NEURAL INFORMATION PROCESSING SYSTEMS

Brain-JEPA: Brain Dynamics Foundation Model with Gradient Positioning and Spatiotemporal Masking

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Introduction

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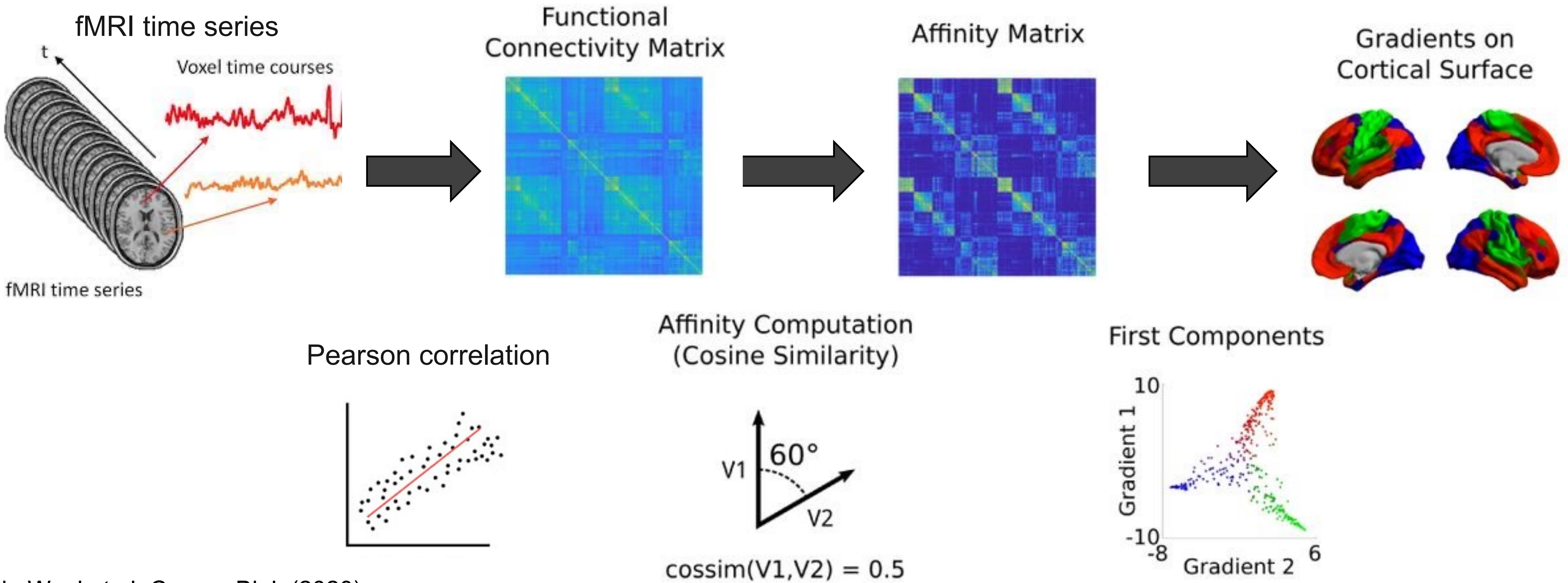
Task-specific training ➡ **Foundation model**

What is next for brain dynamics foundation model?

- How to locate different ROIs in a transformer-based (attention) system?
- Does direct reconstruction of masked fMRI input make sense?
- How to efficiently mask fMRI input?
- ...

