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SEOUL NATIONAL UNIVERSITY OF SCIENCE & TECHNOLOGY

HEEGNet: Hyperbolic embeddings for EEG

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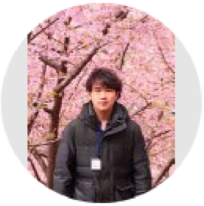
From EEG Structure to Hyperbolic Representation Learning

2026.08.18

MuliLAB Journal Club
인공지능응용학과 허세민

00 Author & Journal



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tu-berlin.de의 이메일 확인됨 - 홈페이지

Machine Learning   AI for Science   Quantum Chemistry   Neuroimaging

제목	인용	연도
SPDIM: Source-Free Unsupervised Conditional and Label Shift Adaptation in EEG S Li, M Kawanabe, RJ Kobler ICLR 2025	13	2024
HEEGNet: Hyperbolic Embeddings for EEG S Li, S Chu, O Koç, Y Ding, Q Zhao, M Kawanabe, Z Chen ICLR 2026	6	2026
BrainPro: Towards Large-scale Brain State-aware EEG Representation Learning Y Ding, M Jiang, W Jiang, S Zhang, X Zhou, C Liu, S Li, Y Li, C Guan arXiv preprint arXiv:2509.22050	3	2025
EEG-Based Multimodal Learning via Hyperbolic Mixture-of-Curvature Experts R Zhou*, S Li*, G Huang, X Zhou, Q Zhao, M Kawanabe, Y Ding, C Guan ICML 2026	1	2026
EEG-DLite: Dataset Distillation for Efficient Large EEG Model Training Y Tang, W Jiang, S Li, Y Li, C Liu, X Zhou, Y Ding, C Guan AAAI 2026	1	2025
Geometric Deep Learning to Enhance Imbalanced Domain Adaptation in EEG S Li, M Kawanabe, RJ Kobler ESANN		2024
Incorporating Importance Weighting in Optimal Transport Based Domain Alignment O Koç, A Soen, S Li, M Sugiyama ICML 2026		

ICLR

International Conference On Learning Representations

Overview

01 Introduction

02 Hyperbolic Foundations

03 HEEGNet

04 Discussion & Conclusion

00 Key Questions

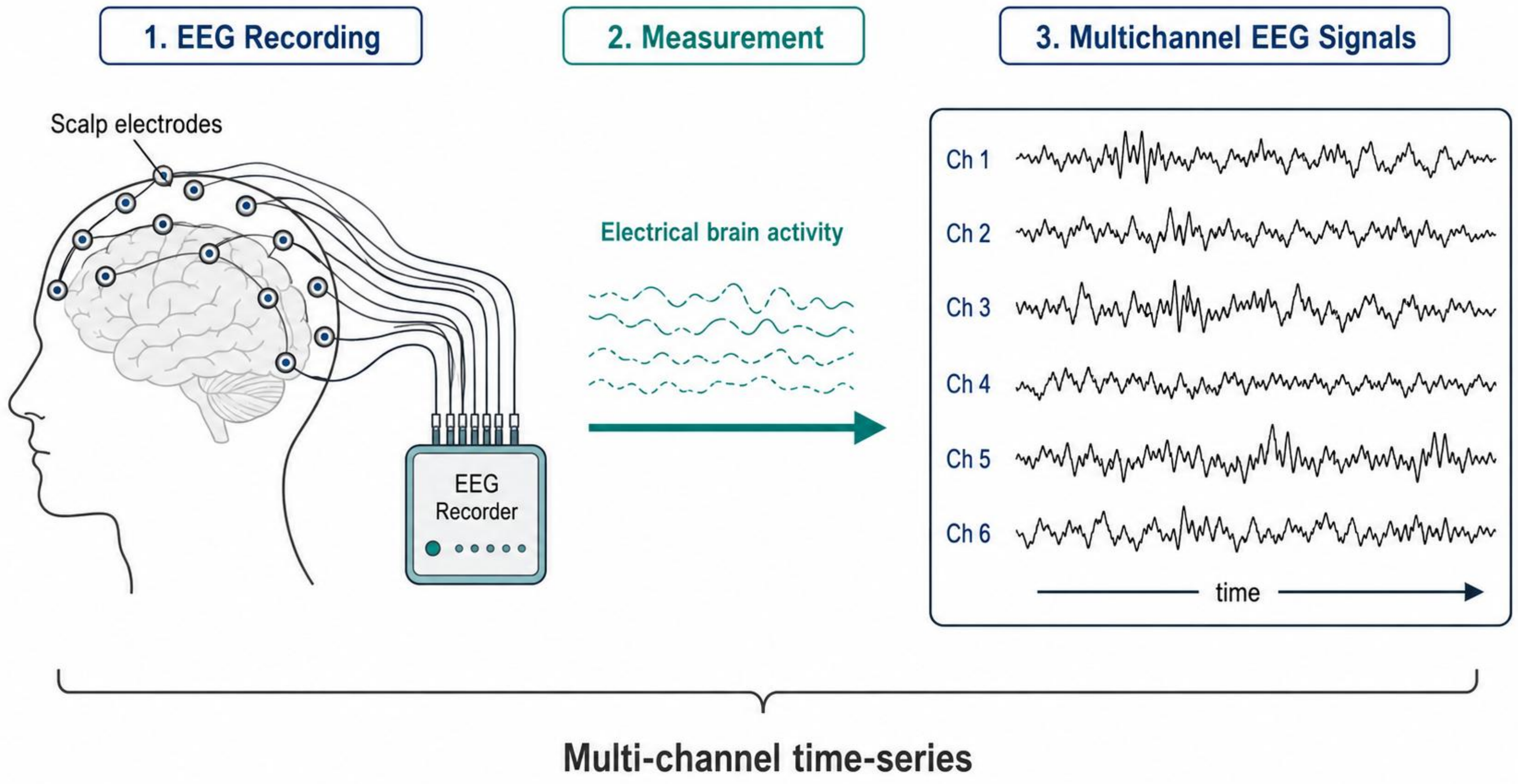
1. Why Hyperbolic?
   - Why does Euclidean space struggle with hierarchical structure?

