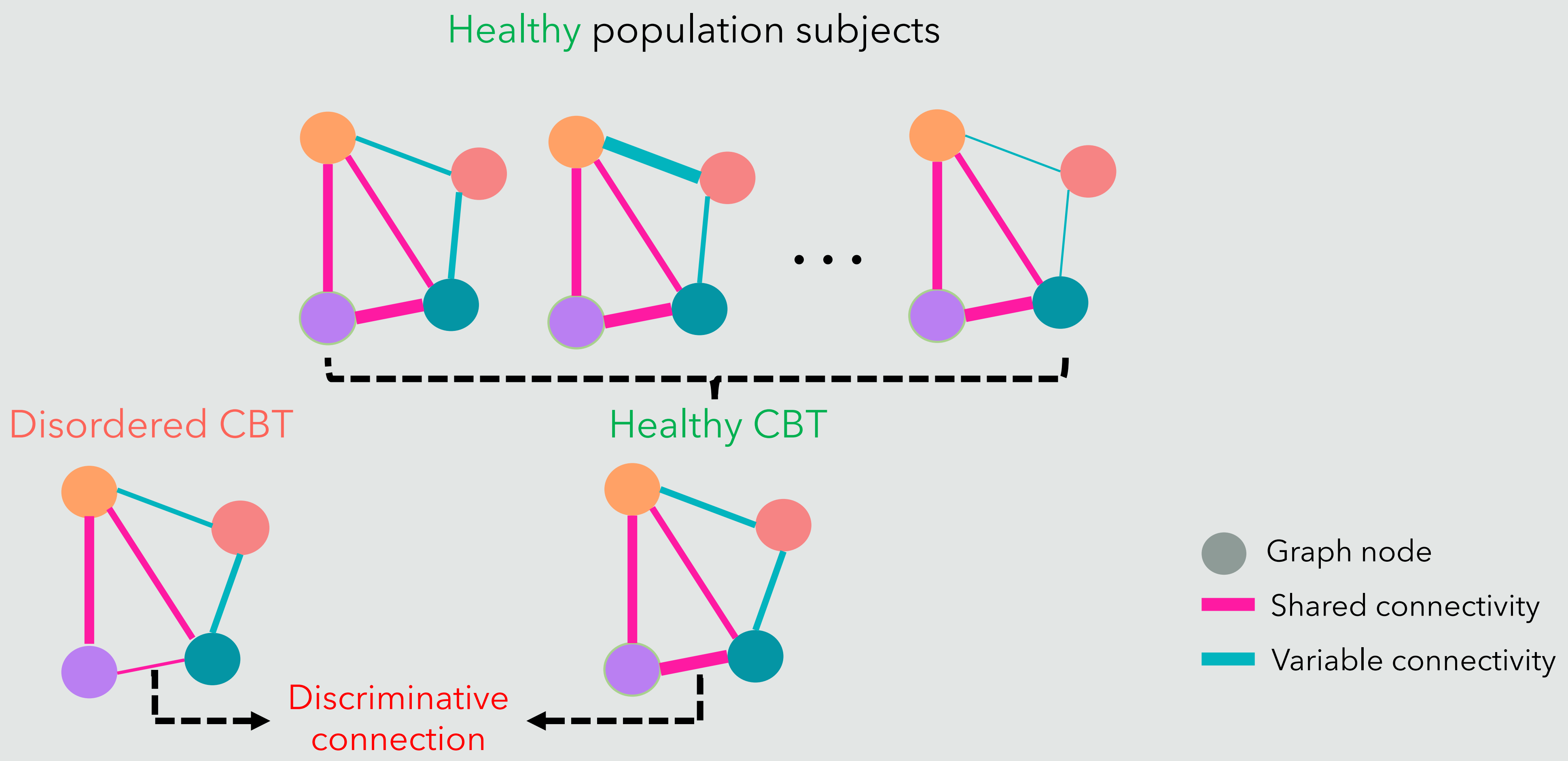
Generative learning

Generate population brain templates

Why CBTs are powerful?

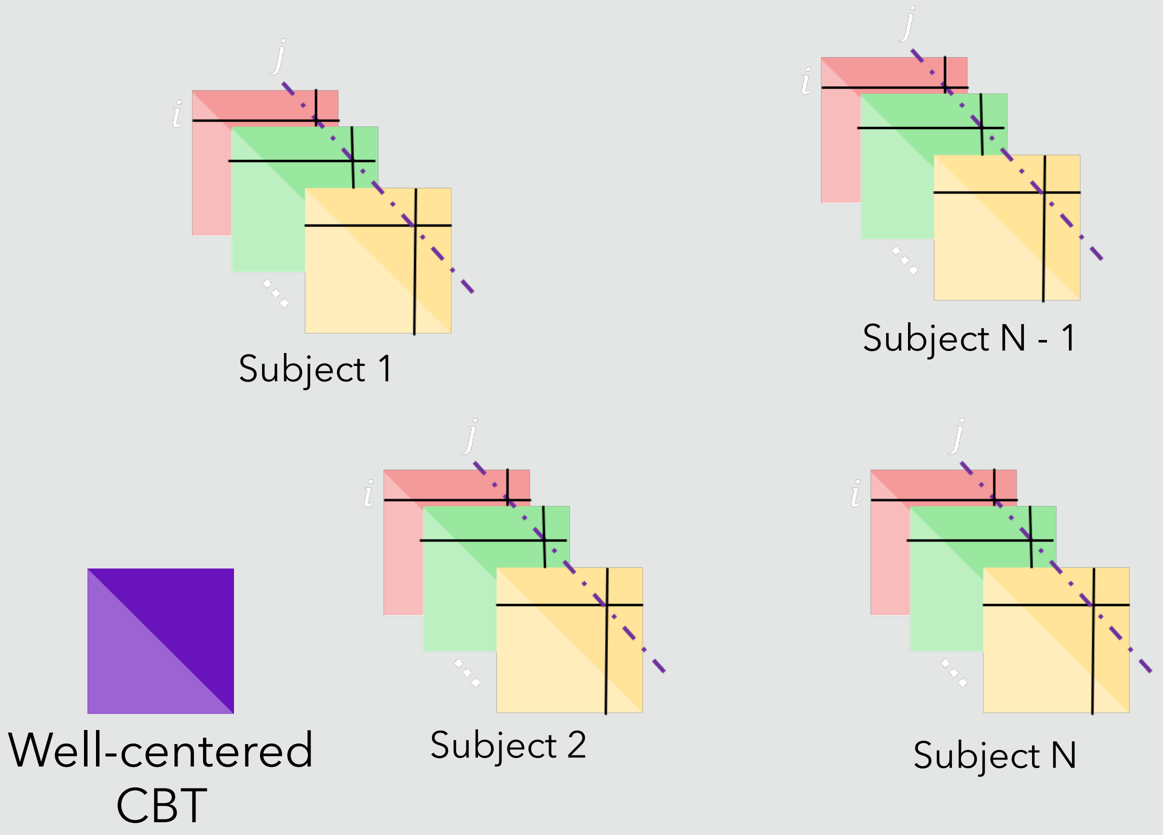
CBTs are powerful tools for group comparison studies and discovering the integral signature of an anomaly.

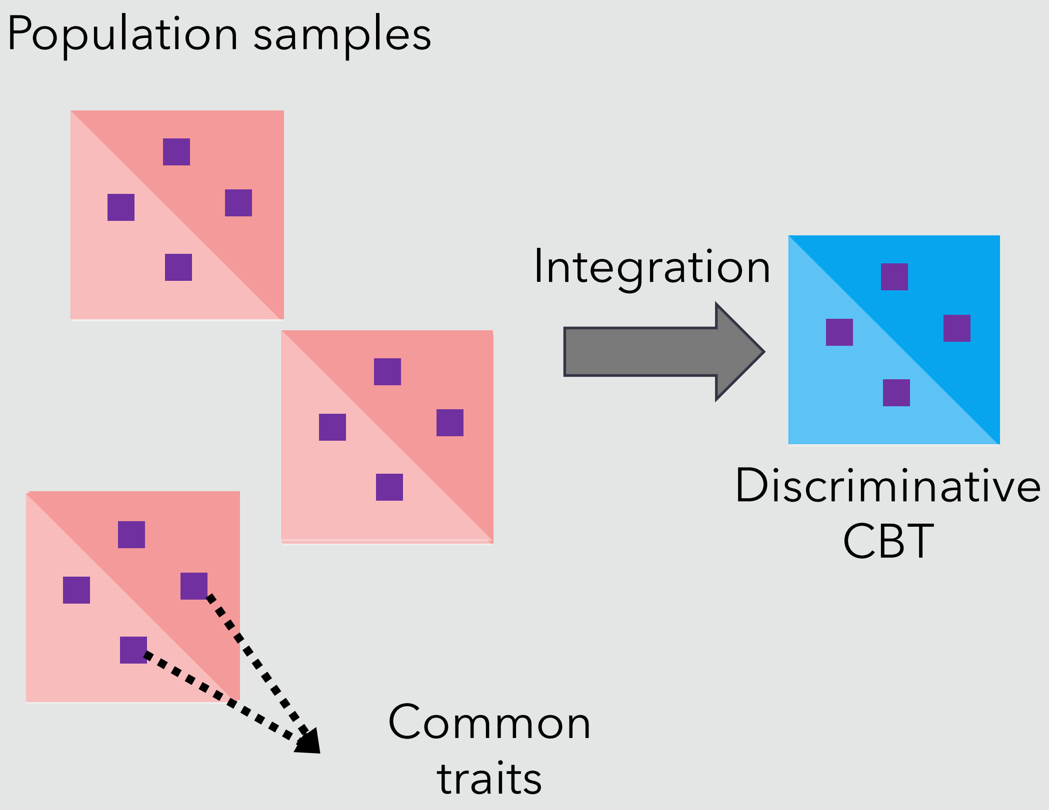


What is a good CBT?

Well-centered ➔ Occupies the center of a population

Discriminative ➔ Captures the unique and common traits of a population



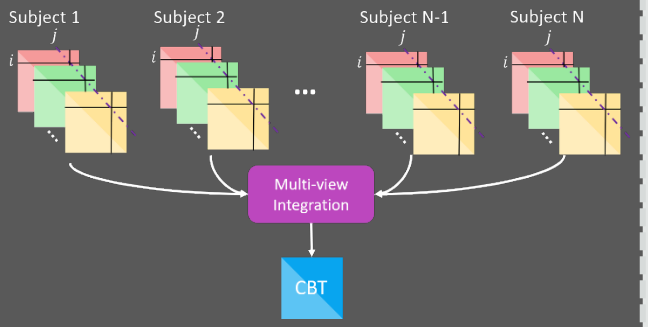


Deep Graph Normalizer: A Geometric Deep Learning Approach for Estimating Connectional Brain Templates

 Mustafa Burak Gürbüz and  Islem Rekik

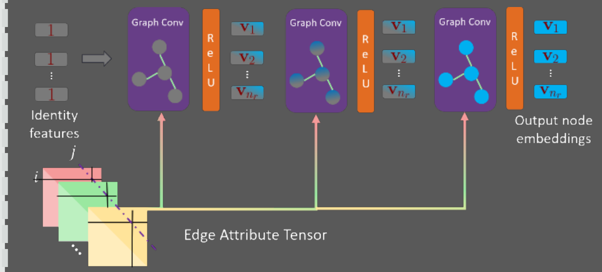
Problem statement

How can we integrate a set of multi-view graph population to estimate a connectional brain template (CBT)?

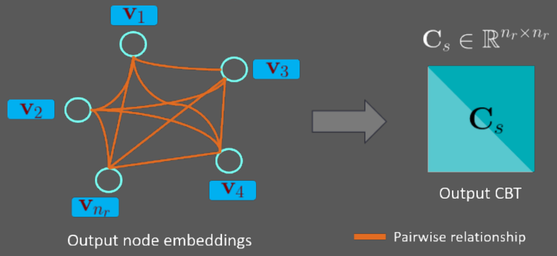


Proposed DGN solution

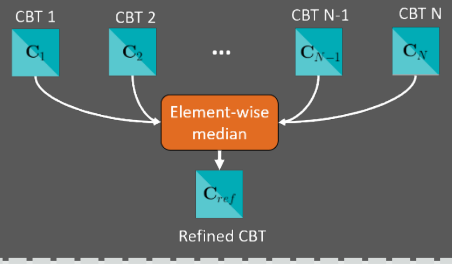
Node embedding learning



CBT generation



CBT refinement after training



Subject Normalization Loss (SNL)

$$SNL_s = \sum_{v=1}^{n_v} \sum_{i \in S} \| \mathbf{C}_s - \mathbf{T}_i^v \|_F \times \lambda_v$$

Frobenius distance between the CBT and randomly selected subjects

Results

Datasets

AD-LMCI* 77 subjects with 4 different views

NC-ASD** 310 subject with 6 different views

Centeredness evaluation

Frobenius distance between views of testing subjects and estimated CBT

DGN outperforms netNorm[1] across 40 comparison

Discriminativeness evaluation

The overlap rate between features selected by an MKL*** feature selection and CBT comparison

DGN more reproducible in discriminability than netNorm[1] across 4 classification tasks

This work is accepted at the MICCAI 2020 conference (early accept), Lima, Peru.

Gürbüz, M. B., & Rekik, I. (2021). MGN-Net: A multi-view graph normalizer for integrating heterogeneous biological network populations. Medical Image Analysis.