Question-1

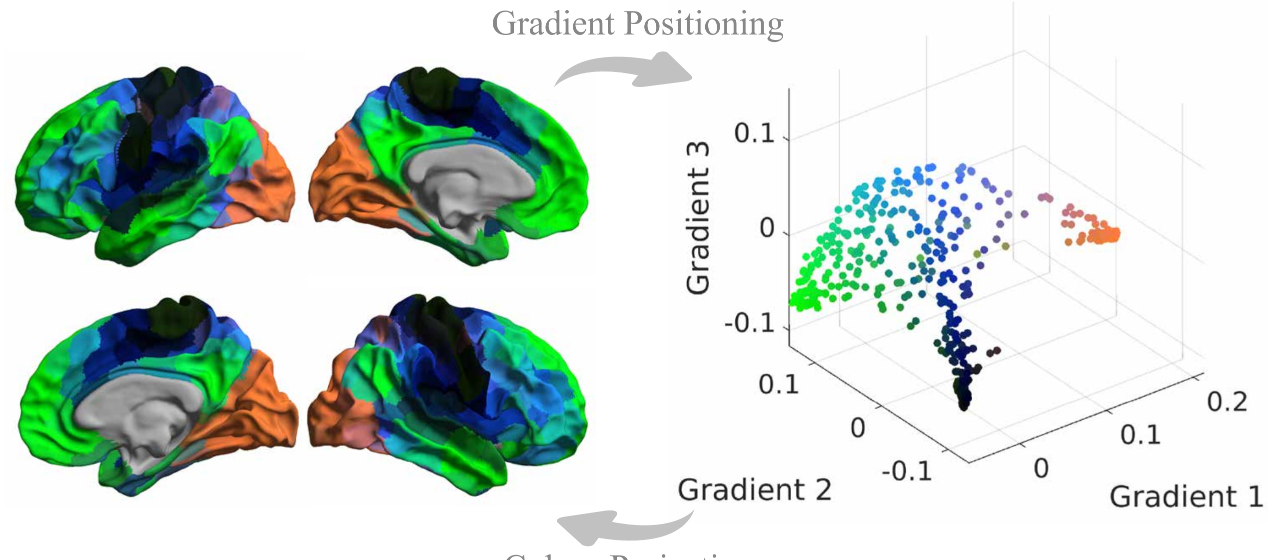
How to locate different ROIs in a transformer-based (attention) system?
Brain gradient Positioning!



Vos de Wael et al. Comm. Biol. (2020).

Question-1

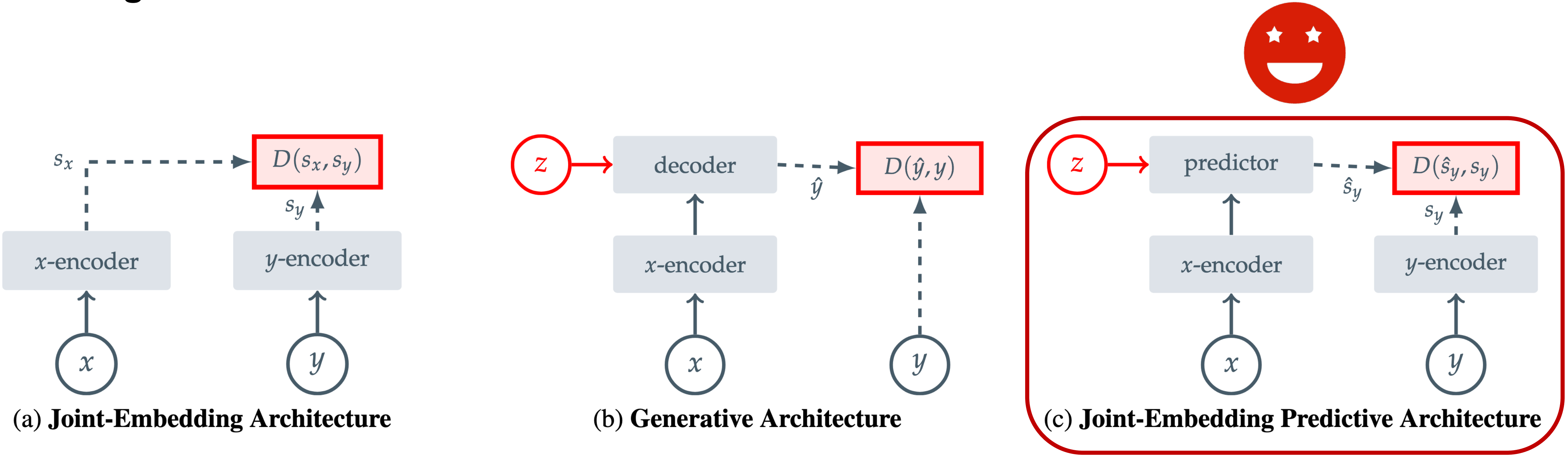
How to locate different ROIs in a transformer-based (attention) system?
Brain gradient Positioning!