2. Why EEG?
   - Does EEG exhibit tree-like structure?

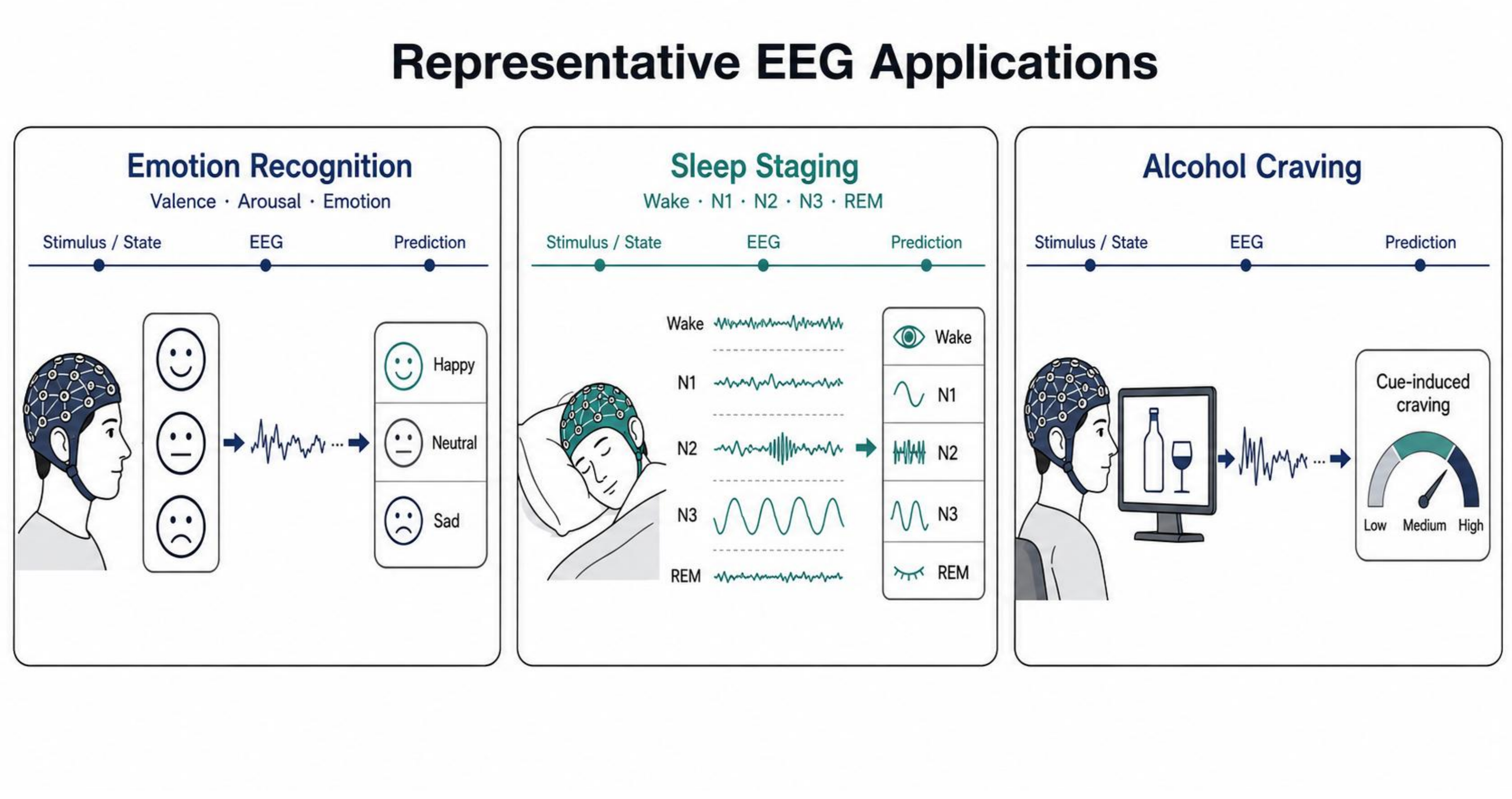
3. Why HEEGNet?
   - Can hyperbolic representation improve cross-subject EEG generalization?

Introduction

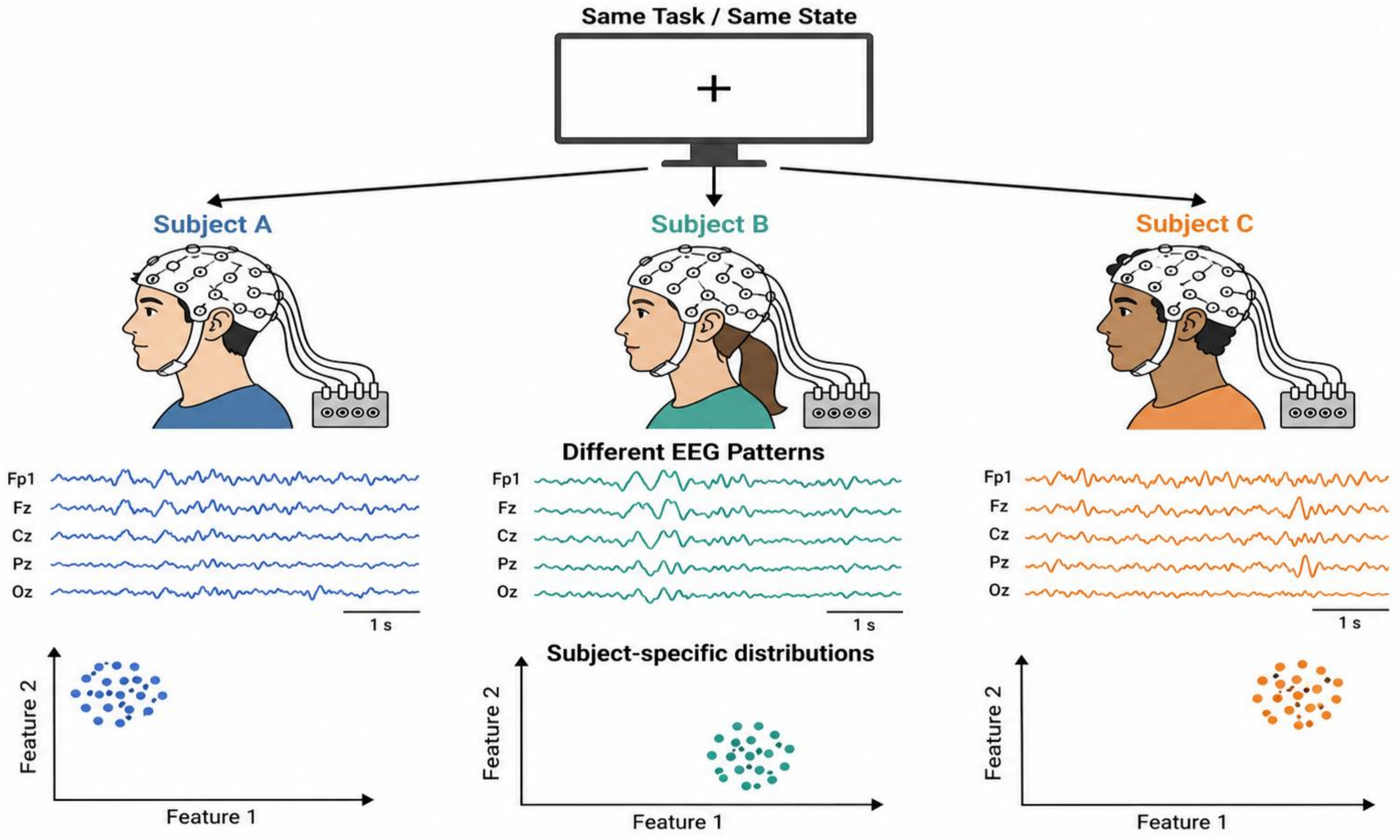
01 EEG : A non-invasive window into fast brain dynamics