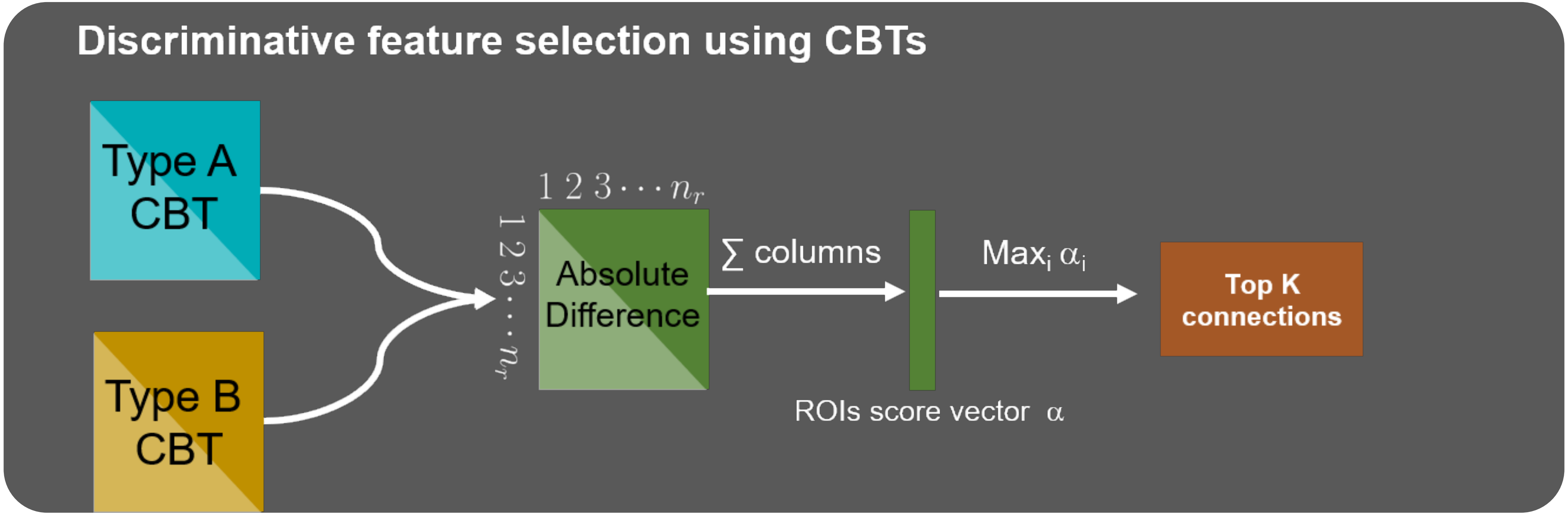
GitHub code: https://github.com/basiralab/DGN

[1]Dhifallah, S., Rekik, I. ,"Estimation of connectional brain templates using selective multiview network normalization. Medical Image Analysis" 59 (2019)

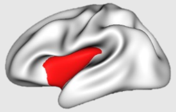
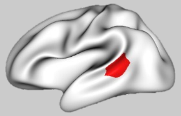
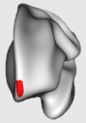
* **AD-LMCI:** Alzheimer's Diseases & Late Mild Cognitive Impairment ** **NC-ASD:** Normal Control & Autism Spectrum Disorder ***

Comparison methods and results (Discriminativeness)

We spot the top 5 most discriminative brain regions where a type-A CBT largely differs from a type-B CBT.

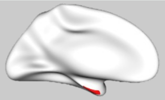


Discovery of most discriminative brain regions for ASD and NC

ASD/NC dataset	
Region of Interest	**Effect on brain**
Insula cortex (left hem.) 	Abnormalities in emotional and affective functions (Yamada et al., 2016)
Superior temporal sulcus (left hem.) 	Social perception impairment (Pelphrey et al., 2009)
Frontal pole (right hem.) 	Atypical right dominant face asymmetry (Hammond et al., 2008)

Yamada, T., et al. "Altered functional organization within the insular cortex in adult males with high- functioning autism spectrum disorder: evidence from connectivity-based parcellation." Molecular Autism 7 (2016)
Pelphrey, K., Carter, E., "Brain mechanisms for social perception lessons from autism and typical development" Annals of the New York Academy of Sciences 1145 (2009)
Hammond, P., et al., "Face-brain asymmetry in autism spectrum disorders." Molecular psychiatry 13 (2008)

Discovery of most discriminative brain regions for AD and LMCI

AD/LMCI dataset		
Region of Interest		**Effect on brain**
Temporal pole (left hem.)		Pathological changes in temporal pole (Arnold et al., 1994)
Entorhinal cortex (right hem.)		Greater atrophy in the right entorhinal cortex in AD patients (Zhou et al., 2015)

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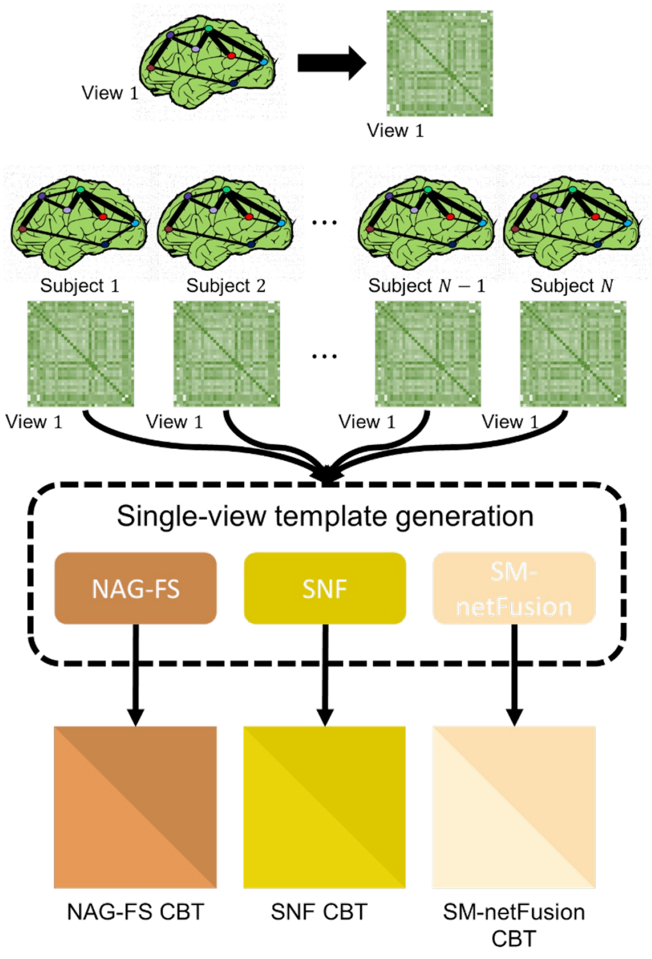
Arnold, S.E., Hyman, B.T., Van Hoesen, G.W., "Neuropathologic Changes of the Temporal Pole in Alzheimer's Disease and Pick's Disease." Archives of Neurology 51 (1994)
Zhou, M., et al., "Entorhinal cortex: A good biomarker of mild cognitive impairment and mild Alzheimer's disease." Reviews in the neurosciences 27 (2015)

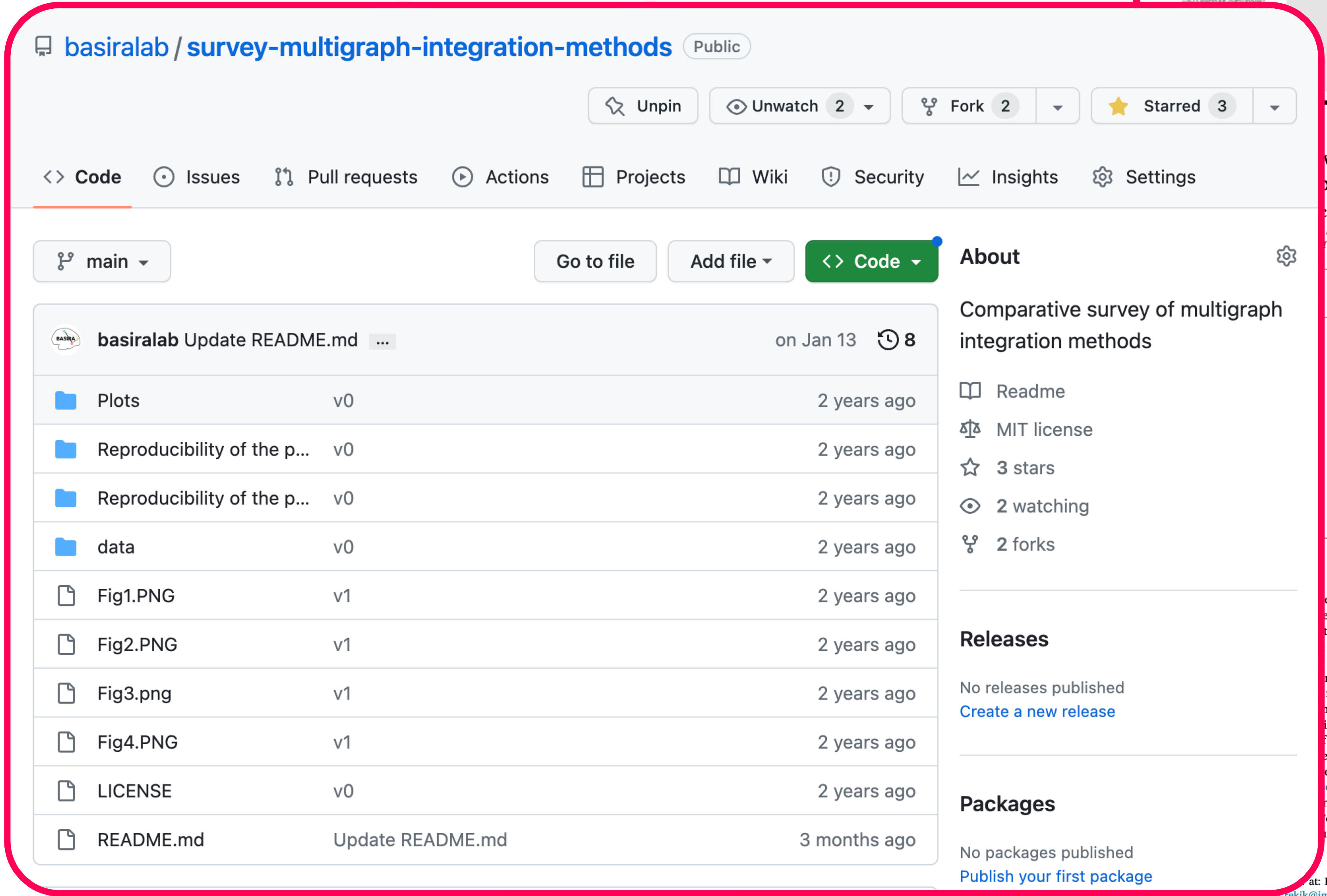
Comparative survey of multigraph integration methods for holistic brain connectivity mapping

Nada Chaari

a)



Chaari, N., Akdağ, H.C. and Rekik, I., 2023. Comparative survey of multigraph integration methods for holistic brain connectivity mapping. *Medical Image Analysis*.




Medical Image Analysis 85 (2023) 102741

Contents lists available at ScienceDirect

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journal homepage: www.elsevier.com/locate/media

…vey of multigraph integration methods for holistic brain …pping

…e Camgöz Akdağ [b], Islem Rekik [a,c,*]

… and Informatics, Istanbul Technical University, Istanbul, Turkey
…Technical University, Istanbul, Turkey
… and Innovation Hub, Imperial College London, London, UK

A B S T R A C T

One of the greatest scientific challenges in network neuroscience is to create a representative map of a population of heterogeneous brain networks, which acts as a connectional fingerprint. The connectional brain template (CBT), also named network atlas, presents a powerful tool for capturing the most representative and discriminative traits of a given population while preserving its topological patterns. The idea of a CBT is to integrate a population of heterogeneous brain connectivity networks, derived from different neuroimaging modalities or brain views (e.g., structural and functional), into a unified holistic representation. Here we review current state-of-the-art methods designed to estimate well-centered and representative CBT for populations of single-view and multi-view brain networks. We start by reviewing each CBT learning method, then we introduce the evaluation measures to compare CBT representativeness of populations generated by single-view and multigraph integration methods, separately, based on the following criteria: Centeredness, biomarker-reproducibility, node-level similarity, global-level similarity, and distance-based similarity. We demonstrate that the deep graph normalizer (DGN) method significantly outperforms other multi-graph and all single-view integration methods for estimating CBTs using a variety of healthy and disordered datasets in terms of centeredness, reproducibility (i.e., graph-derived biomarkers reproducibility that disentangle the typical from the atypical connectivity variability), and preserving the topological traits at both local and global graph-levels.

…e-scale neuroimaging datasets using non-…e imaging (MRI) has substantially increased …traordinarily complex, yet highly organized … human neural architecture; the so-called …Sporns, 2009; Fornito et al., 2015). Using …ments, one can derive, for the same subject, …networks (Guan et al., 2020). Having such …e can represent each subject by a multi-…iew corresponds to an imaging modality …f brain connectivity network, each node of …egion and the edge between two nodes rep-…een pairs of brain regions (Acosta-Mendoza …en, 2011). A multigraph structure encapsu-…multiple relations between two anatomical …or instance, connections in brain networks …nctional magnetic resonance brain imaging (rsfMRI) encode correlations in functional activity among brain regions, whereas diffusion tensor imaging (DTI) networks provide information concerning structural connections (i.e., white matter fiber paths) between these nodes (Tyan et al., 2017; Jiang et al., 2020; Dadashkarimi et al., 2019). Joining both networks results in two different views of brain connectivity, leading to more insights into the brain as a complex interconnected system.