(A) Brain Surface Space (B) Brain Gradient Space

Question-2

Does direct reconstruction of masked fMRI input make sense?
Let's go to JEPA!



(a) **Joint-Embedding Architecture**

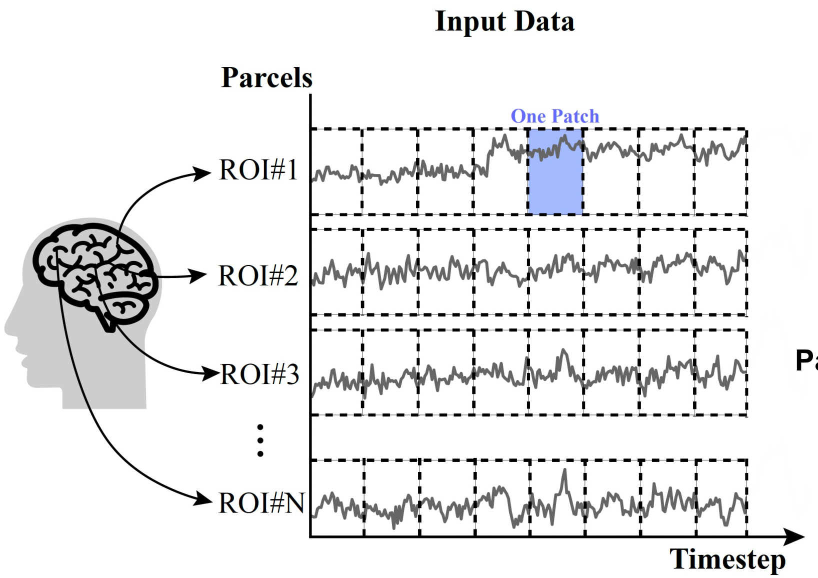
(b) **Generative Architecture**

(c) **Joint-Embedding Predictive Architecture**

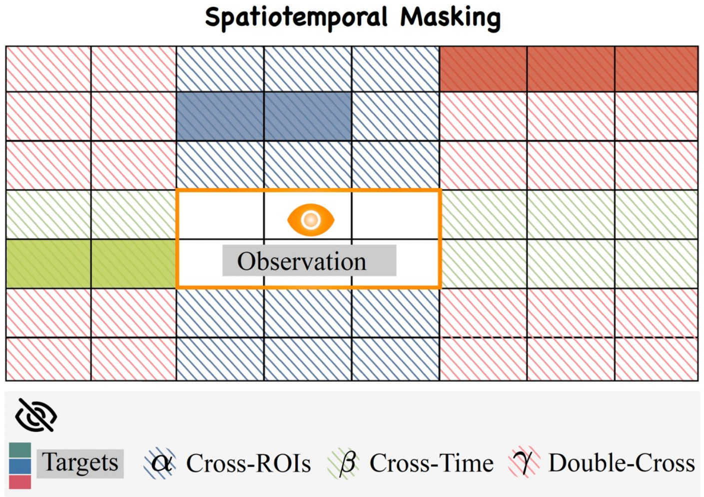
Assran et al. CVPR 2023

Question-3

How to efficiently mask fMRI input?
Spatiotemporal Masking!

