Integrated brain connectivity analysis with fMRI, DTI, and sMRI powered by interpretable graph neural networks

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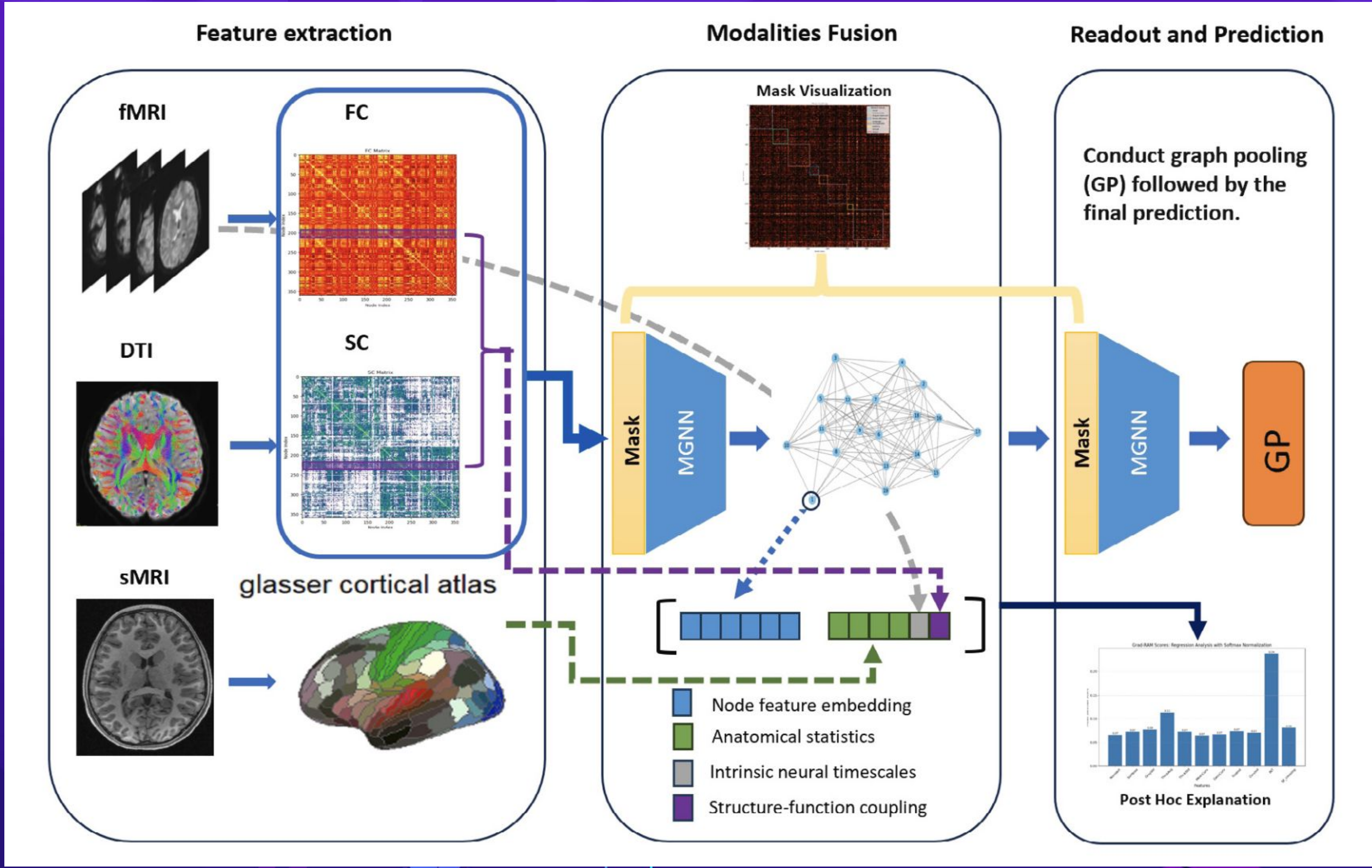
Scope of the paper

- New method for extracting and fusing features from different neuroimaging modalities
- It is used inside a Graph Neural Network which provides *an interpretable sparsity mask output*