Understanding how the brain's structural, morphological, and functional levels interlink offers a more comprehensive picture of the brain facets construction (Bassett and Sporns, 2017). For instance, (Farahani et al., 2019) provides an overview of the existing functional and effective connectivity methods used to construct the brain network. However, analyzing such *multi-modal* (also *multi-view*) connectomic dataset together remains challenging due to the large inter-modality variations across different views of connectivity networks and the heterogeneity of brain networks across population samples (Van Essen and Glasser, 2016; Verma et al., 2019). Nonetheless, mapping brain

… at: BASIRA lab, Faculty of Computer and Informatics, Istanbul Technical University, Istanbul, Turkey.
E-mail address: i.rekik@imperial.ac.uk (I. Rekik).
URL: http://basira-lab.com/ (I. Rekik).

https://doi.org/10.1016/j.media.2023.102741
Received 30 December 2021; Received in revised form 27 December 2022; Accepted 3 January 2023
Available online 6 January 2023

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https://github.com/basiralab/survey-multigraph-integration-methods

Generative learning

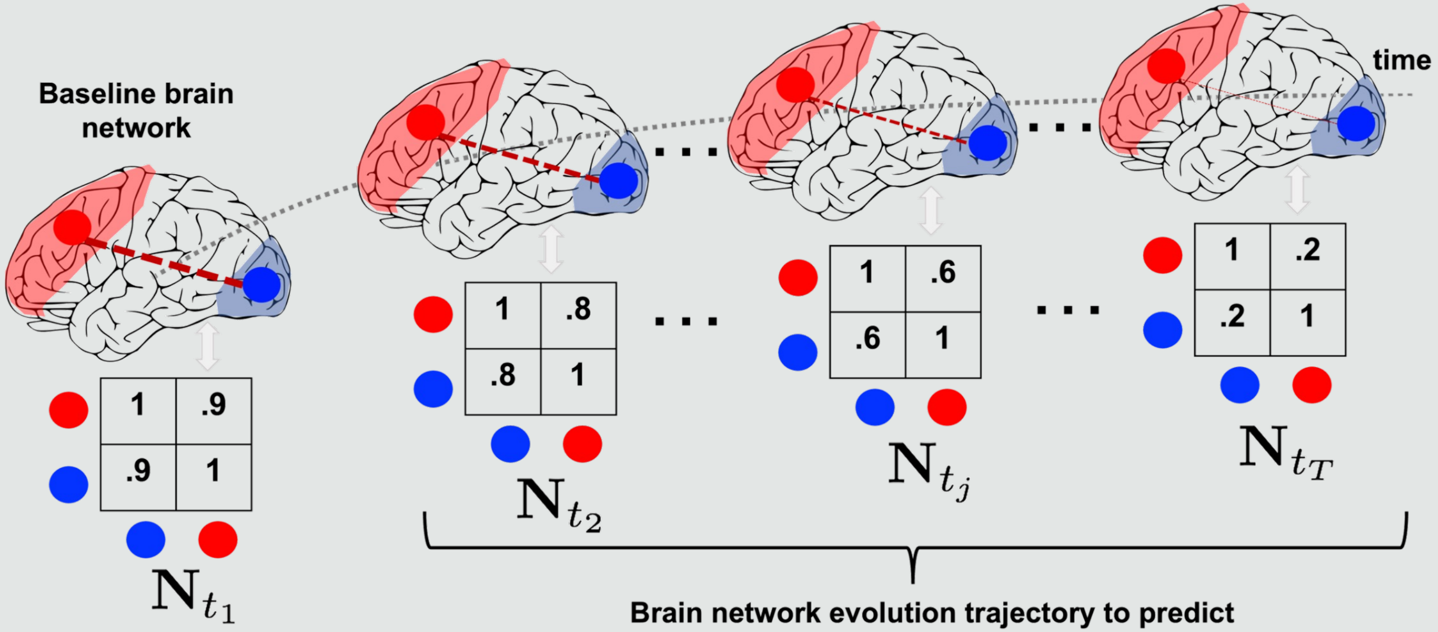
Generate *multidimensional* brains

Generate connectional brain templates

Federated learning

Federate to generate the future of the brain

Cross-time generation & federation



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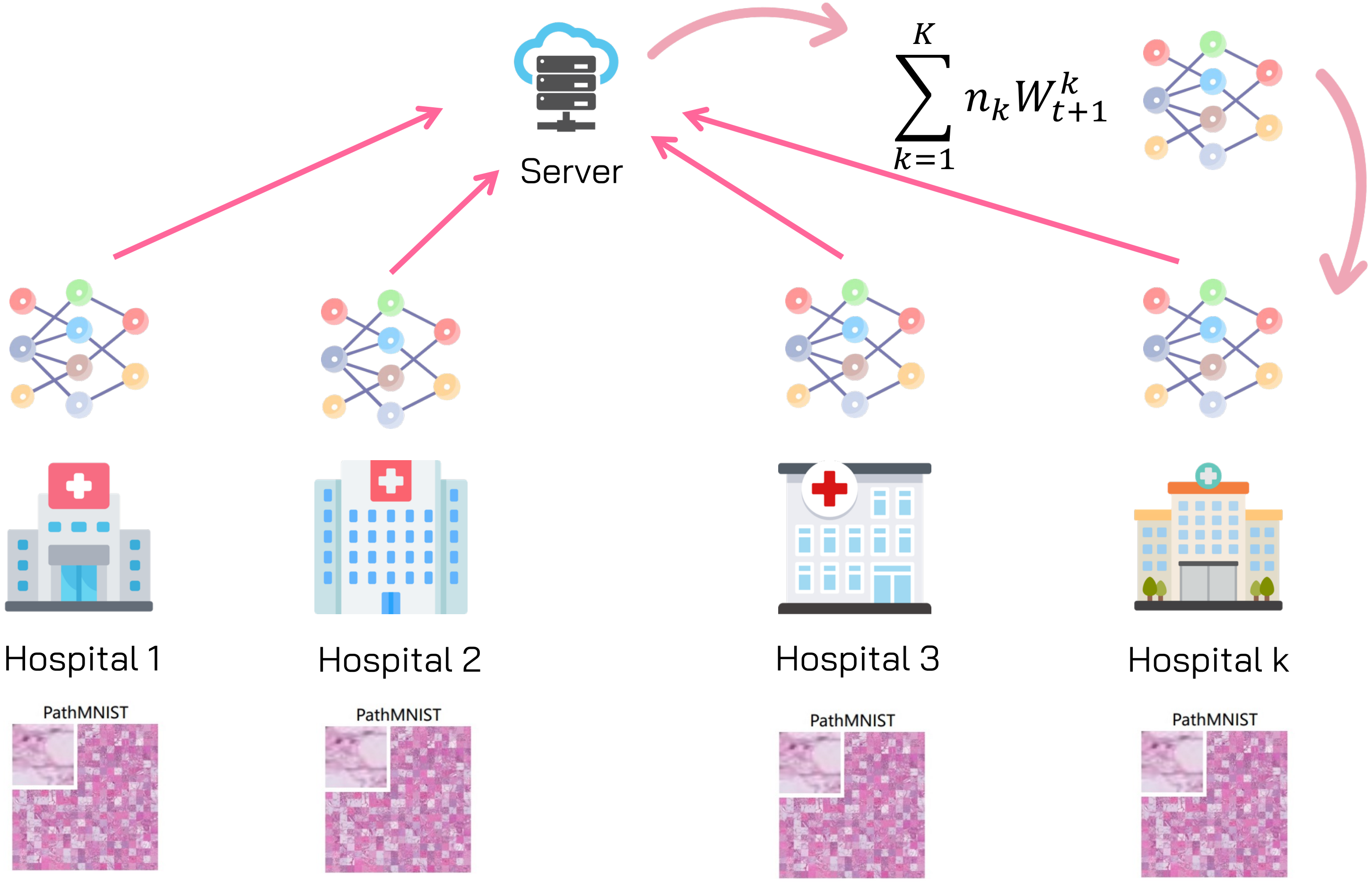
Federated learning

Can we learn better together *without sharing our data*?

Yes, with federated learning!

➔ A decentralized framework for training global models without sharing local datasets, ensuring privacy and security.

FedAvg



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McMahan, Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." Artificial intelligence and statistics. PMLR, 2017.

Federated learning

Full-stack federated learning

Low-cost and privacy-preserving

New system protects patient data through federated learning

Share Share Share

Publications & research news

25 January 2024

The Big Data Institute along with the collaborators have developed a new, easy-to-use technique for hospitals to contribute to developing artificial intelligence (AI) models, without patient data leaving the hospital's premises.

A scalable federated learning solution for secondary care using low-cost microcomputing: privacy-preserving development and evaluation of a COVID-19 screening test in UK hospitals

Andrew A S Soltan, Anshul Thakur, Jenny Yang, Anoop Chauhan, Leon G D'Cruz, Phillip Dickson, Marina A Soltan, David R Thickett, David W Eyre, Tingting Zhu, David A Clifton

Summary

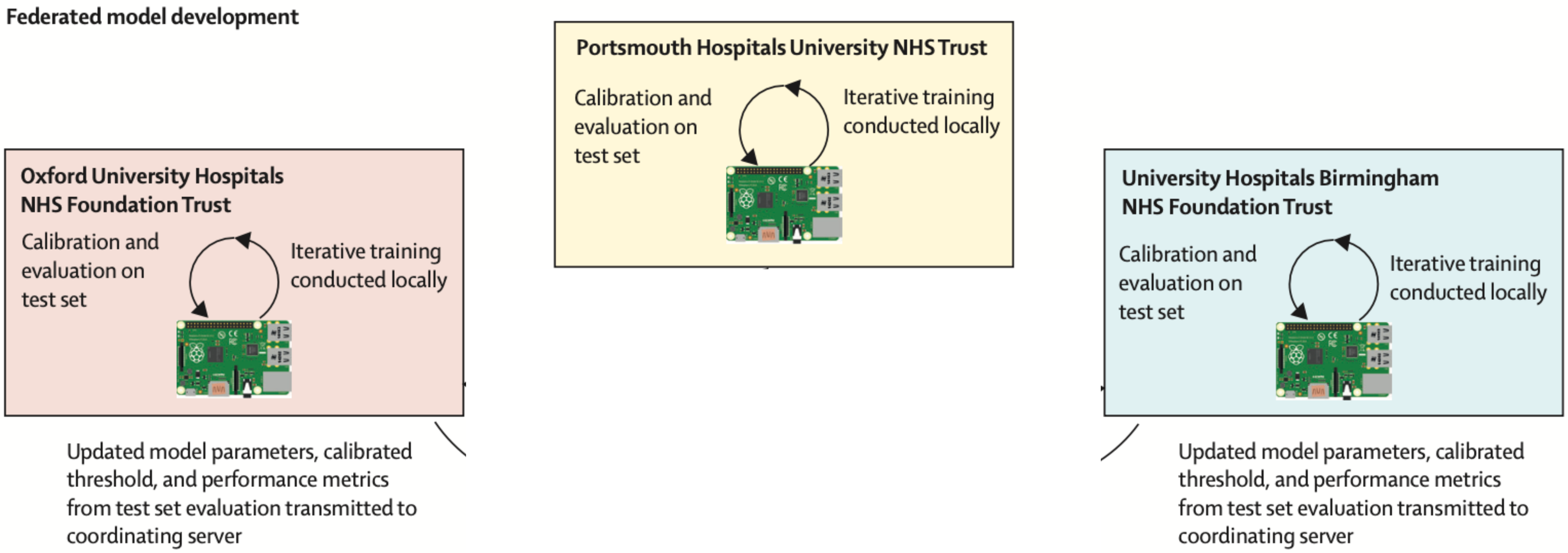
Background Multicentre training could reduce biases in medical artificial intelligence (AI); however, ethical, legal, and technical considerations can constrain the ability of hospitals to share data. Federated learning enables institutions to participate in algorithm development while retaining custody of their data but uptake in hospitals has been limited, possibly as deployment requires specialist software and technical expertise at each site. We previously developed an artificial intelligence-driven screening test for COVID-19 in emergency departments, known as CURIAL-Lab, which uses vital signs and blood tests that are routinely available within 1 h of a patient's arrival. Here we aimed to federate our COVID-19 screening test by developing an easy-to-use embedded system—which we introduce as full-stack federated learning—to train and evaluate machine learning models across four UK hospital groups without centralising patient data.