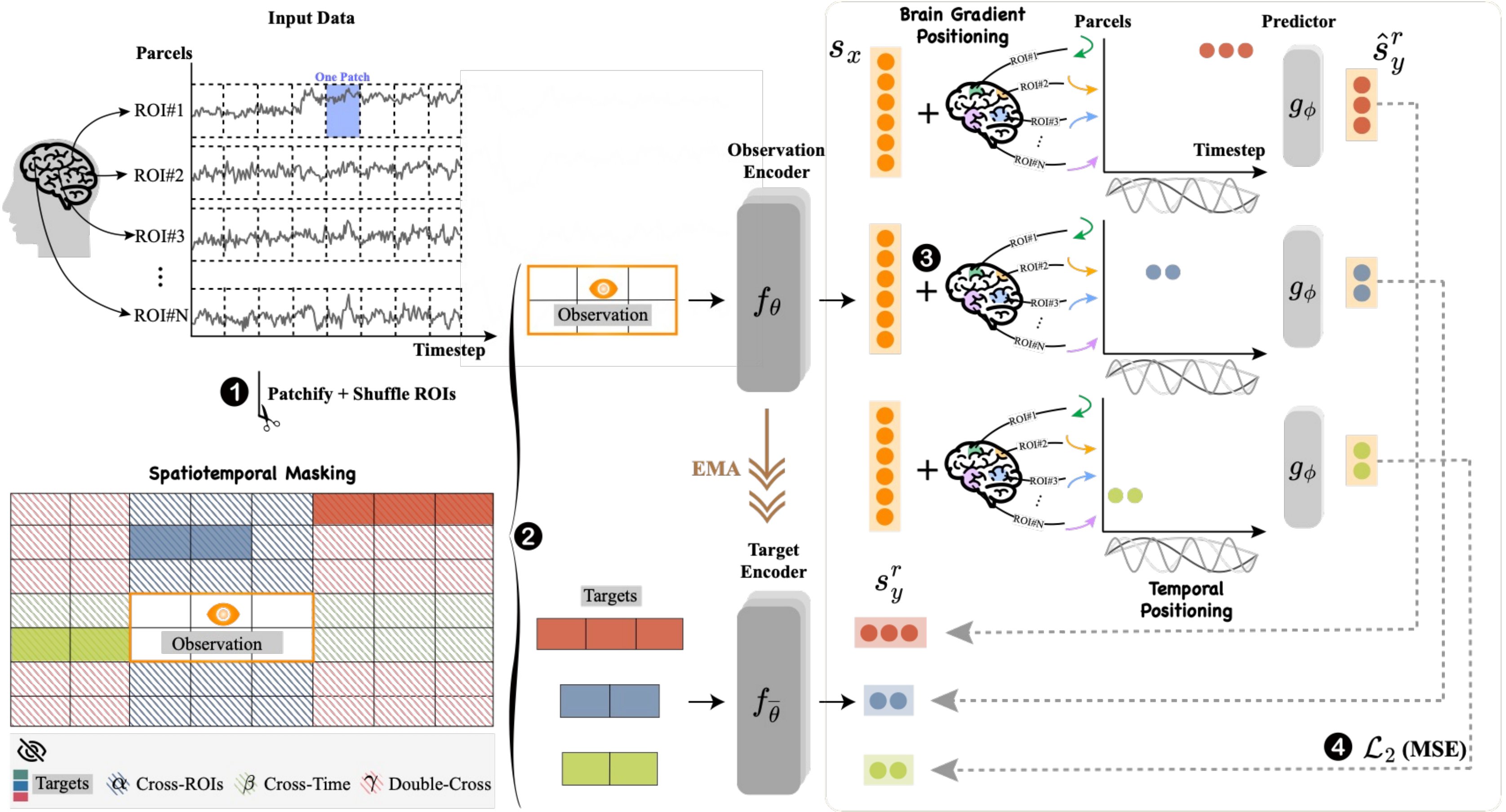


Patchify + Shuffle ROIs



Architecture

Brain-JEPA!



Main Results

- Internal tasks: prediction of demographics on UKB

Table 1: Internal tasks of age and sex prediction on UKB 20% held-out.

