A Quick Look at My Research

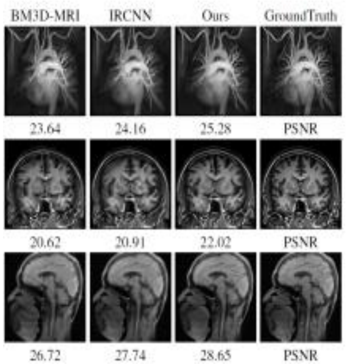
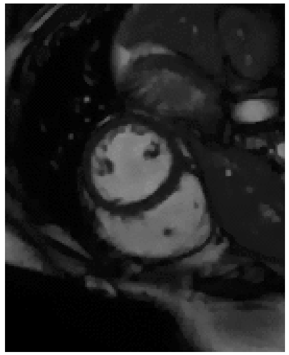


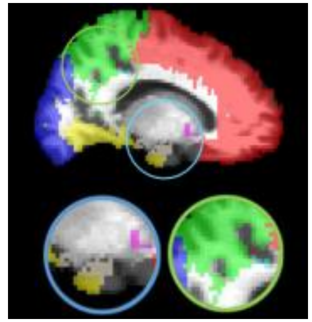
Image Reconstruction /Continuous Parameter Tuning

e.g. Optimisation + Reinforcement Learning



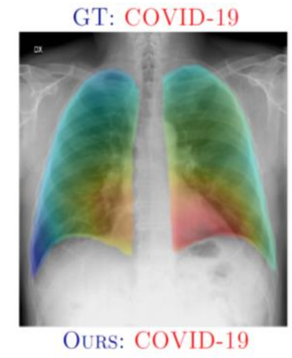
Multi-Task Learning Techniques

e.g. Motion Estimation + Reconstruction + SuperResolution



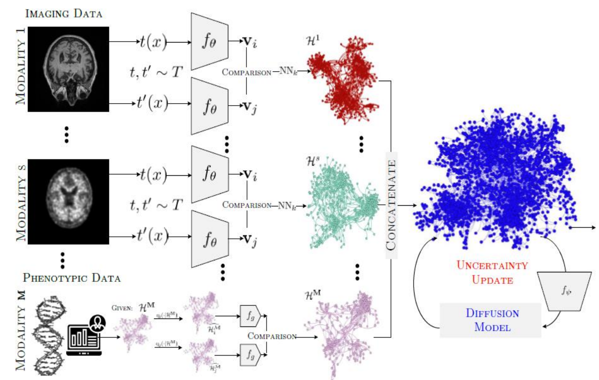
Unsupervised Image Registration & Segmentation

e.g. for diagnosis, improving reconstruction



SSL Medical Image Classification

e.g. Cancer Diagnosis, COVID diagnosis, Parasite detection in thin blood smear images etc



Self-Supervised / Semi-Supervised techniques.
e.g. prognosis and diagnosis of Alzheimer Disease

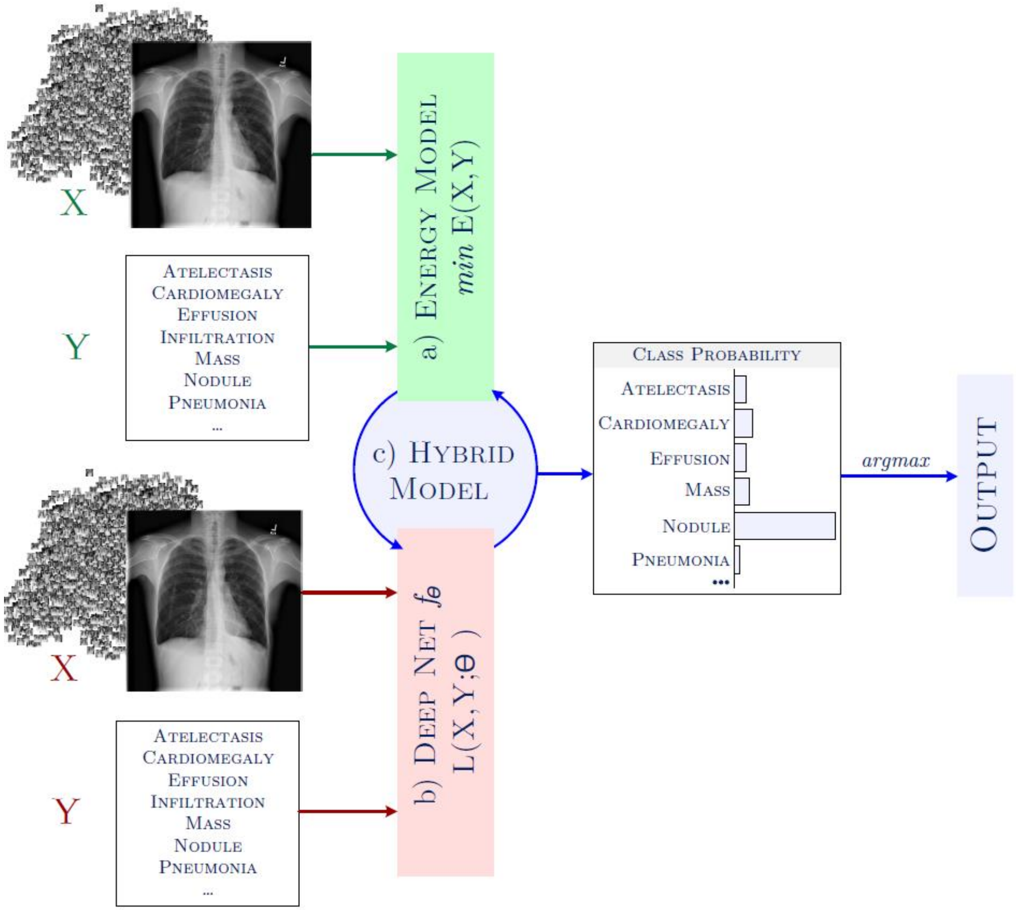
We tackle a major challenge in medical imaging – the need for manual parameter tuning