BASIRA

https://www.ndm.ox.ac.uk/news/new-system-protects-patient-data-through-federated-learning – https://www.thelancet.com/journals/landig/article/PIIS2589-7500(23)00226-1/fulltext

Federated learning

Full-stack federated learning

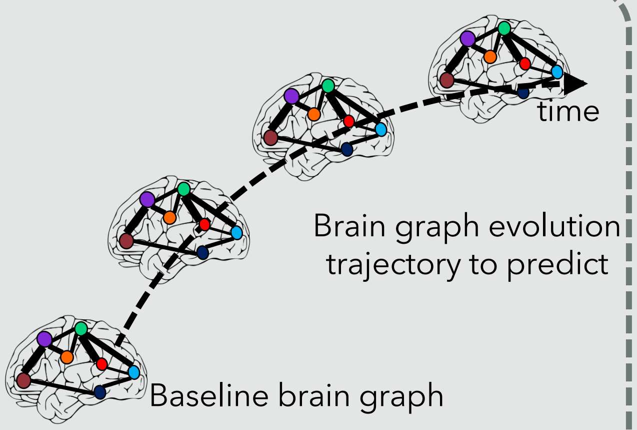


Cross-domain | **Cross-resolution** | **Cross-time**

Federated Time-dependent GNN Learning from Brain Connectivity Data with Missing Timepoints

Zeynep Gurler , and Islem Rekik 

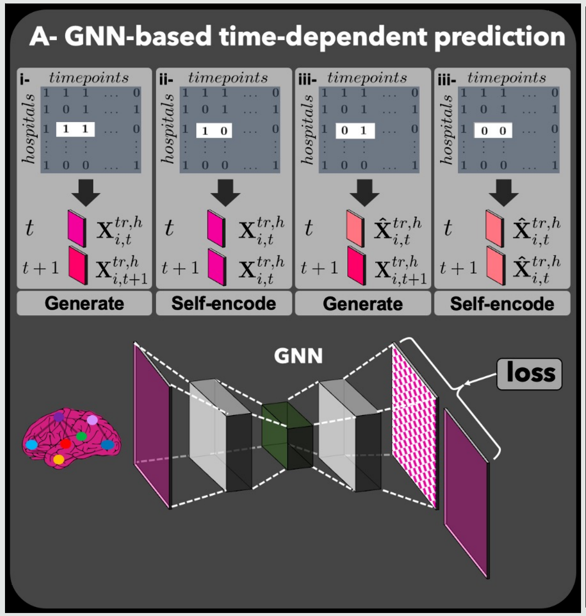
Problem statement

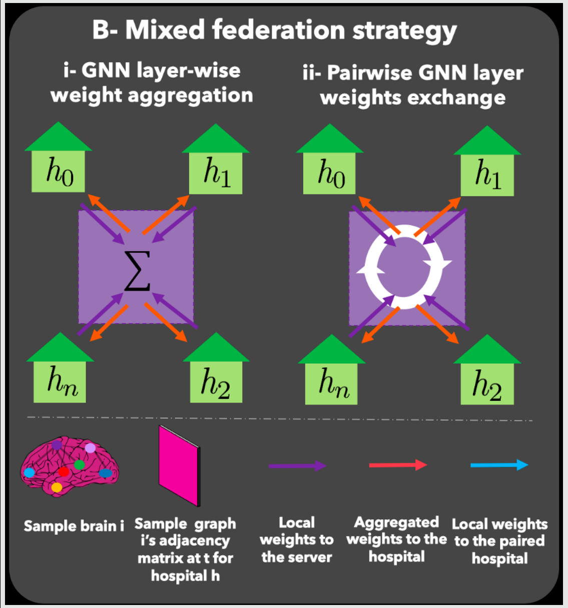


How to predict its evolution trajectory over time in a federated manner?

☹ *Limitation* ➔ Absence of federated models for time-dependent graph evolution prediction

Proposed 4D-FED-GNN+





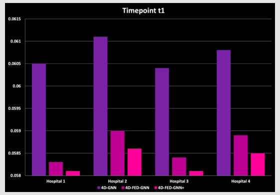
Results

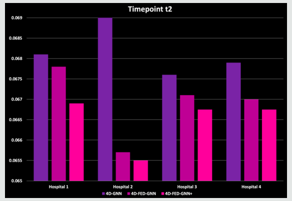
Dataset

- We used 113 subjects from the OASIS-2 longitudinal dataset.
- Each subject was scanned on two or more visits, separated by at least one year.
- We used 5-fold CV for evaluation.
- In each run: 1 fold for testing and remaining 4 each allocated to a local hospital.

Comparison

a) 4D-GNN: the vanilla method where hospitals train their local data without federation.
b) 4D-FED-GNN: single federation strategy based on GNN layer-wise weight aggregation.





This work is part of my research project at BASIRA lab: https://basira-lab.com
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GitHub code: https://github.com/basiralab/4D-FED-GNN

[1]Tekin, A., et al. "Recurrent brain graph mapper for predicting time-dependent brain graph evaluation trajectory." Domain Adaptation and Representation Transfer, and Affordable Healthcare and AI for Resource Diverse Global Health (2021)
[2]Marcus, D.S., et al. , Fotenos, A.F., Csernansky, J.G., Morris, J.C., Buckner, R.L.: Open Access series of imaging studies: longitudinal MRI data in nondemented and demented older adults. Journal of cognitive neuroscience

Cross-domain | Cross-resolution | Cross-time

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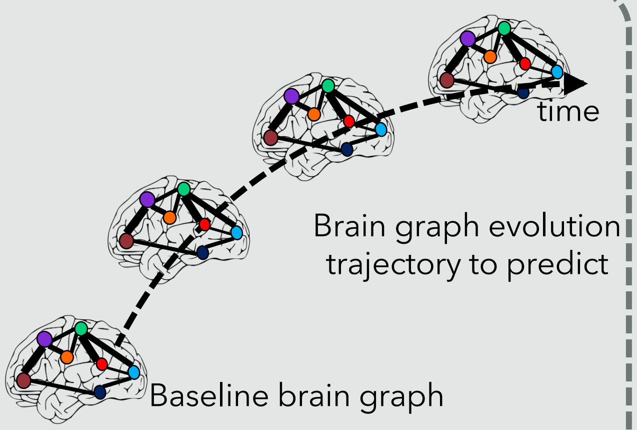

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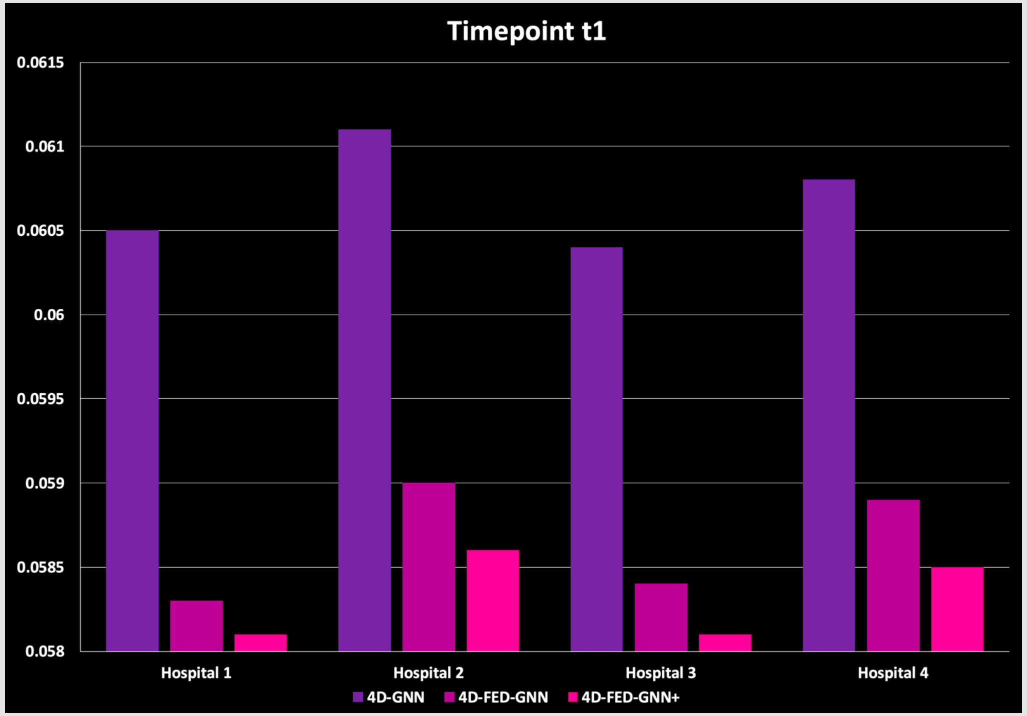
Bar plots



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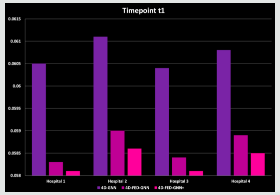

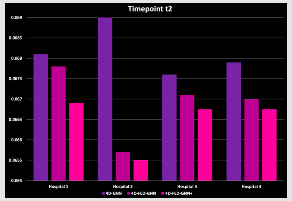

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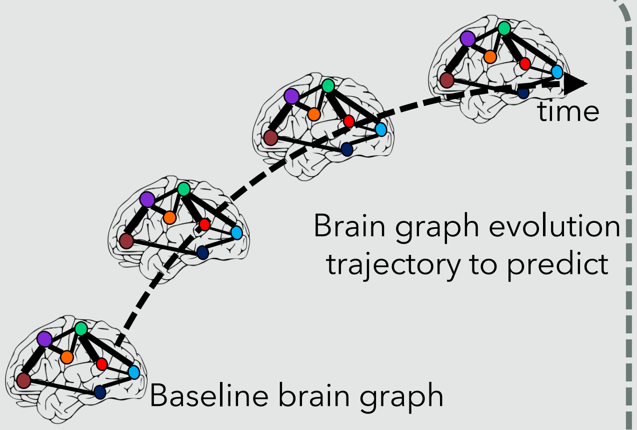
Federated Time-dependent GNN Learning from Brain Connectivity Data with Missing Timepoints

Zeynep Gurler , and Islem Rekik 

Problem statement | Bar plots | Results



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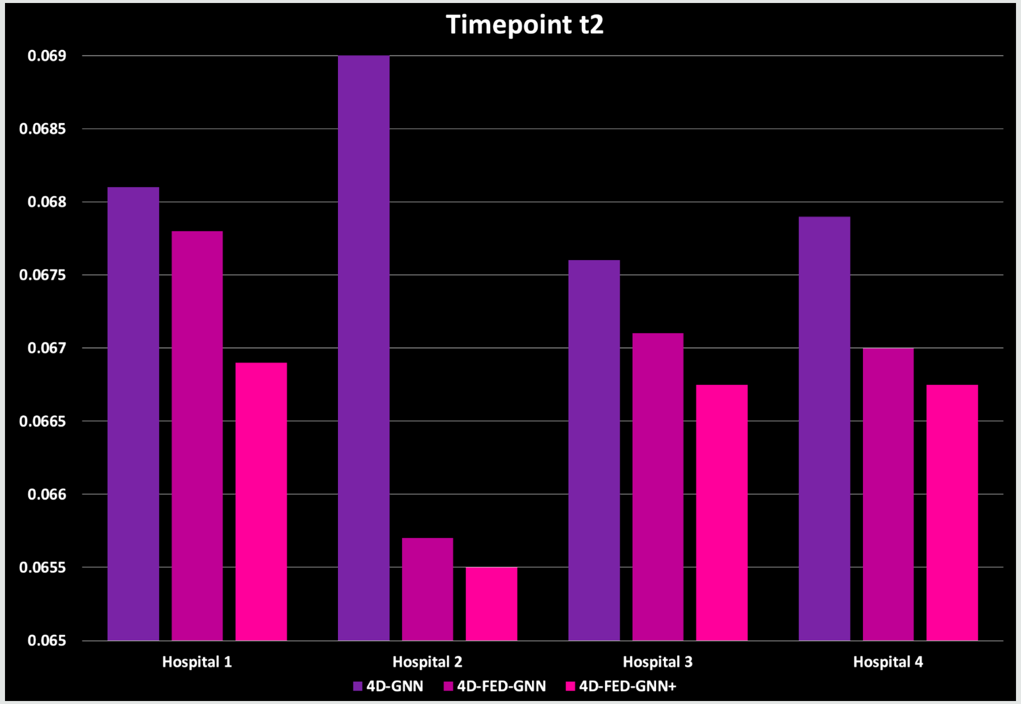

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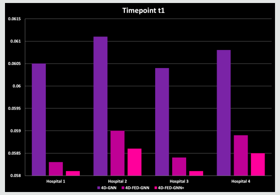

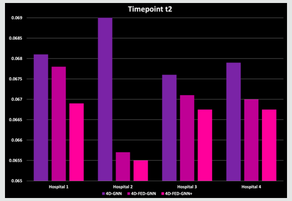

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Federated Time-dependent GNN Learning from Brain Connectivity Data with Missing Timepoints

Zeynep Gurler and Islem Rekik

BASIRA lab, Faculty of Computer and Informatics, Istanbul Technical University, Istanbul, Turkey

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This work is part of my research project at BASIRA lab:
https://basira-lab.com/prime-miccai-2022/
GitHub code: https://github.com/basiralab/4D-FED-GNN

4D-FED-GNN code

Federated Time-dependent GNN Learning from Brain Connectivity Data with Missing Timepoints

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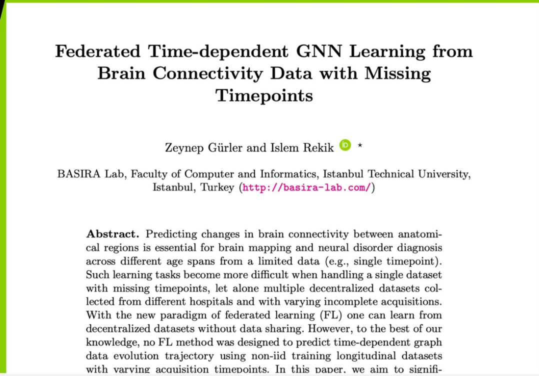
http://basira-lab.com/prime-miccai22/
GitHub code: https://github.com/basiralab/4D-FED-GNN

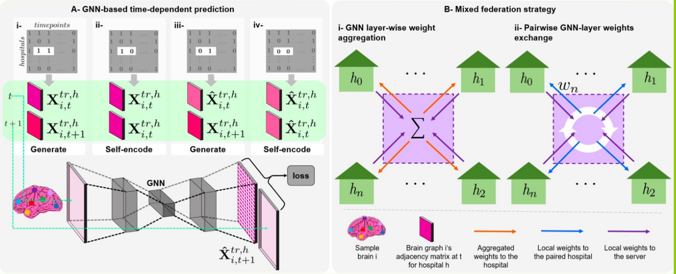


Federated Time-dependent GNN Learning from Brain Connectivity Data with Missing Timepoints

Zeynep Gürler and Islem Rekik *

BASIRA Lab, Faculty of Computer and Informatics, Istanbul Technical University, Istanbul, Turkey (http://basira-lab.com/)