01 **Applications** : EEG supports diverse brain-state decoding tasks



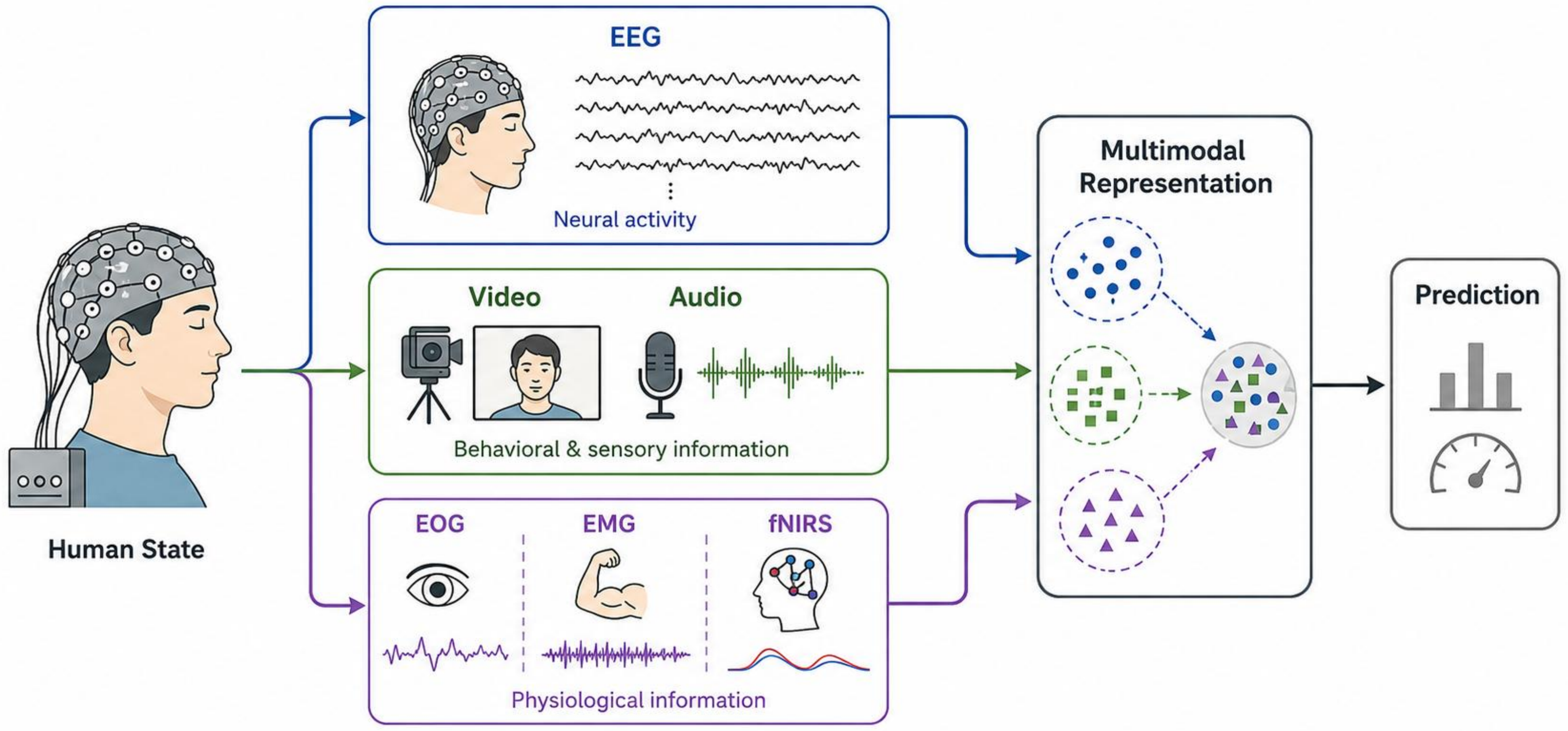
01 **Variability** : EEG distributions vary substantially across subjects



Same state ≠ Same EEG distribution

Inter-subject variability makes EEG generalization difficult.

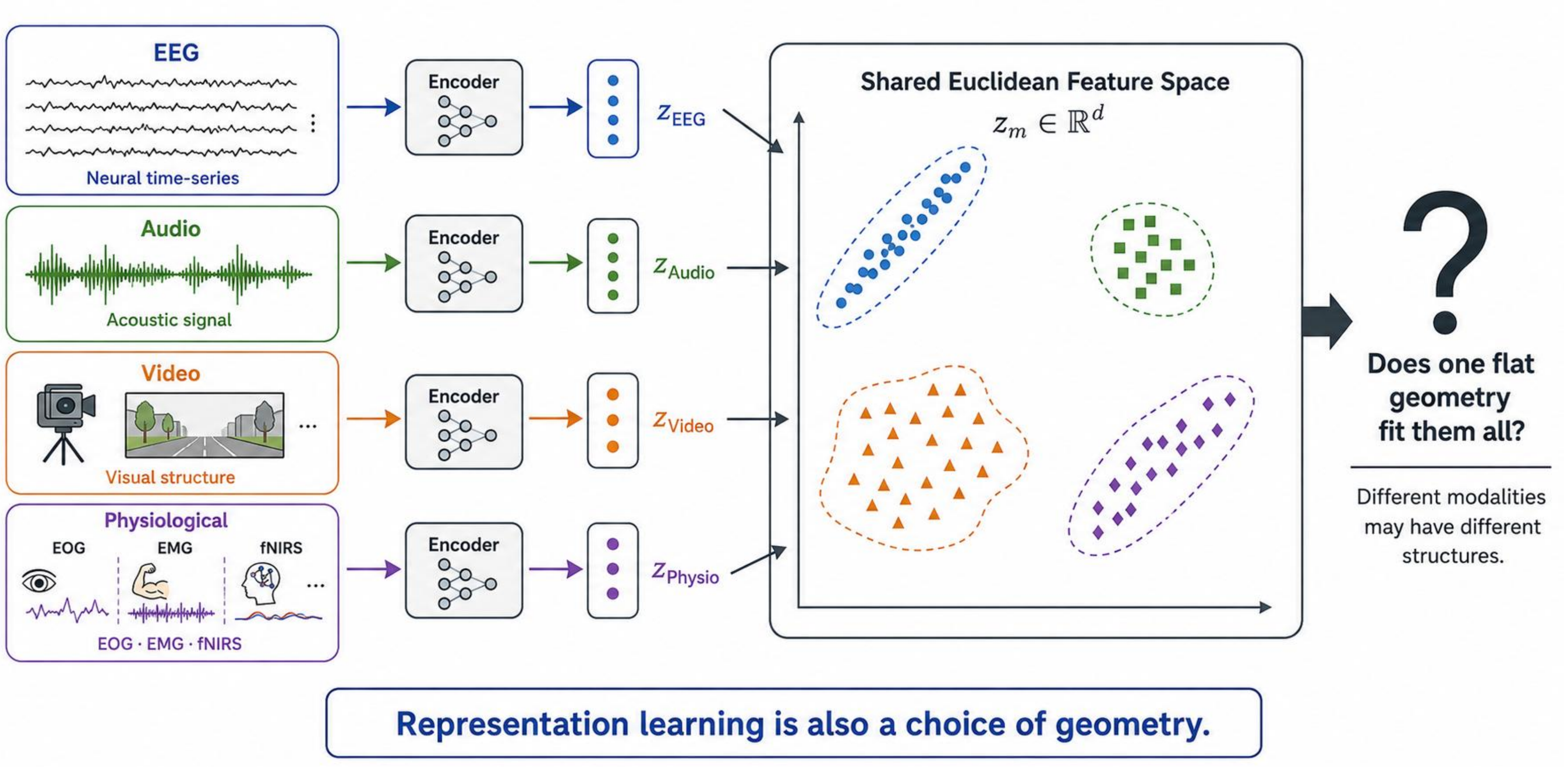
01 **Multimodality** : Complementary signals provide different views of the same state