Another major challenge in medical imaging – the need for a large and well-representative labelled set

Multi-Modal Data: Diagnosis and Prognosis of Alzheimer's Disease

e.g. (ICCV, MICCAI19, MICCAI20, TIP20a,b, MedIA20, ICML20 (Outstanding Paper Award), MedIA21a, MedIA21b, Inverse Problems21, TIP21, Radiology21, Pattern Recognition22, JMLR22, MICCAI22...)

Hybrid Models... For Multi-Modal Data?



(AI Aviles-Rivero et al, 2021b)

GraphXNet /CREPE-Model / LaplaceNet / Deep Walkers/GraphXCOVID

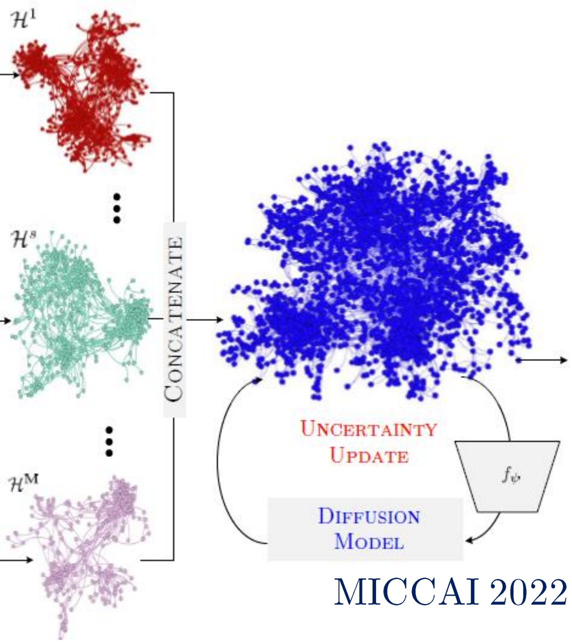
e.g., (AI Aviles-Rivero et al, 2019), (AI Aviles-Rivero et al, 2020), (P Sellars, AI Aviles-Rivero et al, 2021), (AI Aviles-Rivero et al, 2022)

Existing Hybrid and DL Techniques:
Focus on designing better Network Mechanisms
*using existing energy models

Our Work:
To develop better energy models and analyse their theoretical properties

What is the Goal of this Flash Talk?