Abstract. Predicting changes in brain connectivity between anatomical regions is essential for brain mapping and neural disorder diagnosis across different age spans from a limited data (e.g., single timepoint). Such learning tasks become more difficult when handling a single dataset with missing timepoints, let alone multiple decentralized datasets collected from different hospitals and with varying incomplete acquisitions. With the new paradigm of federated learning (FL) one can learn from decentralized datasets without data sharing. However, to the best of our knowledge, no FL method was designed to predict time-dependent graph data evolution trajectory using non-iid training longitudinal datasets with varying acquisition timepoints. In this paper, we aim to signifi-



Generative learning	Generate *multidimensional* brains	Generate connectional brain templates
Federated learning	Federate to generate the future of the brain	Federate heterogeneous diagnostic tasks

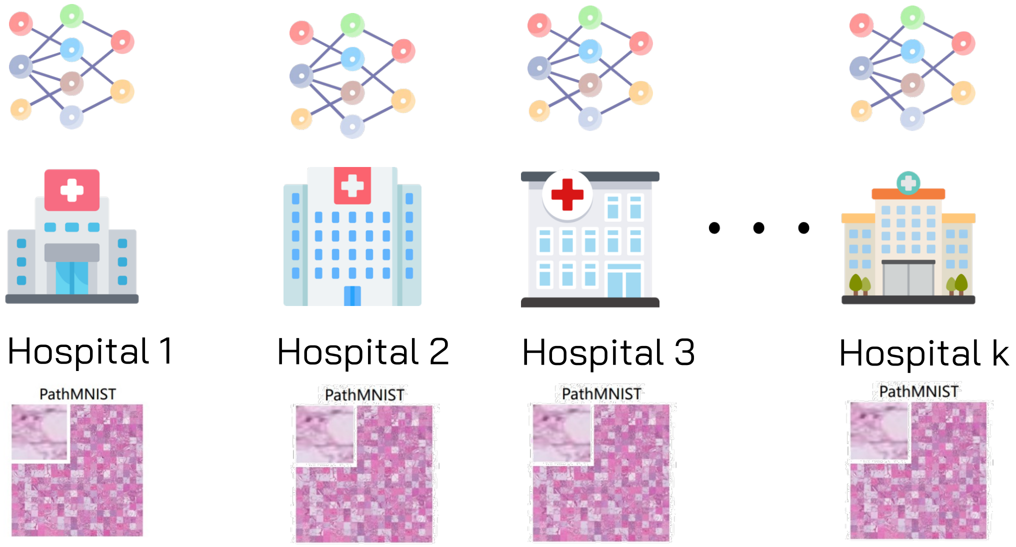
Federated learning

Federate heterogeneous diagnostic tasks

UniFed: A Universal Federation of a Mixture of Highly Heterogeneous Medical Image Classification Tasks

Atefe Hassani

same dataset types = same learning task (i.e., disease)



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This work is accepted at the MICCAI MLMI 2024 conference (poster presentation), Marrakesh, Morocco.

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Federated learning

Federate heterogeneous diagnostic tasks

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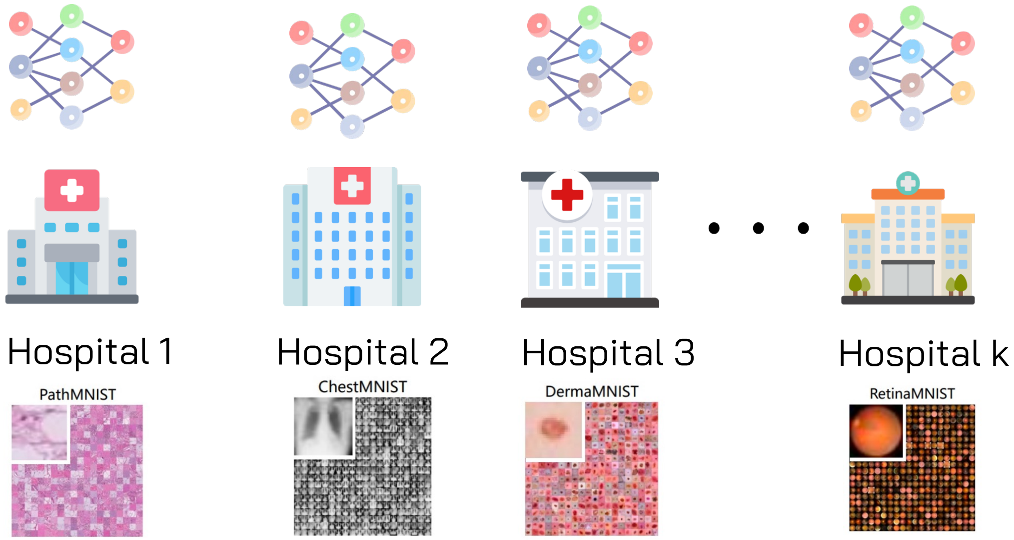

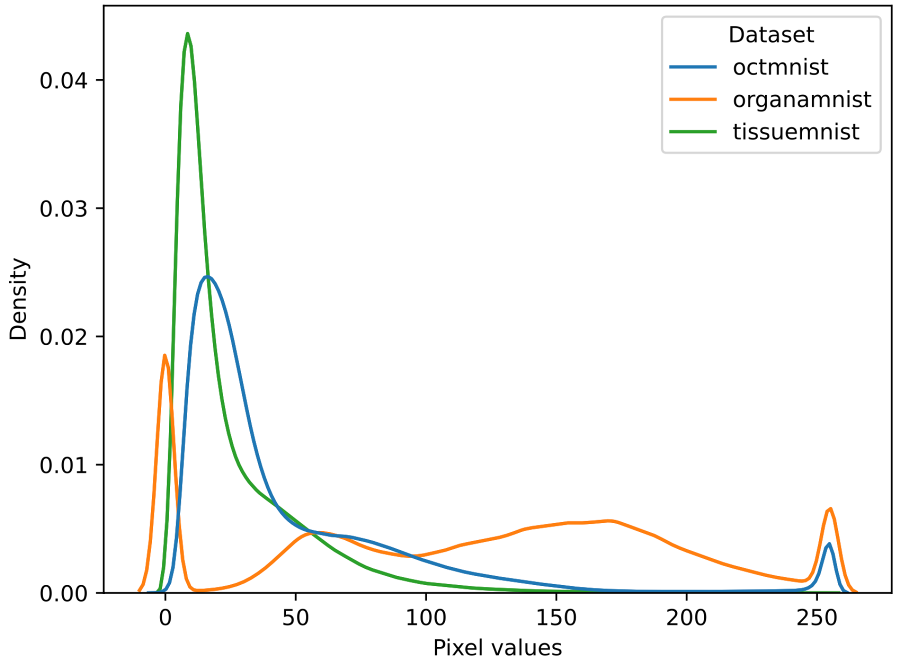

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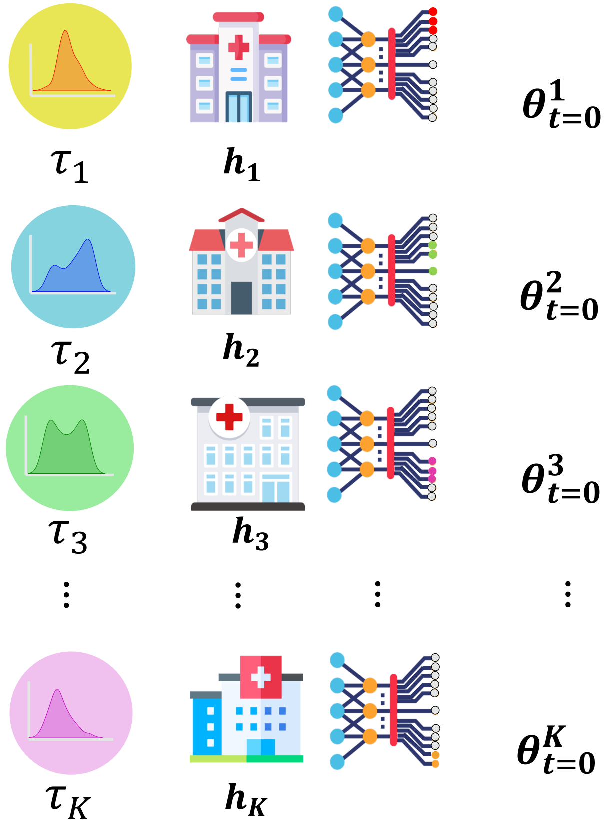
Federated learning

Federate heterogeneous diagnostic tasks

Proposed UniFed learning architecture

Initial client training



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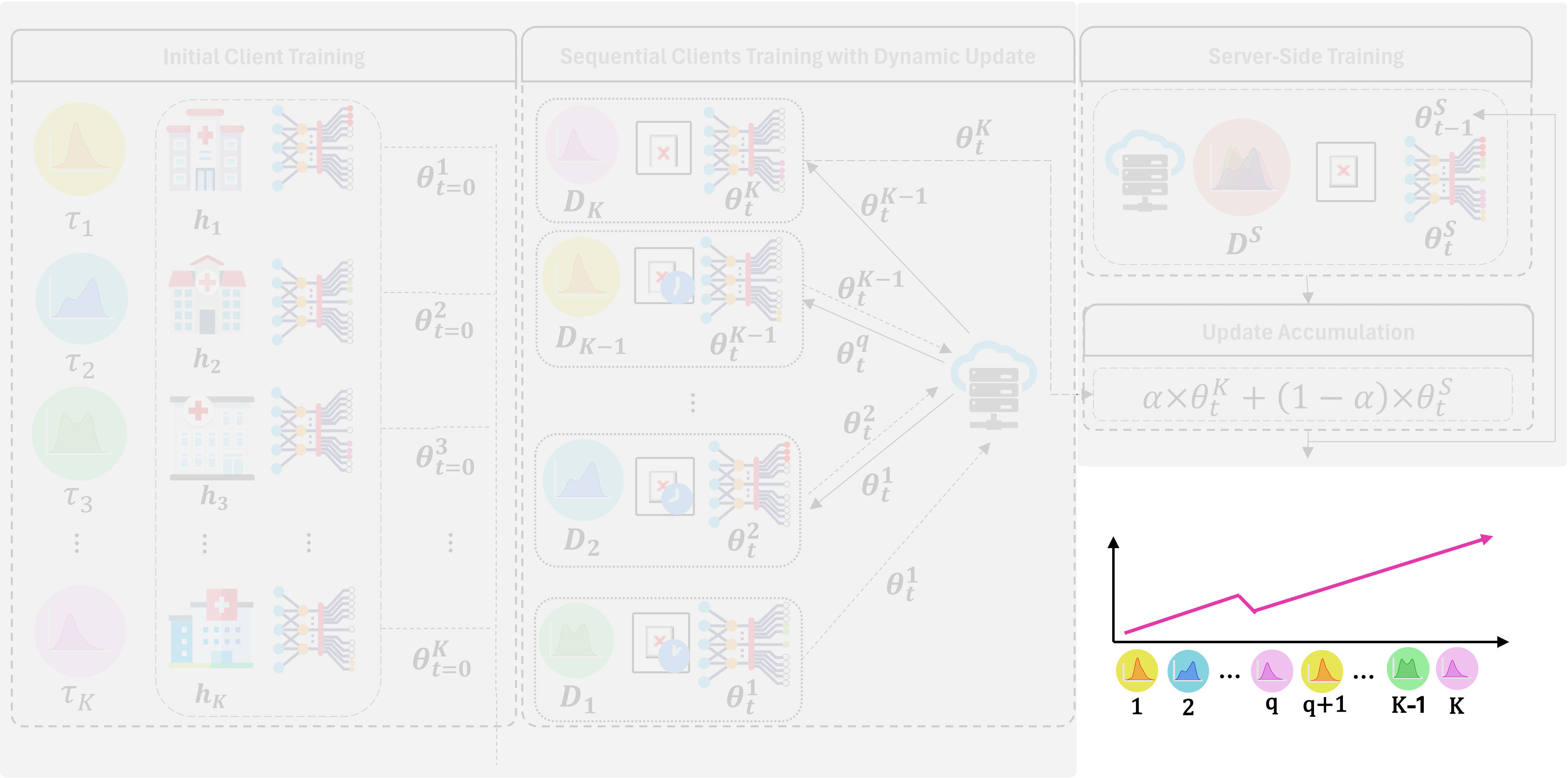
Federated learning