Complementary information, heterogeneous representations

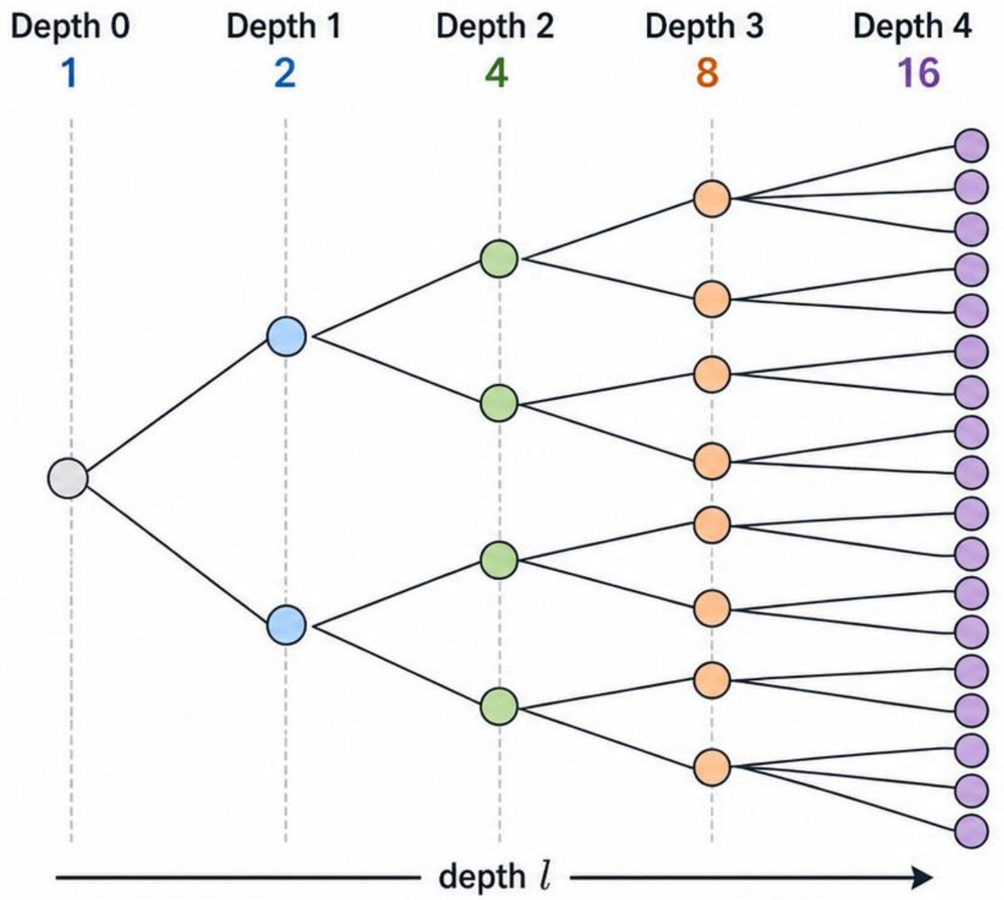
Different modalities describe the same state in different ways.

01 **Representation**: How should heterogeneous neural signals be represented?



Hyperbolic Foundations

02 Hierarchy : Tree structures grow exponentially with depth

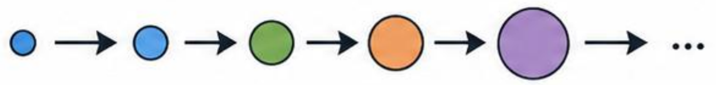


$$N(l) = b^l$$

b : branching factor

l : depth

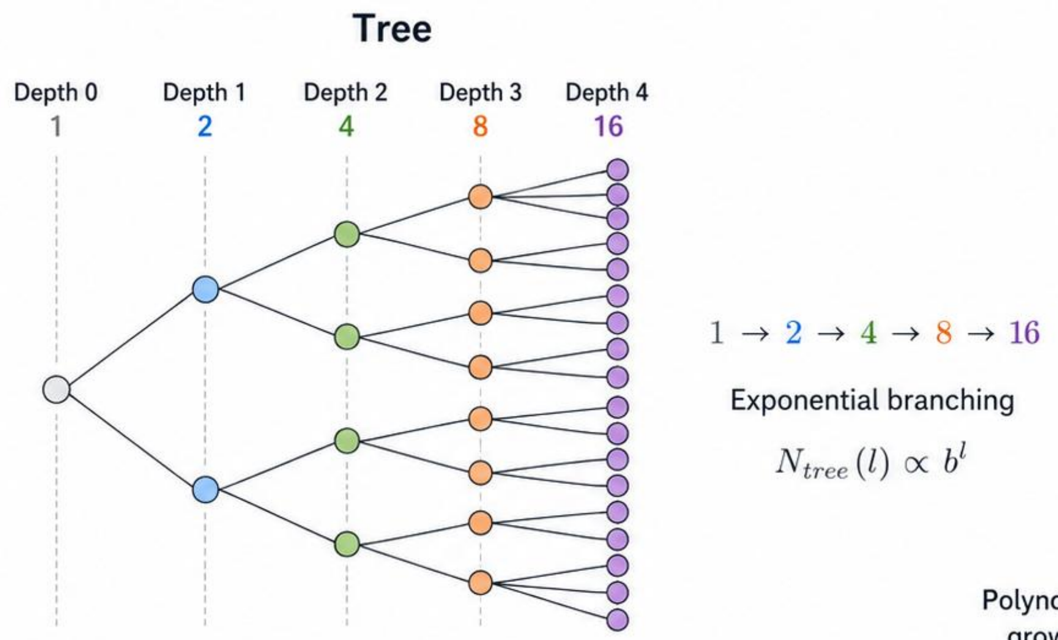
$1 \rightarrow 2 \rightarrow 4 \rightarrow 8 \rightarrow 16 \rightarrow \ldots$