We introduce a novel semi-supervised hypergraph learning framework for Alzheimer's disease diagnosis



MICCAI 2022

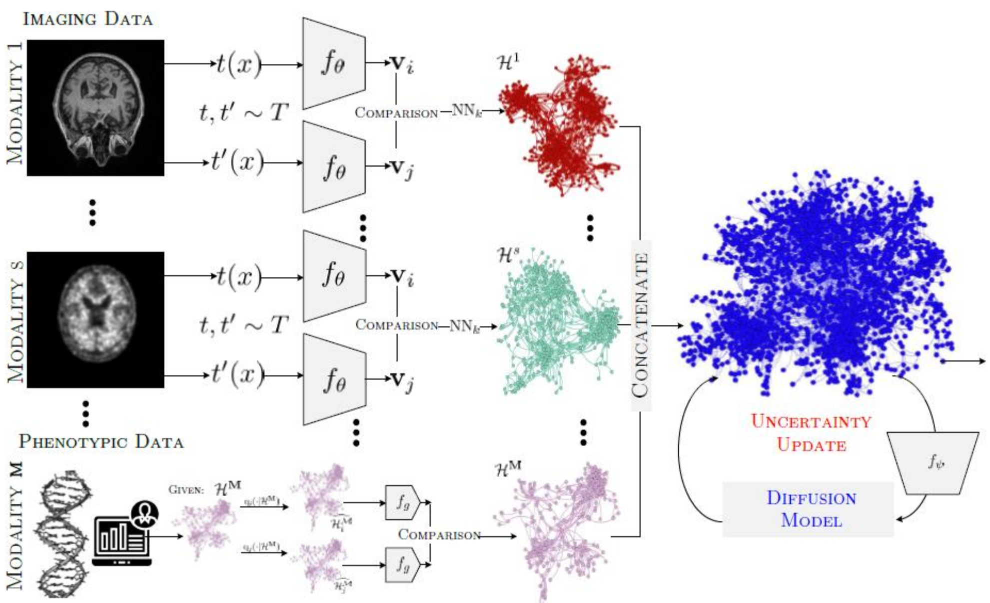
- ✓ We introduce a self-supervised dual multi-modal embedding strategy. The manifold that lies the imaging data and the space of the hyper graph structure
- ✓ We introduce a more robust diffusion-model. It is based on the Rayleigh quotient for hypegraph p-Laplacian and follows a semi-explicit flow
- ✓ Comparison with SOTA SSL hypergraph/graph techniques for a major multi-modal dataset.

AI Aviles-Rivero, C Runkel, N Papadakis, Z Kourtzi & CB Schönlieb. Multi-Modal Hypergraph Diffusion Network with Dual Prior for Alzheimer Classification, MICCAI 2022. (arXiv:2204.02399)

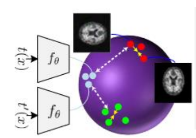
Our setting: Hybrid HyperGraph Based SSL

Problem Statement – Semi-Supervised Learning Setting

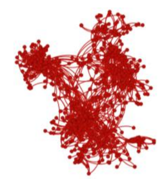
Given a set of samples $X = (x_1, ..., x_l, x_{l+1}, ..., x_n)$ where $x_i \in \mathcal{X}$, we assume that a tiny subset is labelled $X_L = \{(x_i, y_i)\}_{i=1}^{l}$ with provided labels $\{y_i\}_{i=1}^{l} \in \mathcal{L} = \{1, .., L\}$ for L classes, and a large subset is unlabelled $X_u = \{x_i\}_{i=l+1}^{n}$ such that $X_L << X_u$. We then seek to infer a function $f : \mathcal{X} \mapsto \mathcal{L}$ such that f gets a good estimate for $\{x_i\}_{i=l+1}^{n}$ with minimum generalisation error.



(AI Aviles-Rivero et al, 2022)



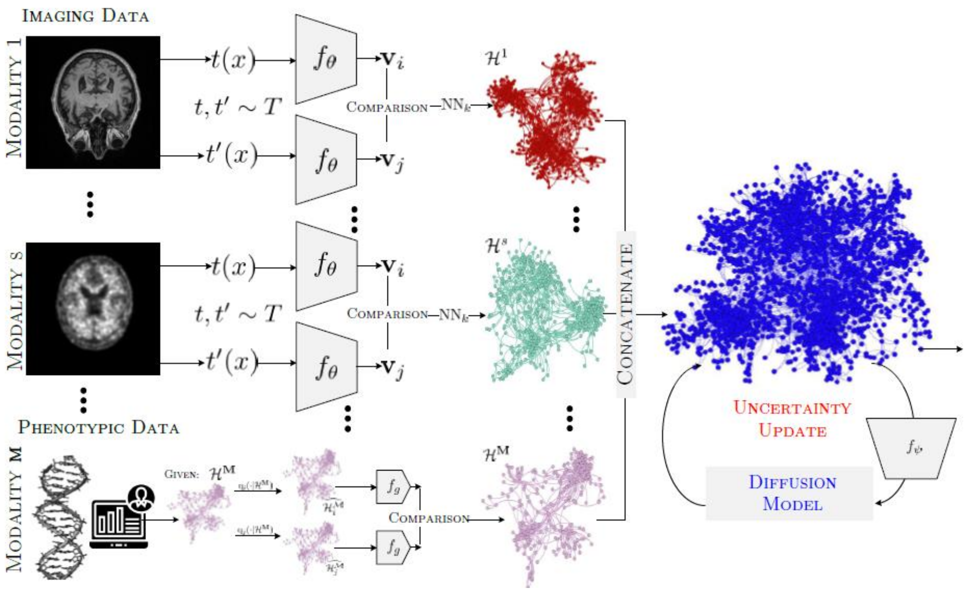
Part I: Our self-supervised dual embedding strategy