Overview of the whole thing



Part 1. Inside the model

It is a variation of convolution graph network spiced with learnable sparsity mask

weights

degree matrix

$$\boldsymbol{H}^{l+1} = \mathrm{MaskGNN}(\boldsymbol{H}^{l}) = \phi^{l}((\boldsymbol{\mathcal{M}} + \boldsymbol{I}) \odot (\tilde{\boldsymbol{D}}^{-\frac{1}{2}} \tilde{\boldsymbol{A}} \tilde{\boldsymbol{D}}^{-\frac{1}{2}}) \boldsymbol{H}^{l} \boldsymbol{\Theta}^{l}),$$

output

activation

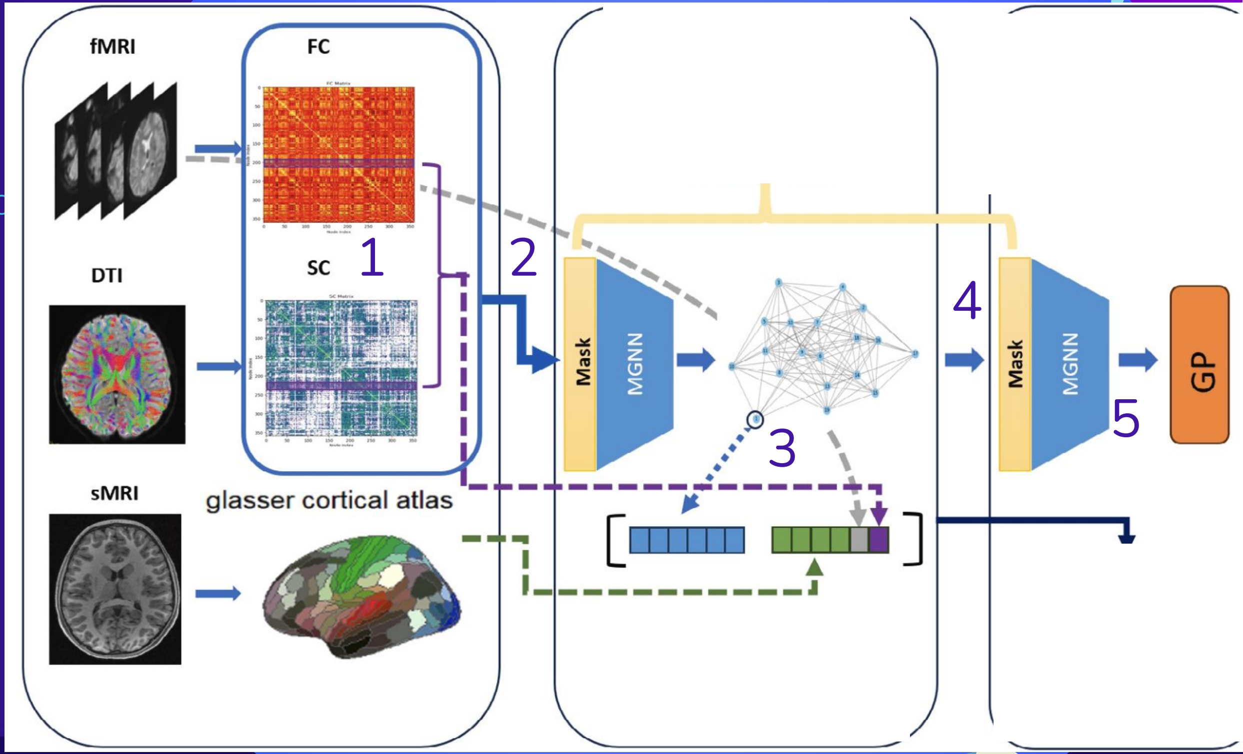
learnable sparsity

adjacency matrix

node features

Part 1. Forward pass

1. Build graph from FC and SC
2. Pass through GCN layer
3. Inject more features
4. Pass through GCN layer
5. Classify



Part 1. Training objective

$$L = L_e(\hat{\mathbf{y}}, \mathbf{y}) + \alpha L_{manifold} + L_{mask},$$

Overall loss

$$L_{mask} = \lambda_1 \|\mathcal{M}\|_1 + \lambda_2 \|\mathcal{M}\|_F^2 + \lambda_3 \|\mathcal{M}\mathcal{M}^\top - \mathbf{I}_Q\|_F,$$

Sparsity loss

$$L_{manifold} = \frac{1}{2} \sum_{q}^{Q} \sum_{j \in N_q} \|\boldsymbol{h}_q - \boldsymbol{h}_j\|_2^2 = \operatorname{trace}(\boldsymbol{H}^\top \boldsymbol{L} \boldsymbol{H}),$$