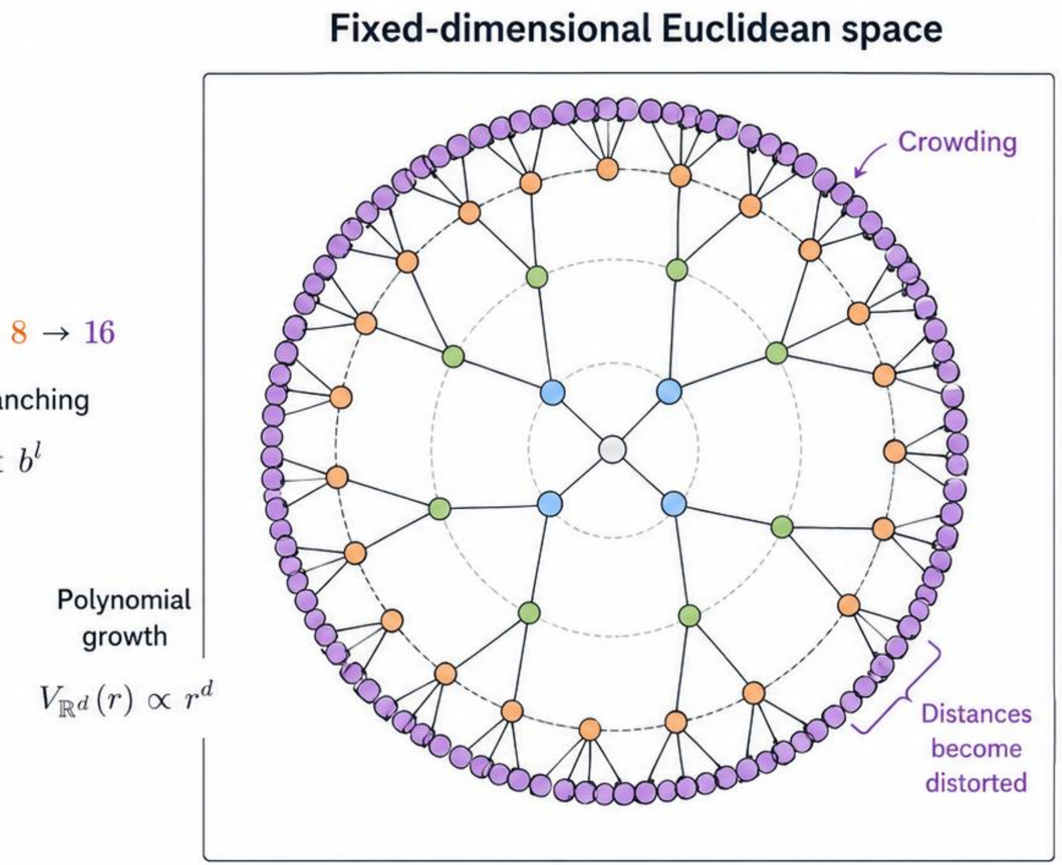


Small increase in **depth** → rapid increase in nodes

Hierarchical structure requires rapidly expanding representational space.

02 **Euclidean Limitation**: Polynomial volume growth causes crowding and distortion



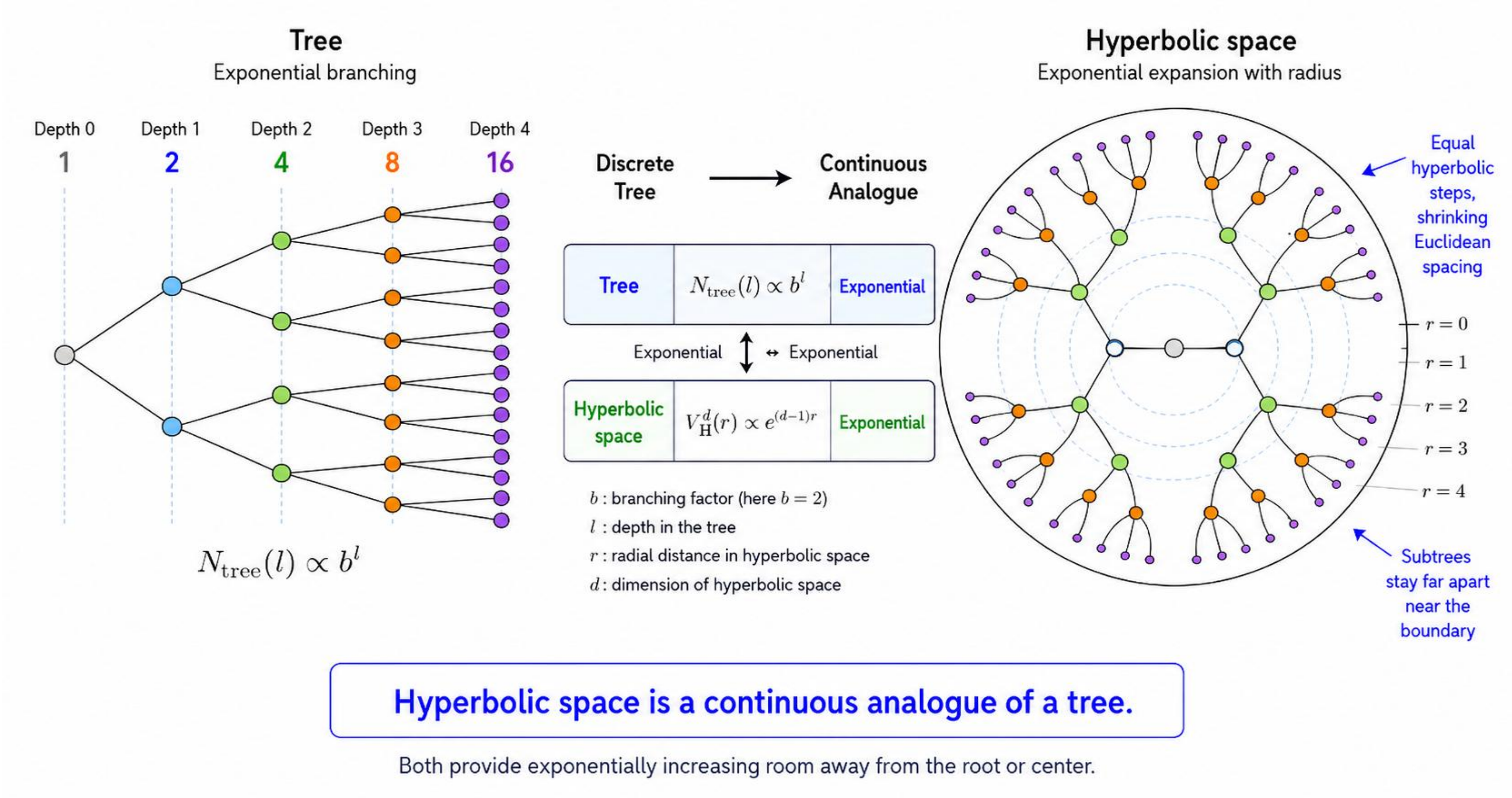


	Tree	$N_{tree}(l) \propto b^l$	Exponential growth
	Euclidean space	$V_{\mathbb{R}^d}(r) \propto r^d$	Polynomial growth