Part II: Our dynamically updated Diffusion Model

Part II: A Hybrid Model – Energy Model + Deep Nets

Dynamically Adjusted Hypergraph

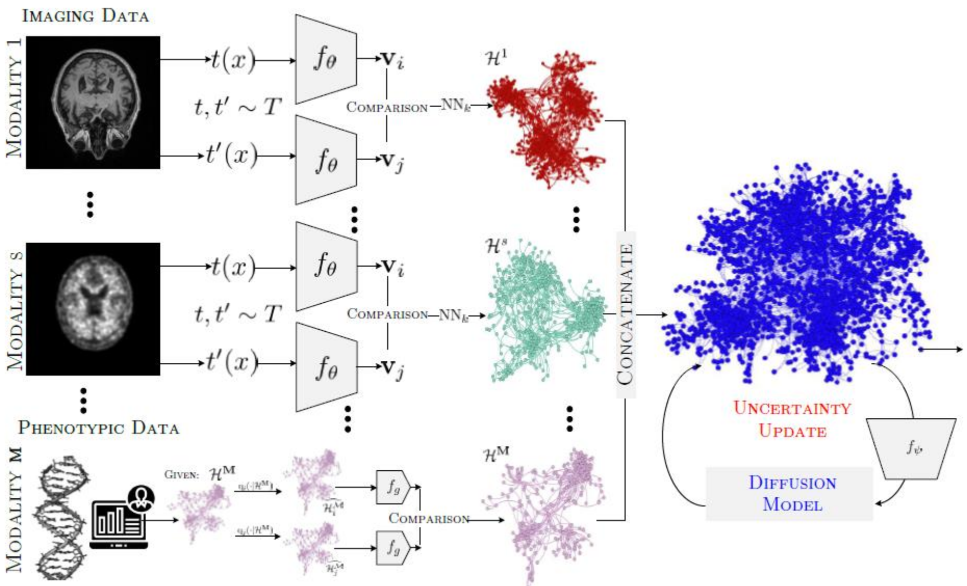


Keys Ideas:

- To produce Pseudo-Labels directly from our energy model not a Network.
- To mitigate network calibration and the confirmation bias in pseudo-labelling.