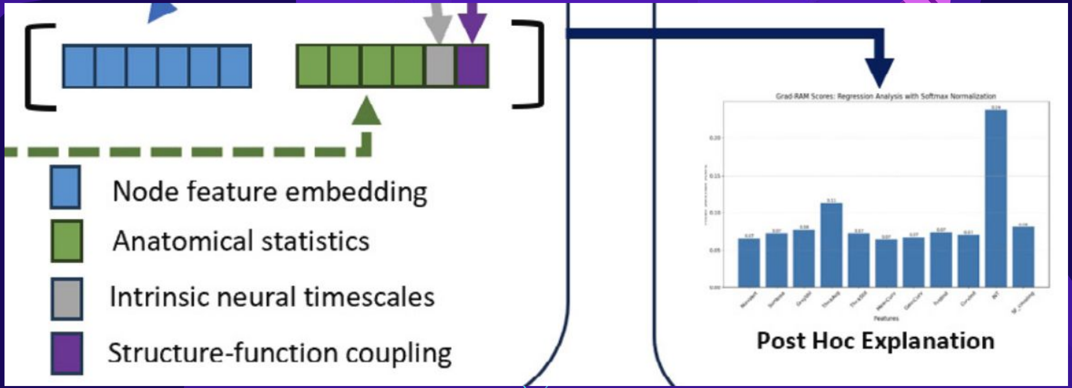
Graph properties loss

L - Laplacian

H - fin nodes

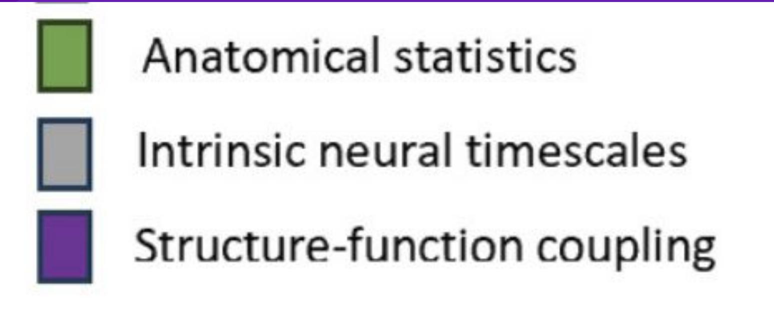
Part 1. Interpretability

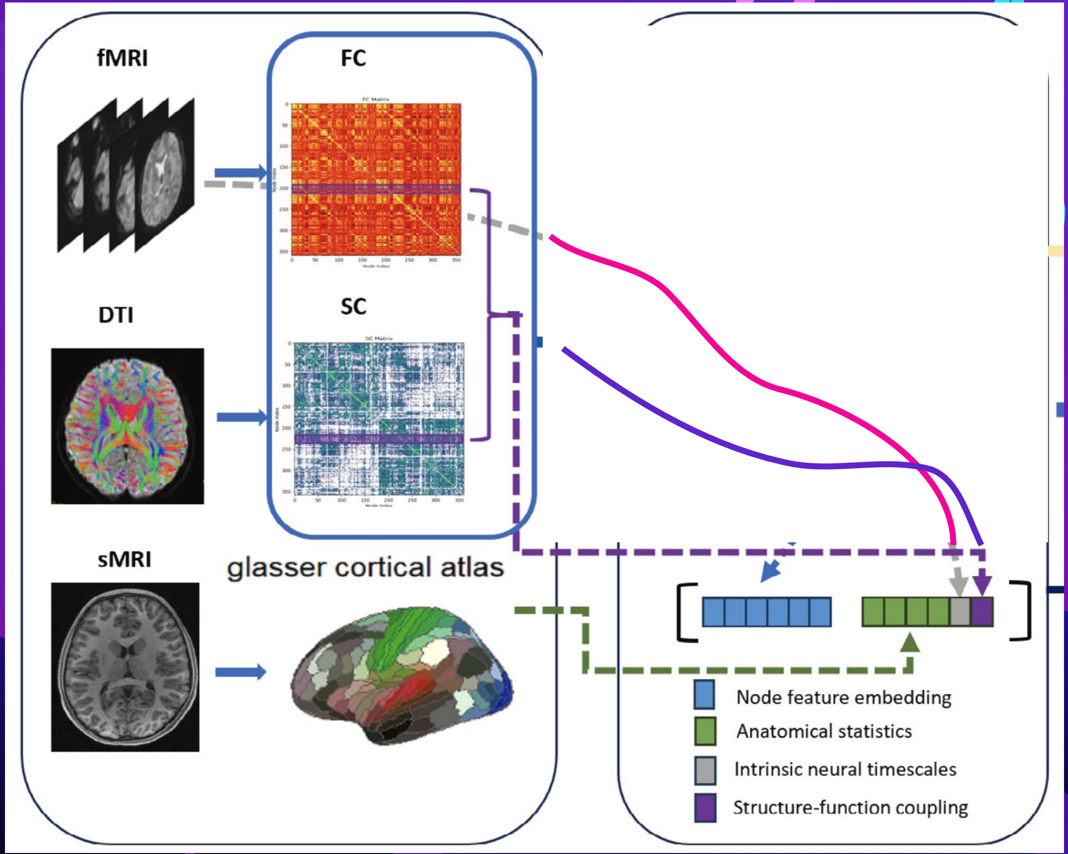
Saliency



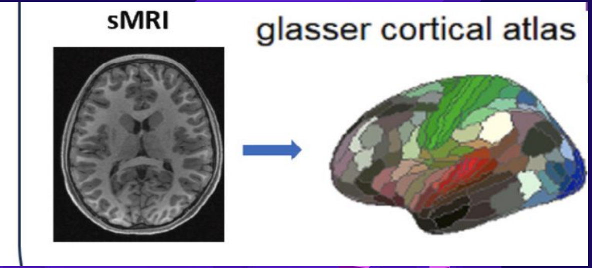
Sparsity mask removes unimportant edges

Part 2. Data fusion





Part 2. Anatomical statistics

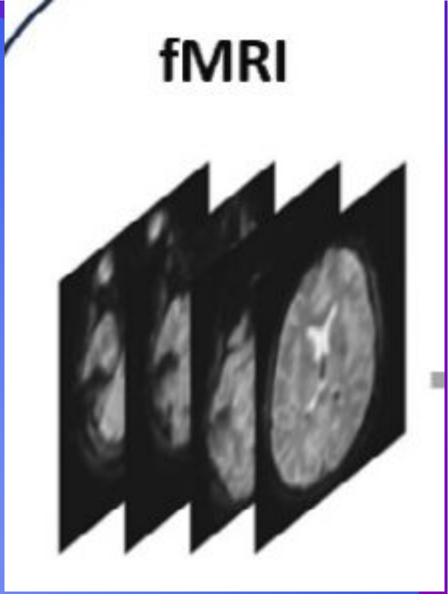


Bunch of metrics from different papers:

1. Surface Morphology and Volumetric Measures
   a. surface area, gray matter volume
2. Cortical Thickness