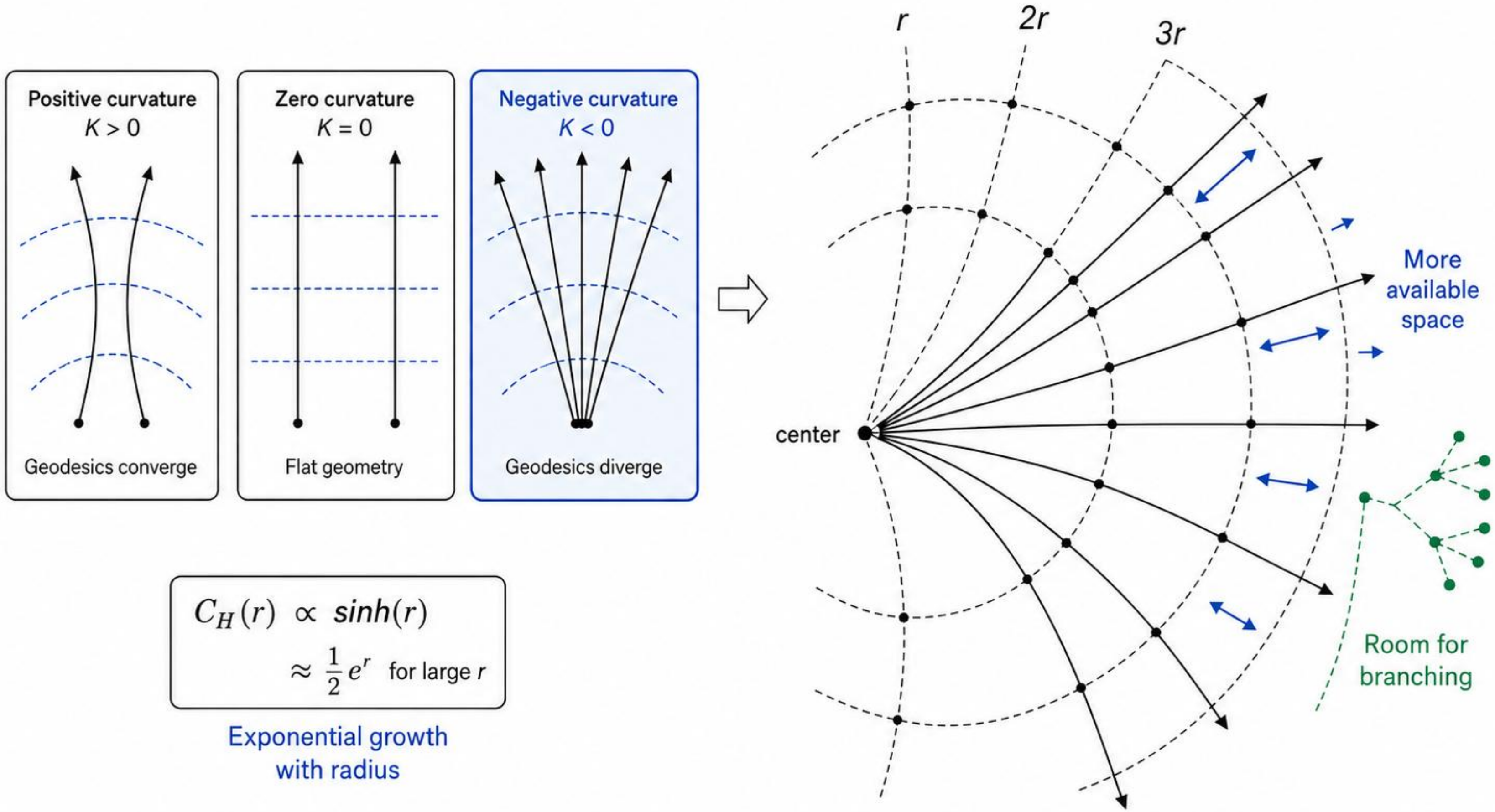
Exponential branching outgrows polynomial Euclidean volume.

Deeper hierarchies lead to crowding and larger distortion.

02 **Continuous Tree** : Hyperbolic space naturally matches hierarchical expansion



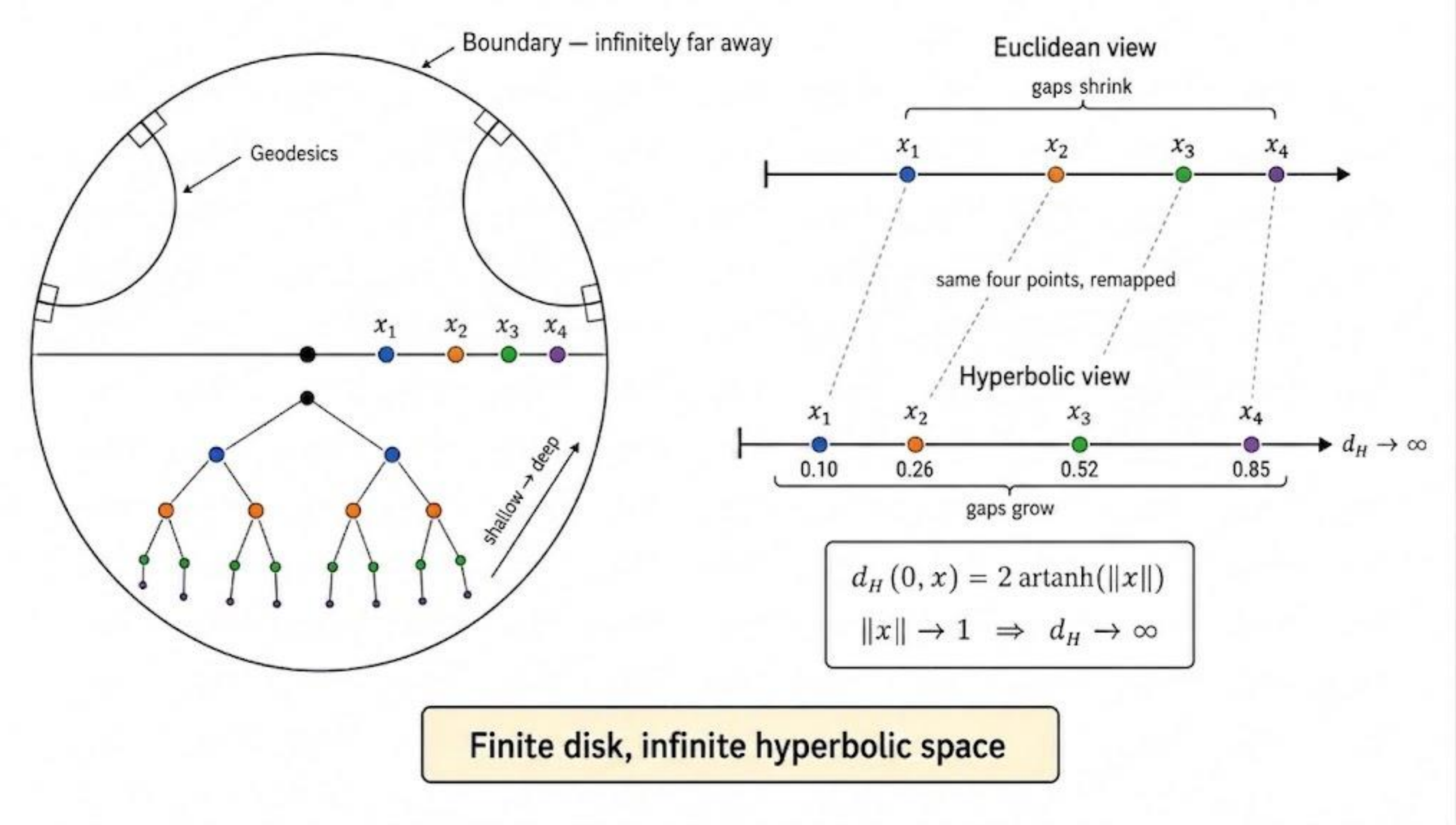
02 Hyperbolic Geometry: Negative curvature creates exponentially expanding space