Part II: A Hybrid Model – Energy Model + Deep Nets

Initialisation: $\mathcal{L}_S(X_L, Y_L; \theta)$



Drivin

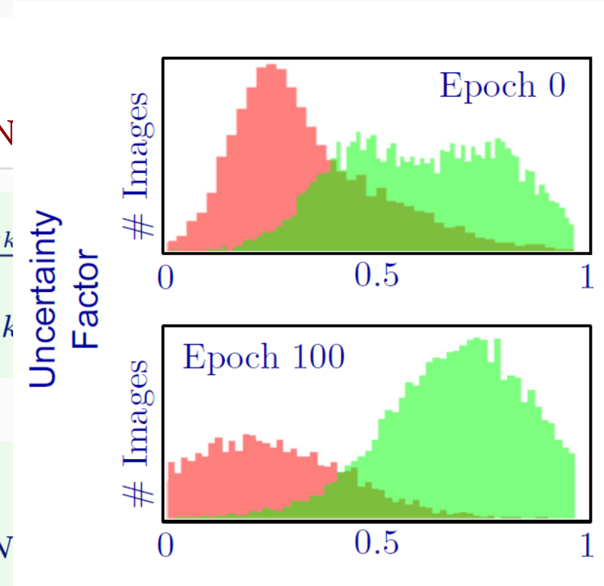
$\Big\{ \; u_k \quad - \phi_{k+1/2},$

u_k

$\mathcal{L}_{DYN} \quad f_\theta(x_i), y_i)$

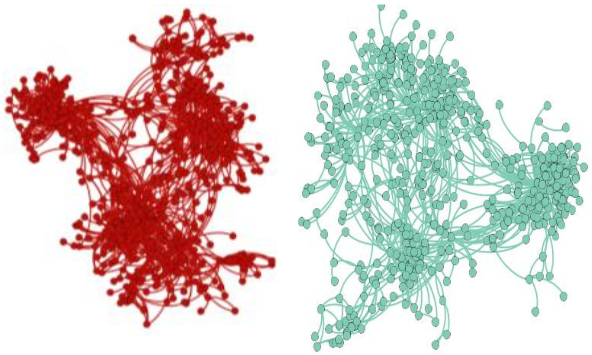
$i=1$

$+ \sum_{i=l+1}^{m} \gamma_i \mathcal{L}_{CE}(f_\theta(x_i), \widehat{y}_i),$



This is the big picture – Details in *(AI Aviles-Rivero et al, MICCAI 2022)

Experimental Results



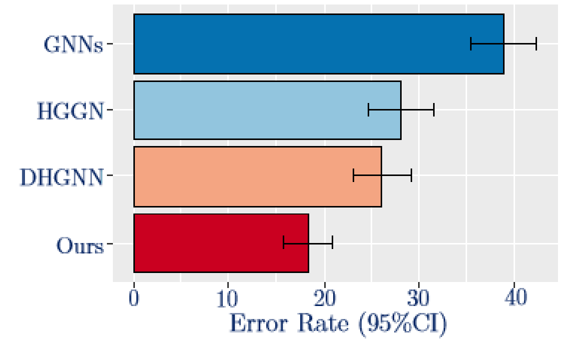
The Alzheimer's disease Neuroimaging Initiative (ADNI) dataset

We consider 500 patients using MRI, PET, demographics and Apolipoprotein E (APOE). 4 Categories (NC, EMCI, LMCI, AD)

Techniques using 20% of Labels

Technique	AD vs NC			EMCI vs LMCI		
	ACC	SEN	PPV	SEN	PPV	ACC
GNNs [19]	81.60±2.81	83.20±3.10	80.62±2.30	75.60±2.50	75.20±3.02	75.80±2.45
HF [24]	87.20±2.10	88.01±2.15	86.60±2.60	80.40±2.02	82.41±2.14	79.23±2.60
HGSCCA [25]	85.60±2.16	87.20±3.11	84.40±2.15	76.01±2.16	75.21±2.01	76.42±2.22
HGNN [11]	88.01±2.60	90.40±2.16	87.59±2.42	80.60±2.05	81.60±2.54	79.60±2.51
DHGNN [16]	89.90±2.40	89.60±2.15	90.21±2.45	80.80±2.47	82.40±2.41	79.80±2.76
Ours	92.11±2.03	92.80±2.16	91.33±2.43	85.22±2.25	86.40±2.11	84.02±2.45

Performance comparison for the four classes case.



Sneak Peak to the Results Due to time constrains - Details in *(AI Aviles-Rivero et al, MICCAI 2022)

Higher Order Graph Learning:
Multi-Modal Hypergraph Diffusion Networks for Alzheimer Classification

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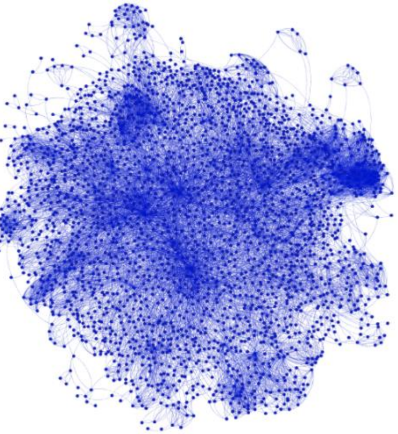

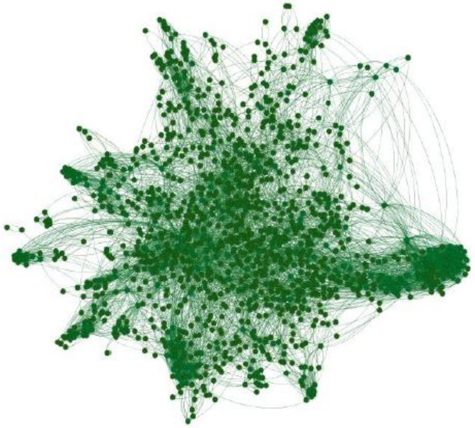

Joint work with:
C Runkel, N Papadakis, Z Kourtzi and CB Schönlieb

Tuesday, July 26th 2022