   a. distance between the outer pial surface and the inner boundary surface of the cortex
3. Curvature
   a. Cortical surface curvature, folding metrics

Part 2. Intrinsic neural timescales

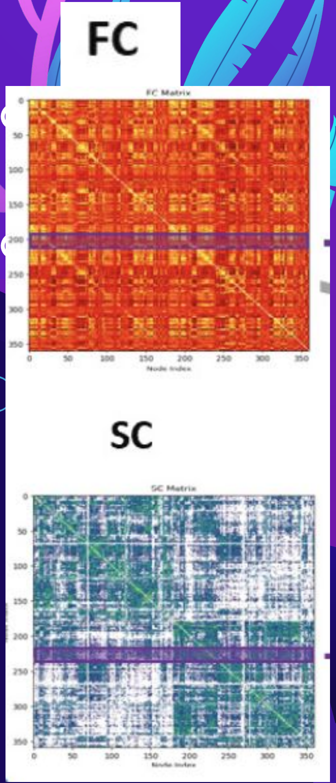
1. Estimated through the magnitude of autocorrelation in fMRI time series
2. Quantifies the duration that neural information is stored in a local circuit 🤷‍♀️
3. Nv is when negative autocorrelation happens



$$INT_v = TR \sum_{k=1}^{N_v} \frac{\sum_{t=k+1}^{T} \left(y_v(t) - \bar{y}_v\right)\left(y_v(t-k) - \bar{y}_v\right)}{\sum_{t=1}^{T} \left(y_v(t) - \bar{y}_v\right)^2},$$