Federate heterogeneous diagnostic tasks

Proposed UniFed learning architecture

Hospital (client) ordering

Atefe Hassani



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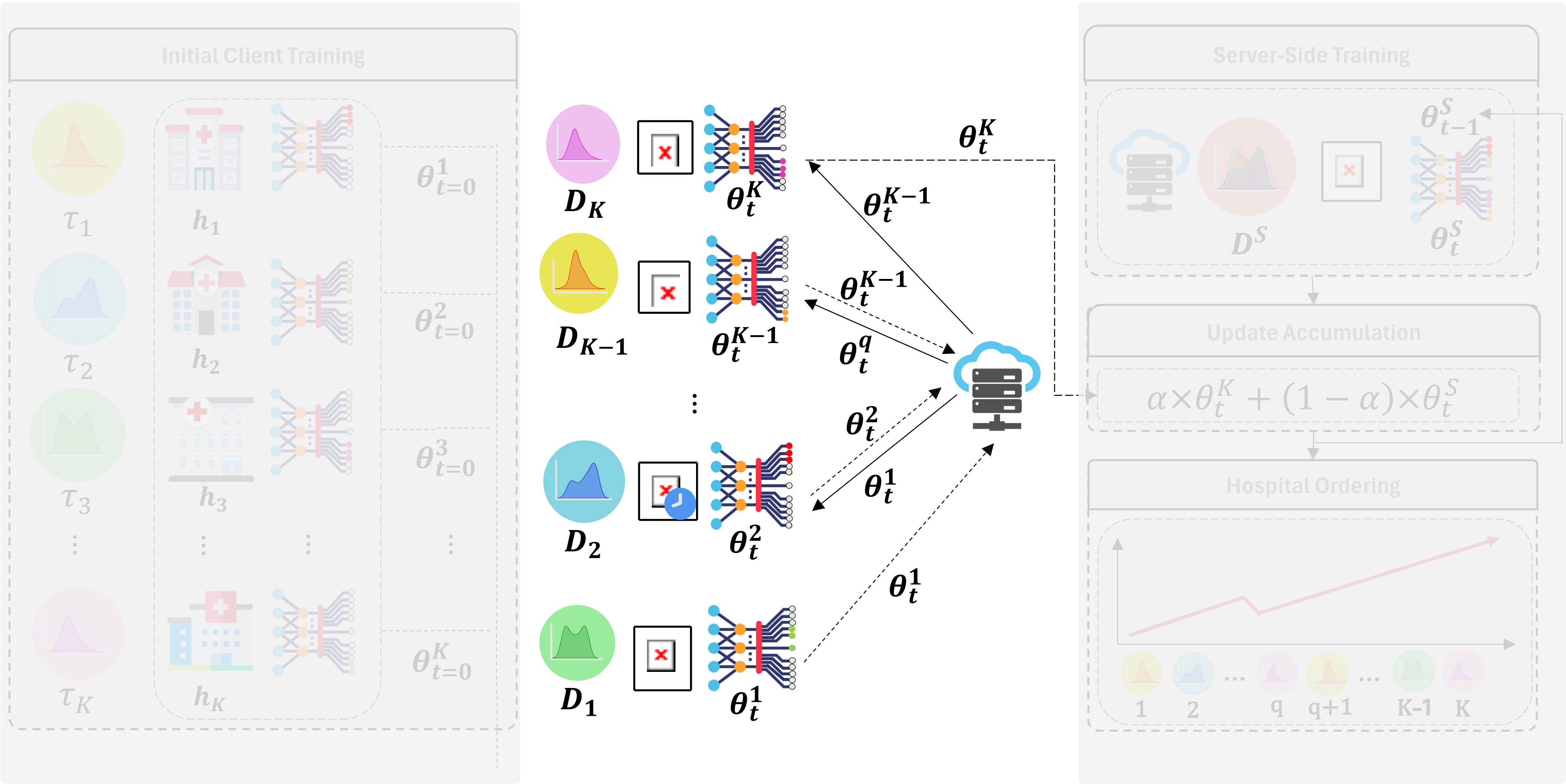
Federated learning

Federate heterogeneous diagnostic tasks

Proposed UniFed learning architecture

Sequential client training + dynamic update



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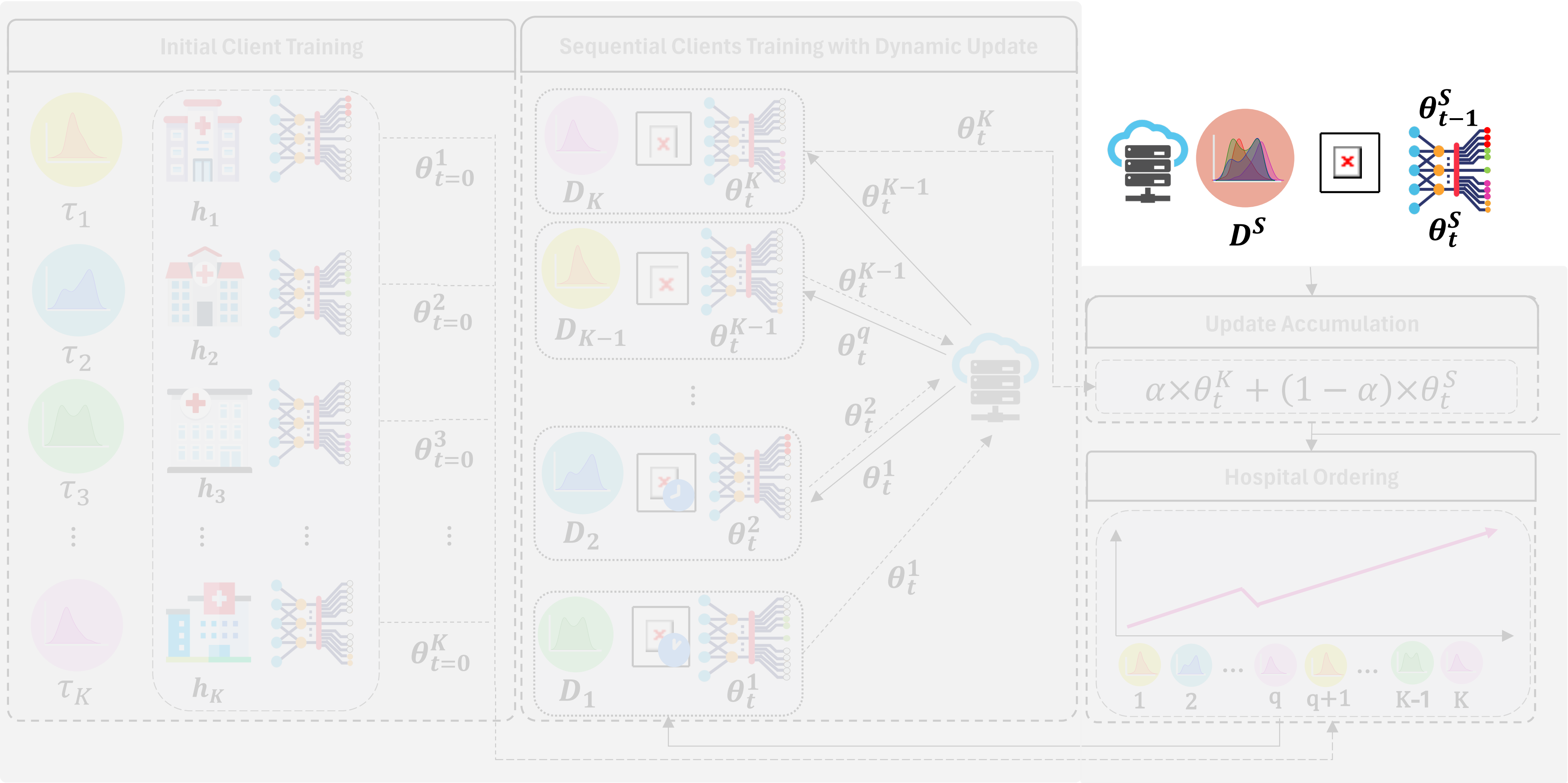
Federated learning

Federate heterogeneous diagnostic tasks

Proposed UniFed learning architecture

Server-side training



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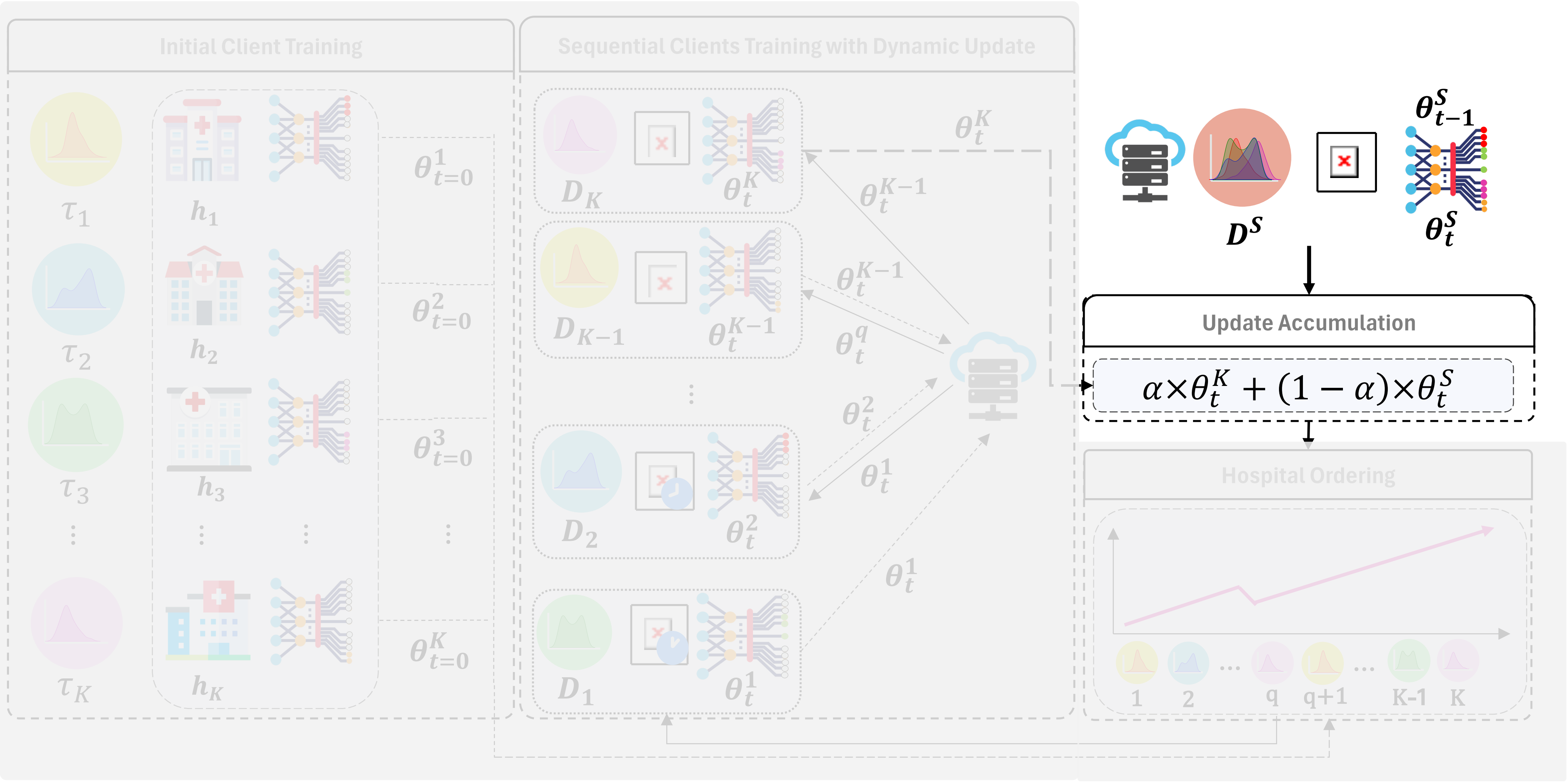
Federated learning

Federate heterogeneous diagnostic tasks

Proposed UniFed learning architecture

Server-side learning and global model update



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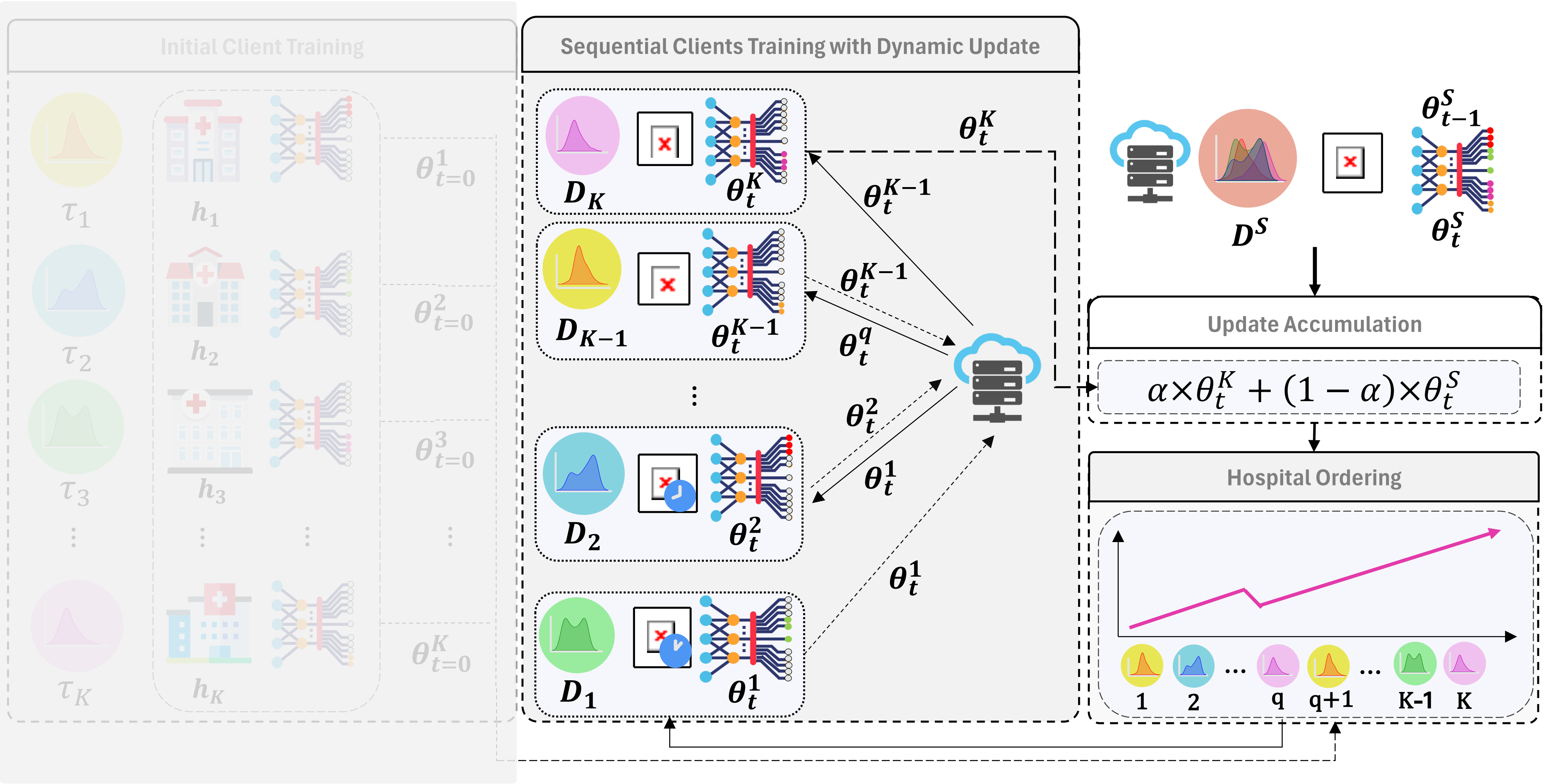
Federated learning

Federate heterogeneous diagnostic tasks

Proposed UniFed learning architecture

Universal federated learning

Atefe Hassani



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Federated learning

Federate heterogeneous diagnostic tasks

Benchmarking varying models and federation paradigms

Atefe Hassani

Table 1. Comparison of model performance (%) in strongly and moderately Non-IID settings.