Methods	Age		Sex	
	MSE ↓	ρ ↑	ACC(%) ↑	F1(%) ↑
BrainNetCNN [6]	0.985 (0.027)	0.225 (0.015)	77.86 (0.98)	78.17 (0.86)
BrainGNN [5]	0.931 (0.038)	0.332 (0.015)	77.31 (0.33)	79.23 (0.31)
BNT [4]	0.863 (0.031)	0.447 (0.017)	80.78 (0.40)	82.42 (0.36)
TFS[†]	0.812 (0.023)	0.487 (0.011)	82.60 (0.59)	83.00 (0.01)
BrainLM [14]	0.612 (0.041)	0.632 (0.020)	86.47 (0.74)	86.84 (0.43)
Brain-JEPA	**0.501*** (0.034)	**0.718*** (0.021)	**88.17*** (0.06)	**88.58*** (0.11)

[†] Trained-From-Scratched.

Main Results

- External tasks: demographics and trait prediction on HCP-Aging, brain disease diagnosis and prognosis on ADNI and MACC

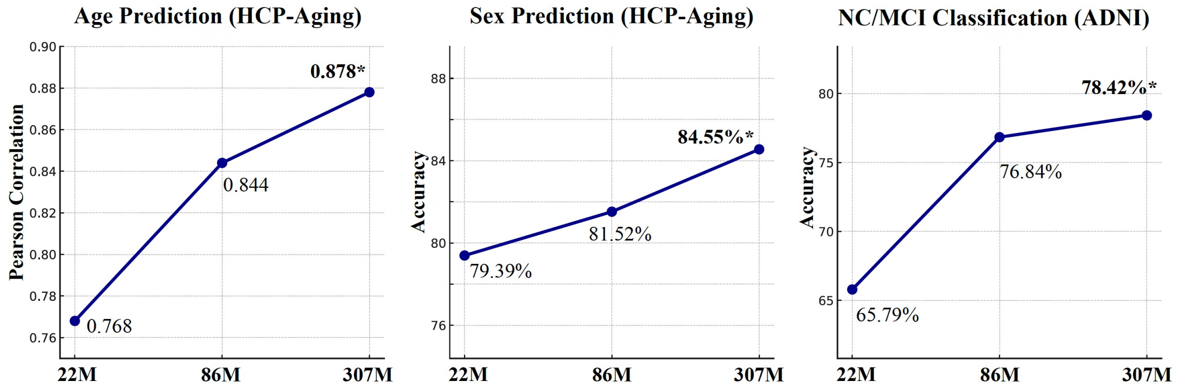
Table 2: External tasks of demographics and trait prediction on HCP-Aging.

Methods	Age		Sex		Neuroticism		Flanker	
	MSE ↓	ρ ↑	ACC (%) ↑	F1 (%) ↑	MSE ↓	ρ ↑	MSE ↓	ρ ↑
BrainNetCNN [6]	0.462 (.017)	0.611 (.023)	71.16 (0.88)	72.23 (0.92)	1.201 (.097)	0.096 (.006)	1.045 (.036)	0.201 (.018)
BrainGNN [5]	0.423 (.015)	0.672 (.024)	72.7 (0.54)	74.09 (0.67)	1.183(.096)	0.098 (.007)	0.982 (.043)	0.309 (.062)
BNT [4]	0.414 (.035)	0.731 (.057)	72.41 (1.09)	73.68 (1.11)	1.199 (.091)	0.101 (.005)	0.997 (.037)	0.307 (.026)
BrainLM [14]	0.331 (.018)	0.832 (.028)	74.39 (1.55)	77.51 (1.13)	0.942 (.082)	0.231 (.012)	**0.971 (.054)**	0.318 (.048)
Brain-JEPA	**0.298 (.017)**	**0.844 (.030)**	**81.52* (1.03)**	**84.26* (0.82)**	**0.897* (.055)**	**0.307* (.006)**	0.972 (.038)	**0.406* (.027)**