Negative curvature creates room for exponential branching.

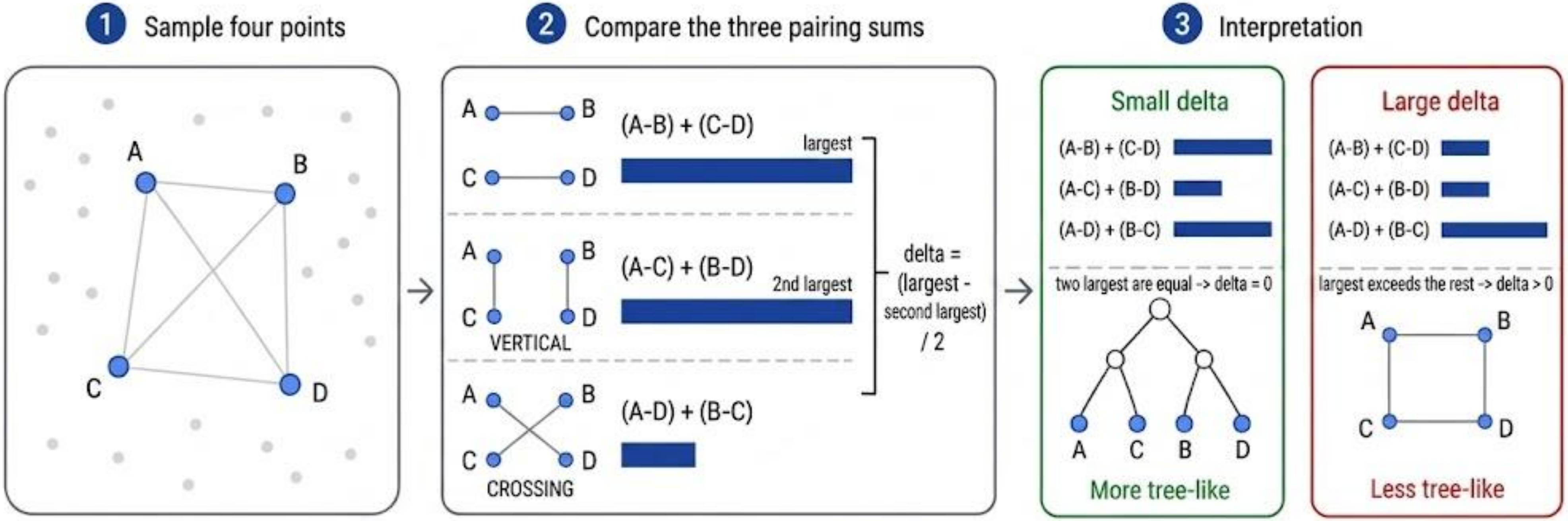
Geodesic divergence creates rapidly increasing space for hierarchical structure.

02 **Poincaré Disk** : A compact visualization of an infinite hyperbolic space



02 Hyperbolicity : How tree-like is a representation?

How tree-like is the representation?



repeat over many quadruples

Lower δ_{rel} → More tree-like

Used to quantify hierarchical structure in EEG representations

delta = $\max_{\text{over all quadruples}}$, $\text{delta}_{rel} = 2 * \text{delta} / \text{diam}(X)$ diam(X) = diameter of the whole point set

HEEGNet

Table 1: **Pilot Study: δ_{rel} of datasets**. The lower the δ_{rel}, the closer the dataset to hyperbolic space. The number of domains in each dataset is indicated by n.

	Visual		Emotion		Intracranial
Dataset **Metric**	Nakanishi (n=9)	Wang (n=34)	Seed (n=45)	Faced (n=123)	Boran (n=37)
Raw δ_{rel}	0.244 ± 0.064	0.219 ± 0.053	0.052 ± 0.026	0.103 ± 0.077	0.157 ± 0.045
Intermediate δ_{rel}	0.263 ± 0.036	0.240 ± 0.045	0.061 ± 0.026	0.111 ± 0.050	0.141 ± 0.041
Classification space δ_{rel}	0.306 ± 0.027	0.333 ± 0.039	0.072 ± 0.025	0.132 ± 0.047	0.017 ± 0.048

03 **Geometry Matters**: Hyperbolic classification improves cross-domain performance

Table 2: **Pilot Study: comparison of Euclidean / Hyperbolic MLR**. The averages of test-set scores are shown above using balanced accuracy (the score and the standard deviation are shown for each dataset). The number of domains in each dataset is indicated by n. Permutation-paired t-tests were used to identify significant differences between EEGNet+HMLR (*Hyperbolic*) and EEGNet (1e4 permutations). Significant differences are highlighted using dots: $\cdot p \leq 0.05$, $\bullet p \leq 0.01$, $\bullet p \leq 0.001$.

	Visual		Emotion		Intracranial
Dataset **Model**	Nakanishi $(n = 9)$	Wang $(n = 34)$	Seed $(n = 45)$	Faced $(n = 123)$	Boran $(n = 37)$
EEGNet	57.2 ± 19.8 •	37.4 ± 12.9 ●	74.5 ± 19.8	24.8 ± 13.7 ●	55.4 ± 9.1
EEGNet + HMLR	60.8 ± 20.7	39.2 ± 13.8	75.1 ± 20.0	38.8 ± 12.4	57.4 ± 8.7

Architecture: Euclidean feature extraction meets hyperbolic representation learning