Part 2. Structure–function coupling

1. Spearman rank correlation between the SC and FC
2. Measures the similarity of FC and SC per node



Part 3. Results

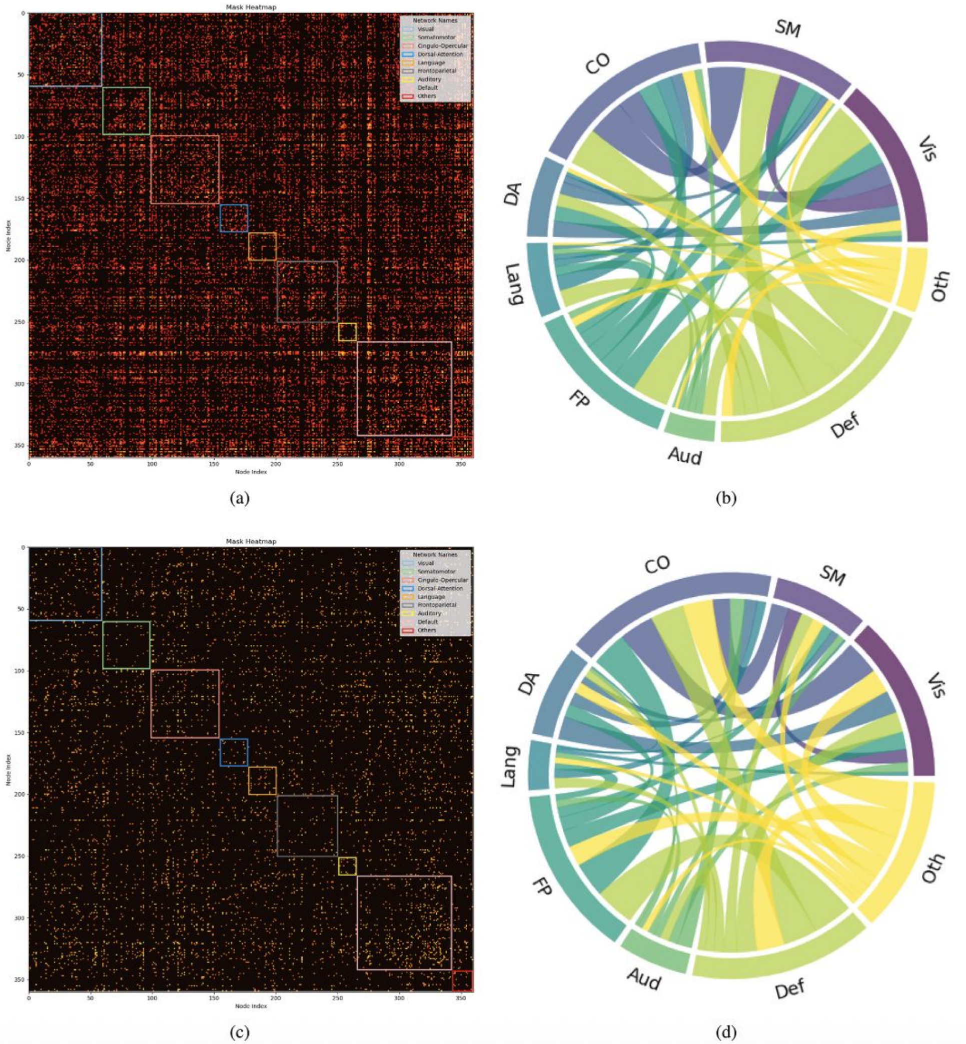
1. They trained it to predict cognitive scores
   a. Crystal/Fluid/Total Cognition Composite
2. And fusing modalities improves the prediction
   a. And their model is better than others: Graph Isomorphism Network (GIN), Graph attention network (GAT)

Table 2
Prediction performance on intelligence scores.