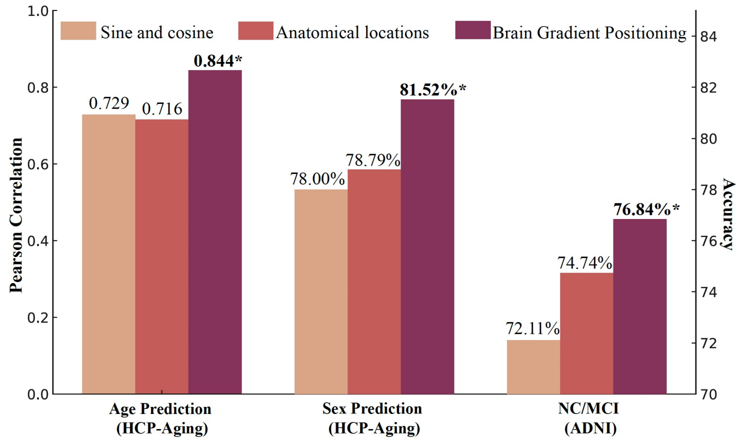
Table 3: External tasks of brain disease diagnosis and prognosis on ADNI and MACC.

Methods	NC/MCI		Amyloid $a\beta$+ve/−ve		NC/MCI (Asian)	
	ACC(%) ↑	F1(%) ↑	ACC(%) ↑	F1(%) ↑	ACC(%) ↑	F1(%) ↑
BrainNetCNN [6]	60.00 (3.51)	64.72 (3.18)	59.00 (2.00)	59.43 (1.14)	57.32 (4.45)	53.92 (4.25)
BrainGNN [5]	67.40 (2.93)	71.42 (2.87)	57.00 (4.00)	62.61 (3.48)	59.79 (2.35)	55.69 (2.29)
BNT [4]	**78.90** (4.12)	83.14 (3.58)	62.00 (2.45)	59.53 (0.58)	62.06 (3.88)	60.45 (4.52)
BrainLM [14]	75.79 (1.05)	85.66 (1.27)	67.00 (7.48)	68.82 (8.48)	61.65 (3.35)	60.26 (3.03)
Brain-JEPA	76.84 (1.05)	**86.32** (0.54)	**71.00*** (4.90)	**75.97*** (3.93)	**65.98*** (2.84)	**64.67*** (2.61)