Data Partition	Method	CNN Acc	CNN F1	CNN Sens	CNN Spec	VGG11 Acc	VGG11 F1	VGG11 Sens	VGG11 Spec	ResNet18 Acc	ResNet18 F1	ResNet18 Sens	ResNet18 Spec
	NoFed	68.17	54.15	56.42	96.63	77.10	65.90	67.31	97.00	74.94	61.26	63.39	96.94
Strongly Non-IID	FedAvg [1]	38.44	24.88	23.89	96.85	4.90	2.33	1.69	96.18	9.79	6.82	9.13	96.10
	FedProx [32]	37.92	23.37	22.32	**96.86**	4.06	2.12	1.78	96.17	9.68	5.45	7.28	96.08
	FedSeq [33]	10.73	1.05	0.59	95.73	26.46	17.24	23.42	96.20	22.81	18.60	23.31	96.09
	UniFed	**69.37**	**55.05**	**55.87**	96.75	**50.52**	**37.41**	**39.18**	**96.56**	**46.77**	**32.45**	**34.32**	**96.45**
Moderately Non-IID	FedAvg [1]	24.58	22.73	24.24	93.00	6.04	1.83	1.83	**94.1**	10.10	5.61	6.59	92.58
	FedProx [32]	24.58	22.72	24.22	92.99	5.10	1.31	1.05	93.80	9.37	5.34	5.55	93.46
	FedSeq [33]	3.75	0.91	0.67	**94.67**	13.75	7.35	8.64	92.74	19.38	19.04	21.46	93.57
	UniFed	**58.02**	**55.97**	**58.36**	94.10	**46.15**	**40.26**	**43.36**	93.11	**32.40**	**28.72**	**31.75**	**95.3**

UniFed outperforms existing federation methods

This work is accepted at the MICCAI MLMI 2024 conference (poster presentation), Marrakesh, Morocco.
GitHub code: https://github.com/basiralab/UniFed

Atefe Hassani

The computation overhead on MedMNIST dataset with **strongly Non-IID setting** and the communication overhead (local epoch for each hospital × number of hospitals × iteration). The computation overhead shows the total training time in minutes.

Method	Computation			Communication		
	CNN	VGG11	ResNet18	CNN	VGG11	ResNet18
NoFed	8.43	23.56	30.58	24000	24000	24000
FedAvg	207.65	251.56	162.02	24,000	24,000	24,000
FedProx	71.26	276.72	244.78	24,000	24,000	24,000
FedSeq	170.58	227.2	169.03	48,000	24,000	24,000
UniFed	98.43	**50.41**	**39.78**	30,327	**7,765**	**6,213**

UniFed is more affordable to train

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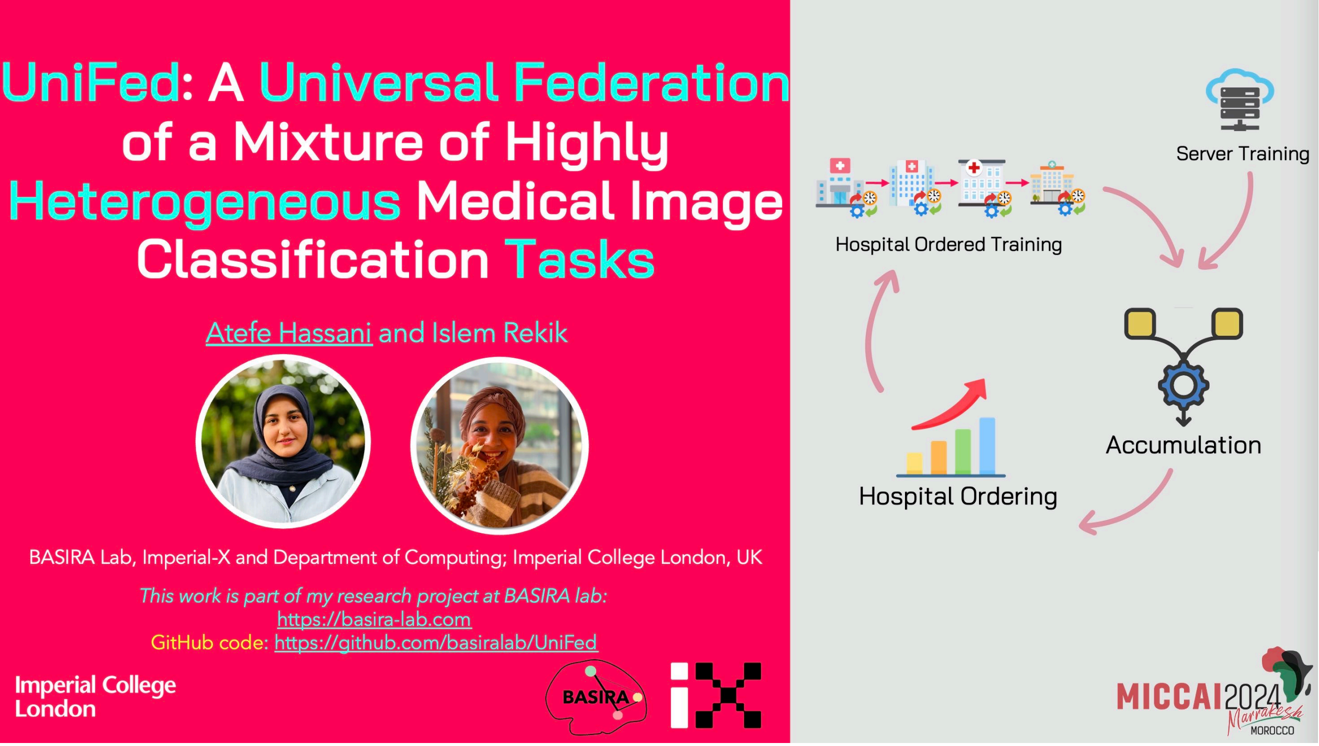

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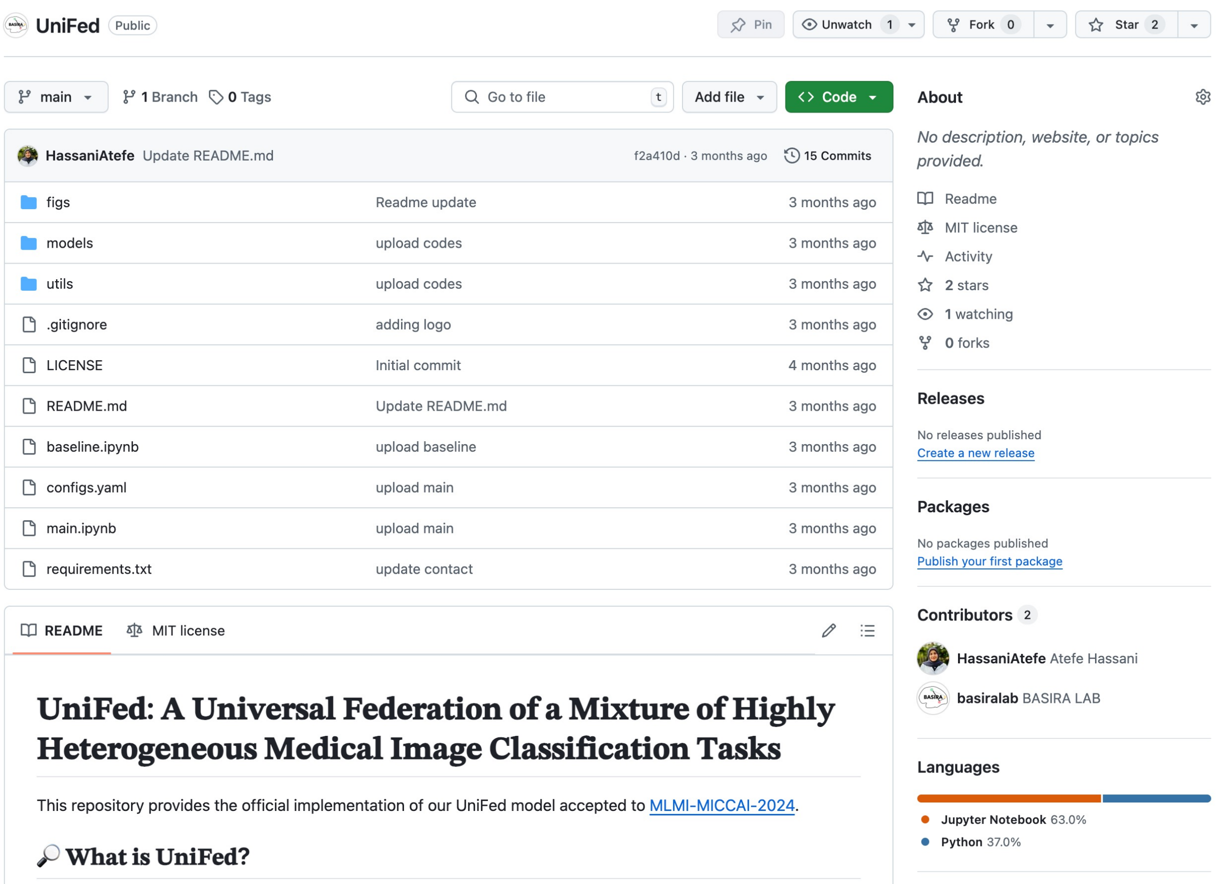

YouTube

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Three trends in the AI-powered healthcare revolution

Generative learning	Generate *multidimensional* brains	Generate connectional brain templates
Federated learning	Federate to generate the future of the brain	Federate heterogeneous diagnostic tasks
Holistic learning	Insights into the future of an inclusive and holistic AI in medicine	

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Holistic learning

Avicenna
Ibn Sina (980–1037),

A Persian **polymath** whose work in **medicine, Islamic philosophy, and science** laid foundational principles that influenced medical practice for centuries.
His visionary insights are particularly noted in ***The Canon of Medicine***, which became a **standard text in medical schools across Europe and the world** for hundreds of years.

(Mental Health)

"The imagination is the intermediary between the bodily organs and the soul."

(Holistic Healing)

"The physician should not treat the disease but the patient who is suffering from it."

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https://www.the-tls.co.uk/regular-features/footnotes-to-plato/avicenna-leading-sage-footnotes-plato

Holistic learning

A History of Population Health: the rise & fall of diseases

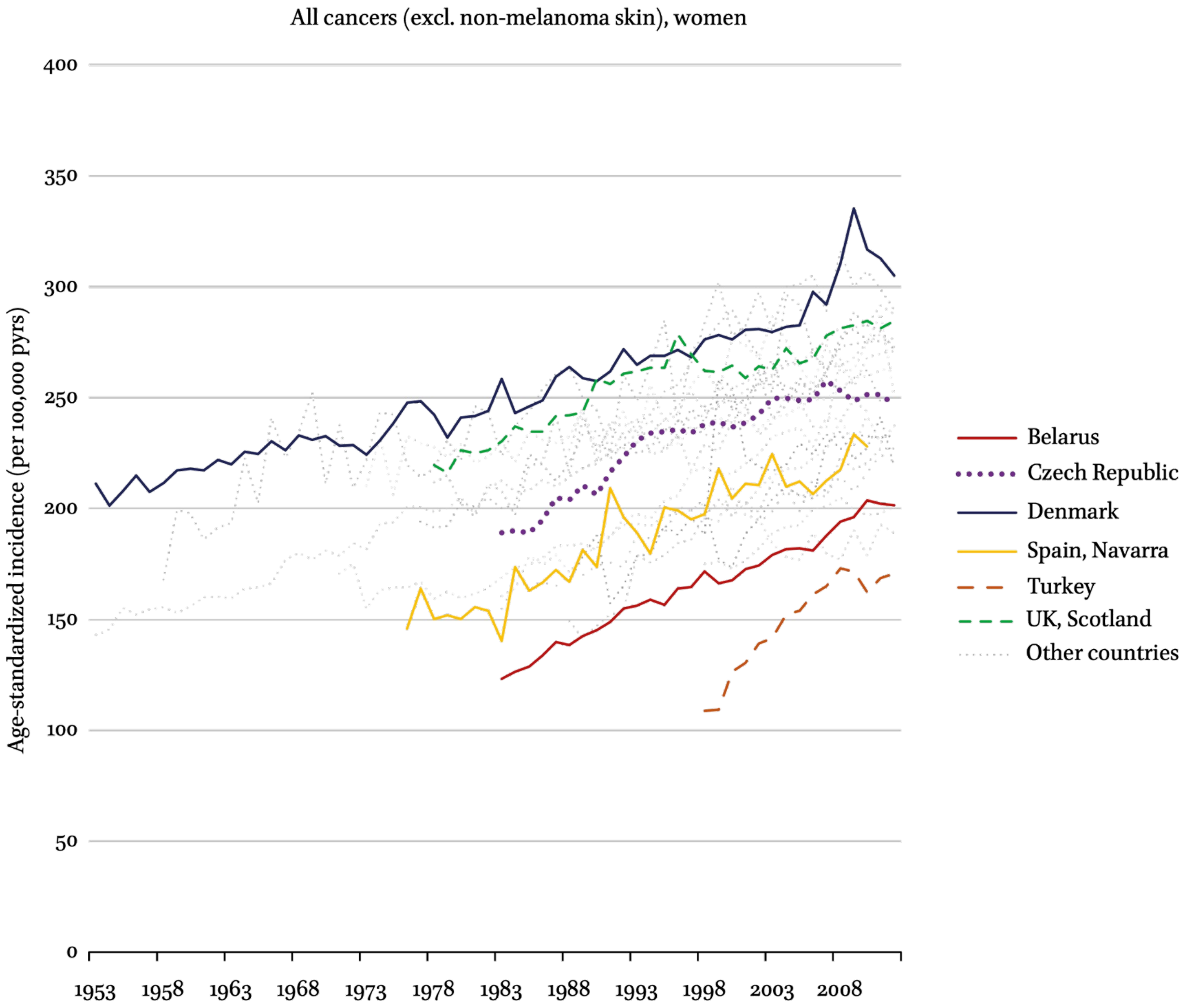

FIGURE 4 Trends in cancer incidence in Europe, 1953–2011
SOURCE OF DATA: NATIONAL OR REGIONAL CANCER REGISTRIES (THROUGH GLOBAL CANCER OBSERVATORY (GCO.IARC.FR; ACCESSED 24/04/2019))