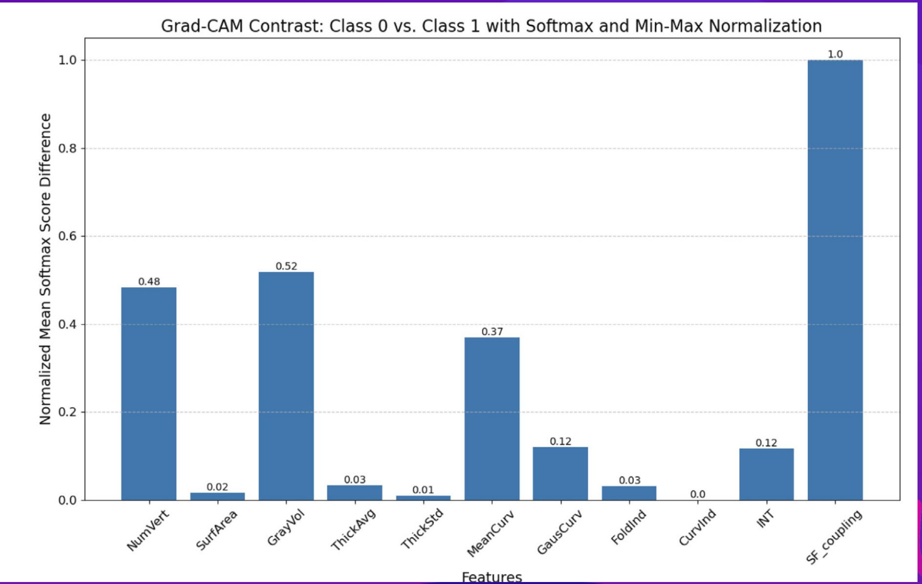
Model	Modalities	CCC RMSE	*P*-value	CCC MAE	*P*-value	FCC RMSE	*P*-value	FCC MAE	P-Value
MaskGNN	FC	17.910 ± 0.118	<0.001	14.847 ± 0.122	<0.001	16.382 ± 0.142	<0.001	12.973 ± 0.107	<0.001
MaskGNN	SC	19.557 ± 0.195	<0.001	15.305 ± 0.090	<0.001	16.957 ± 0.0.021	<0.001	13.468 ± 0.045	<0.001
MaskGNN	FC+SC	17.580 ± 0.060	<0.001	14.687 ± 0.059	<0.001	16.164 ± 0.009	<0.001	12.989 ± 0.039	<0.001
MaskGNN	FC+SC+AS	**14.968 ± 0.819**	–	**12.095 ± 0.534**	–	**14.338 ± 0.754**	–	**11.516 ± 0.542**	–
GCN	FC+SC+AS	15.654 ± 0.127	0.026	12.366 ± 0.074	0.196	16.853 ± 0.110	<0.001	13.727 ± 0.096	<0.001
GAT	FC+SC+AS	16.230 ± 0.517	0.003	12.209 ± 0.099	0.574	17.531 ± 0.307	<0.001	13.987 ± 0.190	<0.001
GIN	FC+SC+AS	16.978 ± 1.004	<0.001	13.768 ± 0.924	<0.001	17.777 ± 0.712	<0.001	14.907 ± 0.786	<0.001
Linear	FC+SC+AS	18.061 ± 0.047	<0.001	15.335 ± 1.776	<0.001	17.092 ± 0.040	<0.001	13.802 ± 1.776	<0.001
MLP	FC+SC+AS	17.804 ± 0.576	<0.001	14.473 ± 0.879	<0.001	17.305 ± 0.520	<0.001	14.430 ± 0.903	<0.001

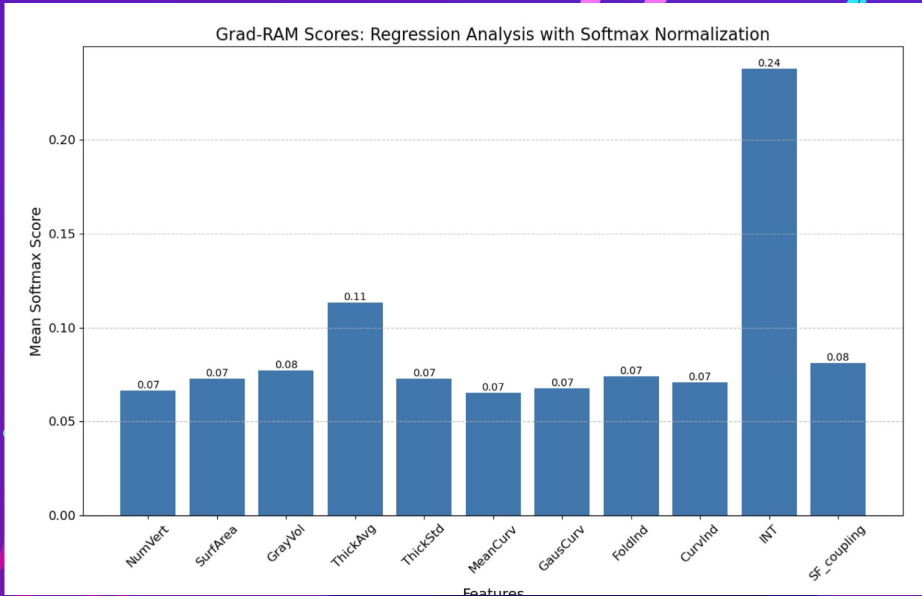
Part 3. Sparsity

Doesn't look very interpretable to me but it's there



Part 3. Feature importance





Saliency maps highlight important node features for cognitive scores.

Implications

- Neuroimaging data fusion can be done by injecting features into graph nodes
- Their methodology for feature engineering looks interesting
  - New ideas for sMRI, fMRI and DTI