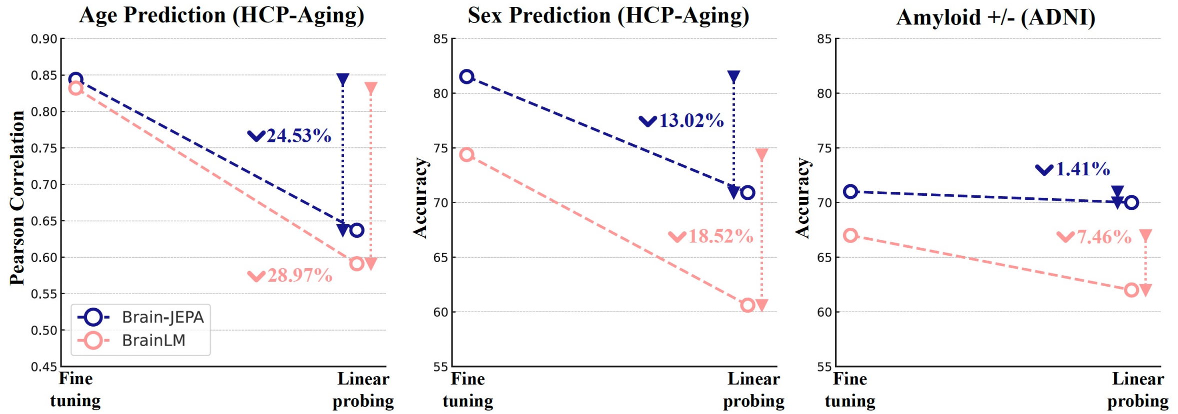
Analysis



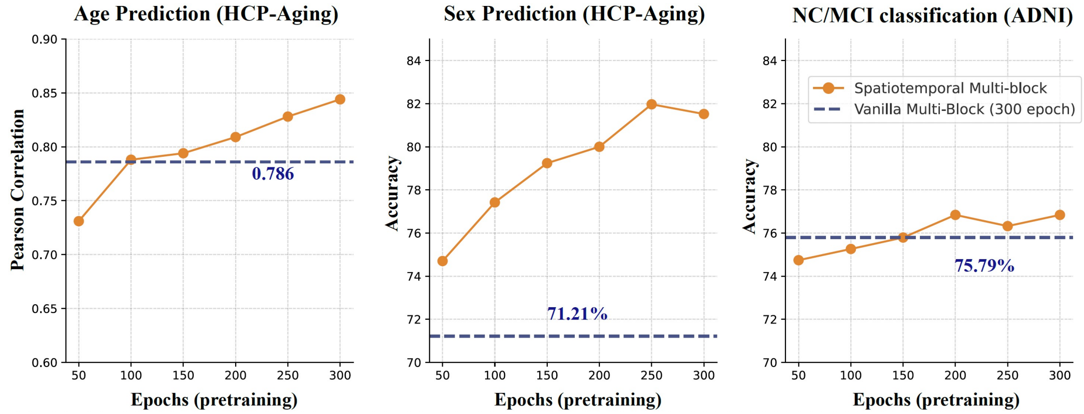
Brain-JEPA demonstrates consistent performance scaling with model size across different tasks.



Brain Gradient Positioning outperforms traditional positional embeddings.

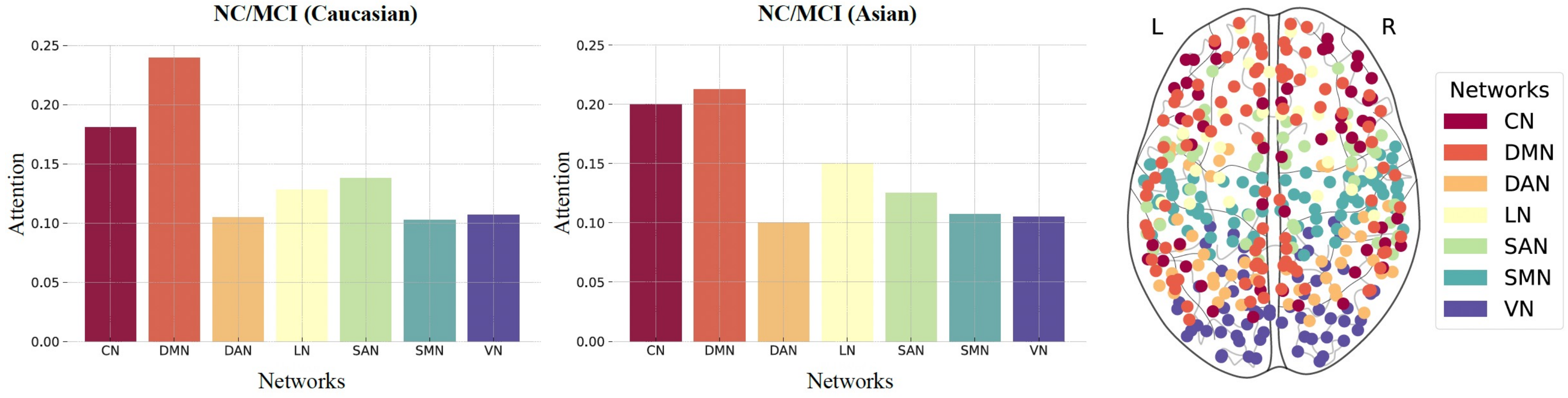


Brain-JEPA demonstrates superior linear probing capabilities compared to BrainLM.



Spatiotemporal Masking demonstrates faster convergence and better performance compared to multi-block sampling.

Analysis



Attention across different brain networks for NC/MCI classification.

Conclusion

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Key Contributions

- First brain foundation model to effectively predict representations rather than reconstruct signals
- Novel Brain Gradient Positioning providing a functional coordinate system
- Efficient Spatiotemporal Masking strategy designed for fMRI characteristics

Impact

- State-of-the-art performance across demographics, disease diagnosis, and trait prediction
- Superior generalization across different ethnic groups
- Robust performance scaling with model size
- More efficient training with better linear probing capabilities

Thanks!

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Spotlight Poster Session: Wed 11 Dec 11 a.m. PST – 2 p.m. PST

Paper **Code** **Our lab**

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