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https://library.oapen.org/handle/20.500.12657/53806

A History of Population Health: the rise & fall of diseases

That 'rise-and-fall' is the usual time-pattern in which diseases afflict human populations must have a deeper explanation. Why have, in the course of human history, so many diseases emerged? Why have, on the other hand and with shorter or longer delay, most of these diseases become less common again, or at least become less lethal? And is there a causal link between the disappearance of one disease and the emergence of another?

We need a more **holistic** approach.

Are we asking the *right* questions and looking at the *right* data?

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https://library.oapen.org/handle/20.500.12657/53806

How much is it costing us to acquire, store and maintain data?

Generative AI needs data, but how much?

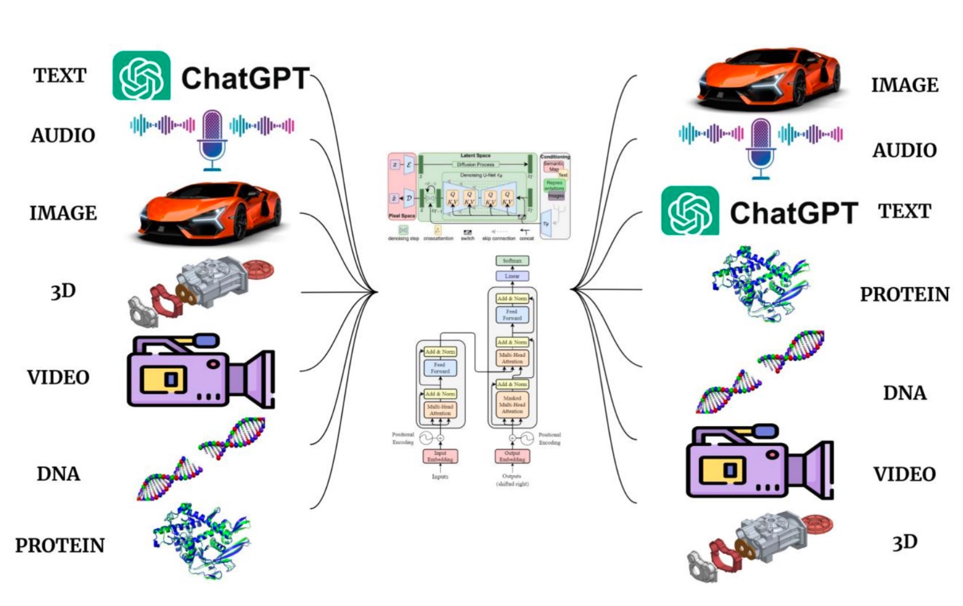
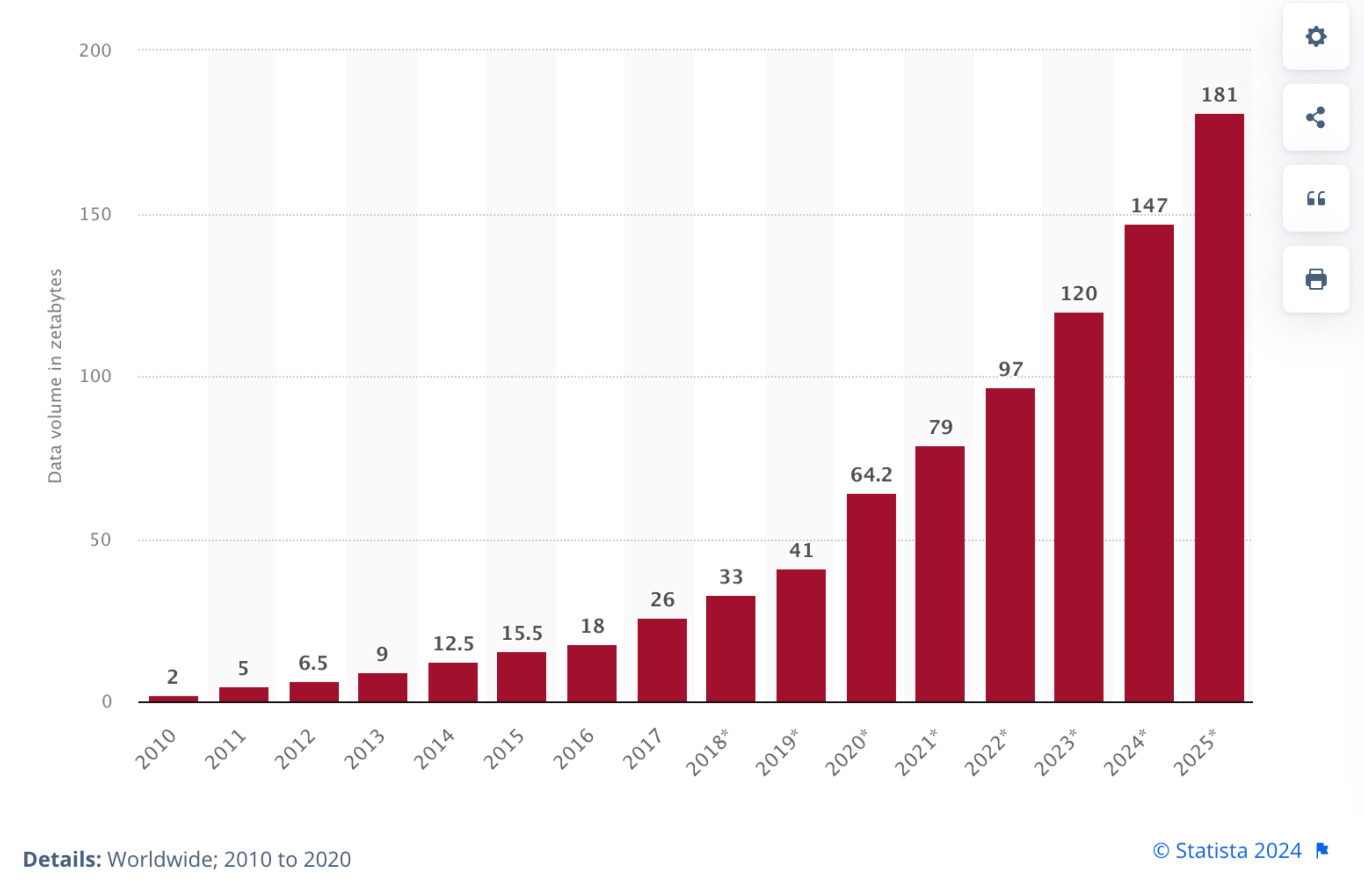


Figure 1. Overview of Generative AI tasks.

Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2020, with forecasts from 2021 to 2025 (in zettabytes = 10^{21} bytes)



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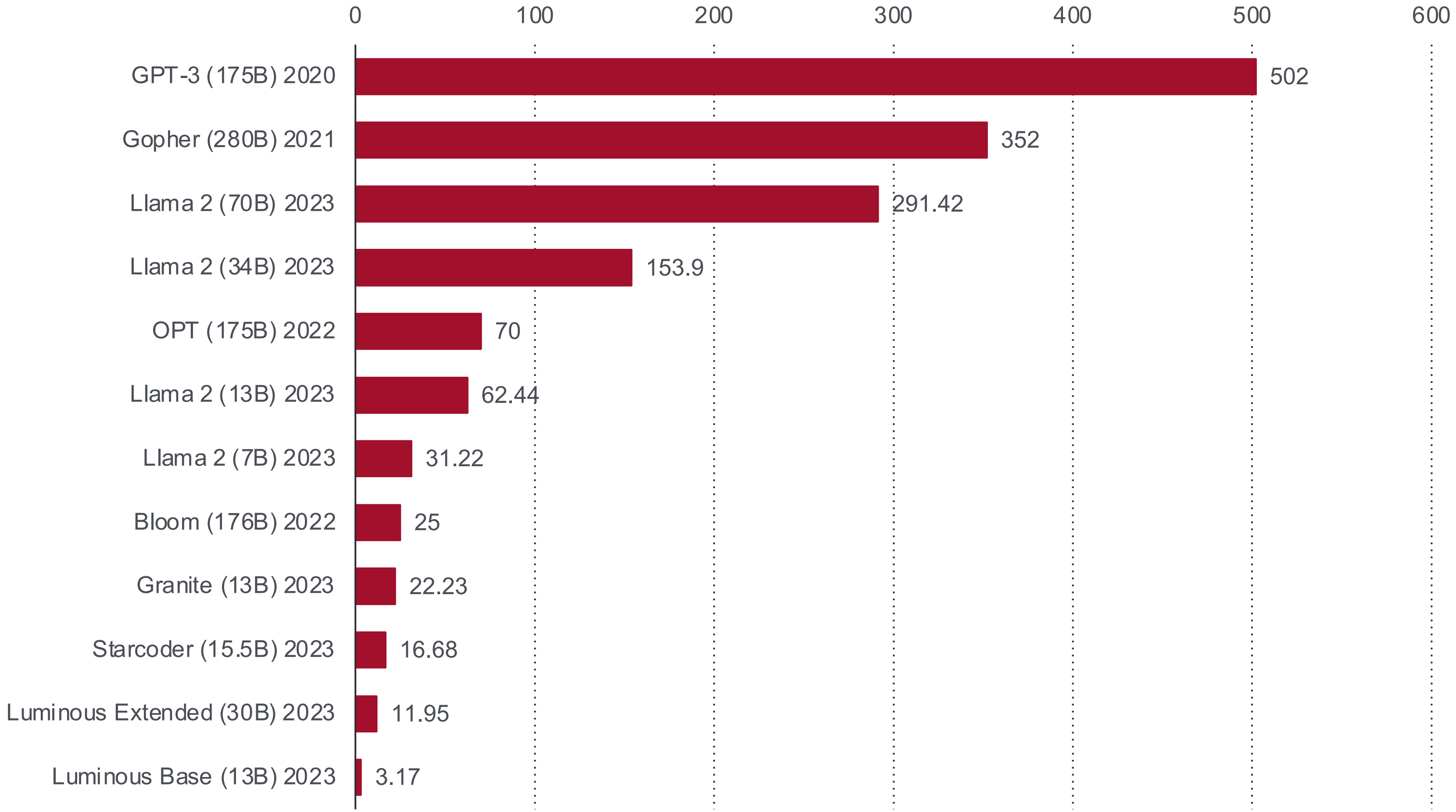
https://www.statista.com/statistics/871513/worldwide-data-created/ ; https://arxiv.org/pdf/2310.00795

CO_2 equivalent emissions by AI models 2024 in tonnes



https://www.statista.com/statistics/871513/worldwide-data-created/ ; **Source:** Stanford UniversityID 1465353

AI BOOK CO-WRITING PROJECT

THURS DAYS

29 MAY 2025

13:00 – 14:00 UK TIME

WRITE A STORY ABOUT AI

01 Join our **weekly online** collective writing session

02 Imagine the good, bad and game-changing future with AI

03 Write a 1–3 page story about AI

04 Your story or another's — let it be heard

05 Join our talented project writers **from all sectors and disciplines**

SCAN ME

"AI: THE GOOD, THE BAD AND THE GAME CHANGER"

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Collaborative Creative Projects

HOW TO JOIN US?

APPLICATION LINK: HTTPS://SHORTURL.AT/YIGFU

DEADLINE: 27 MAY 2025

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Book Editor
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https://basira-lab.com/

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WRAP UP

The main trends

Generative learning

- *improve disease diagnosis/prognosis*
- *generate costly medical data from low-cost*
- *enable the forecasting of health/disease evolution (individual, population)*

Federated learning

- *promote low-cost and privacy-preserving learning from data*
- *increase AI fairness by learning from diverse datasets*
- *learn better together and without data*

The other side to rethink

Holistic learning

Gen-AI, at which cost?
How to enable a more holistic learning and healing of diseases?

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"The requisites of knowledge: a quick mind, zeal for learning, humility, foreign land, a professor's inspiration, and a life of long span."
Juwaini of Nishapur (d.1085)

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Brain **A**nd **SI**gnal **R**esearch & **A**nalysis Lab

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Generative learning

Federated learning

Holistic learning

Imperial College London