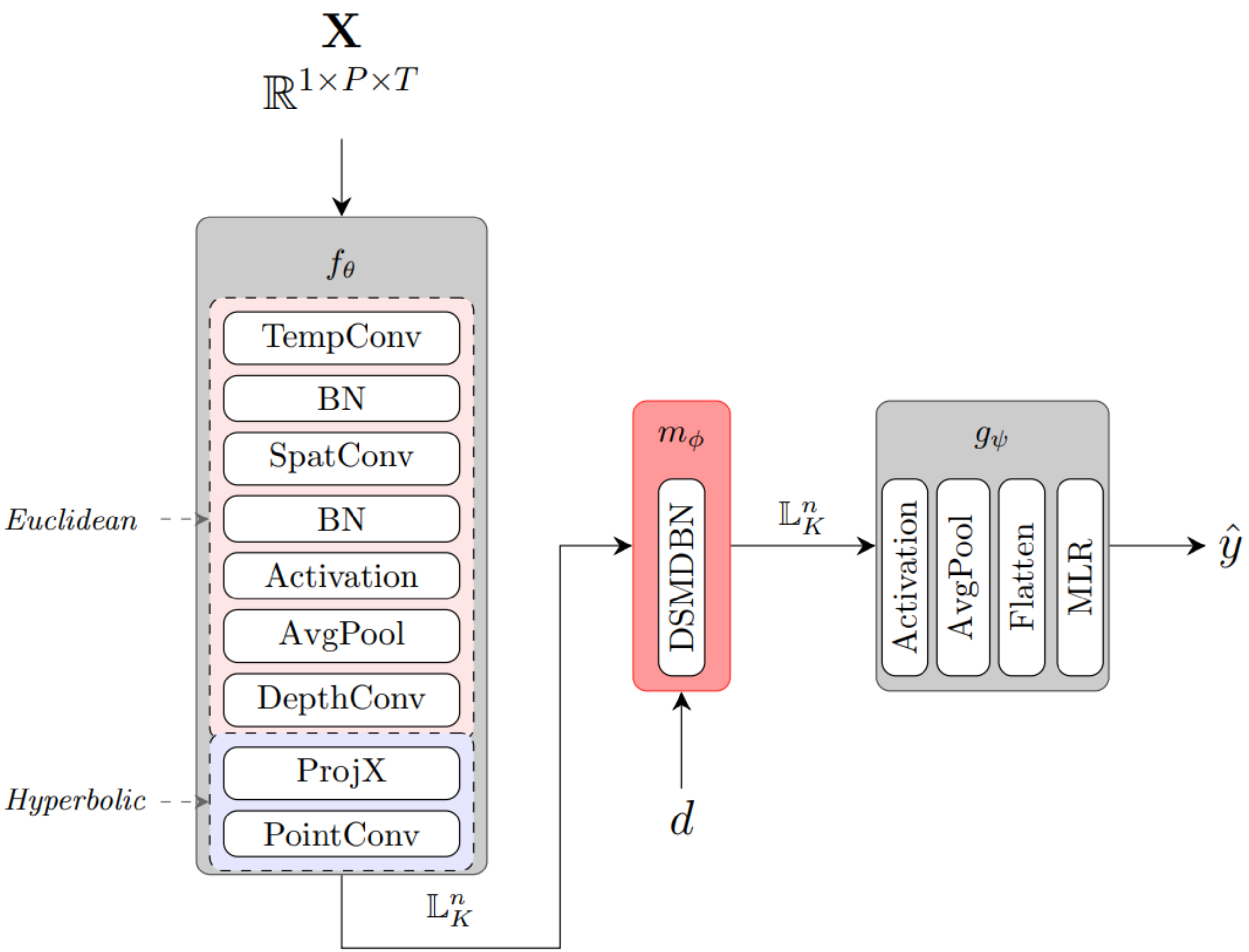
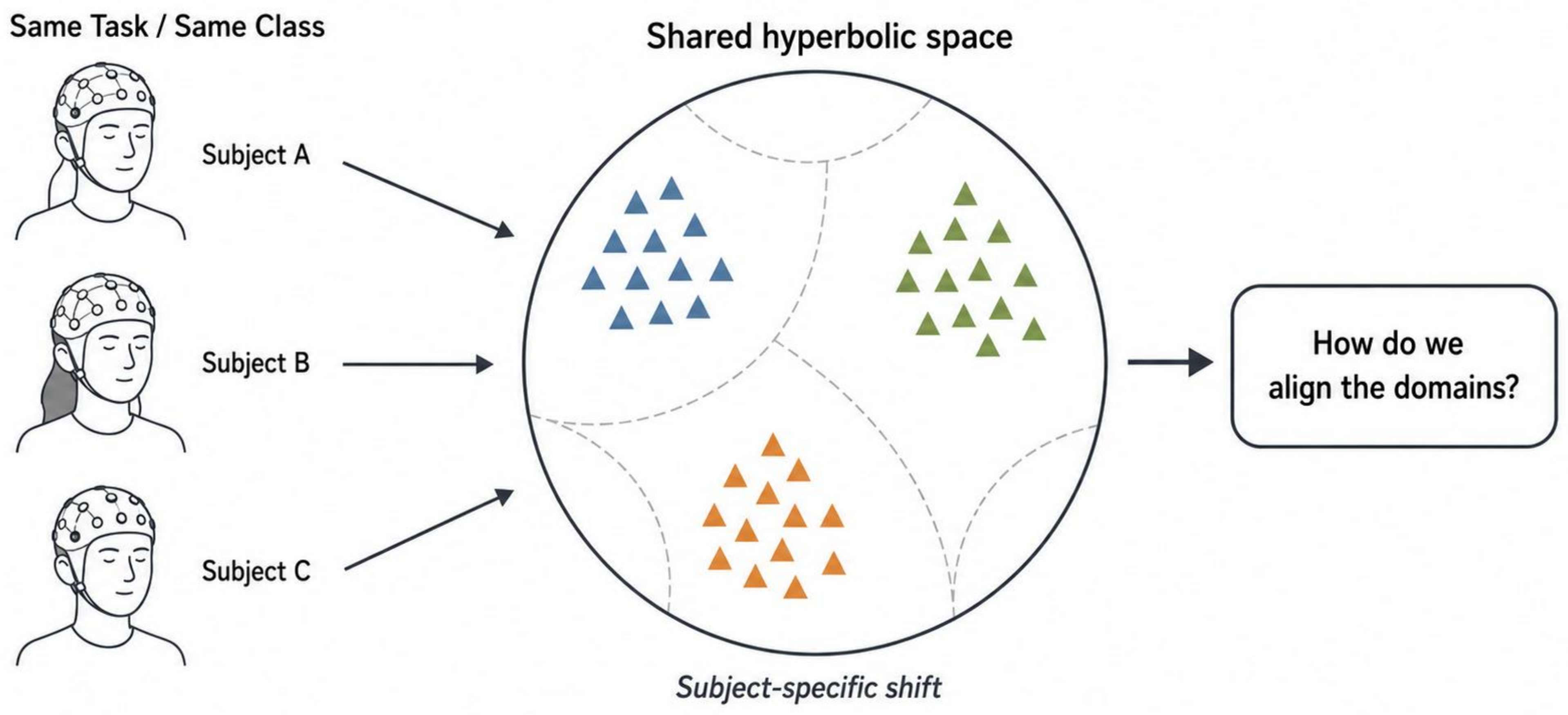


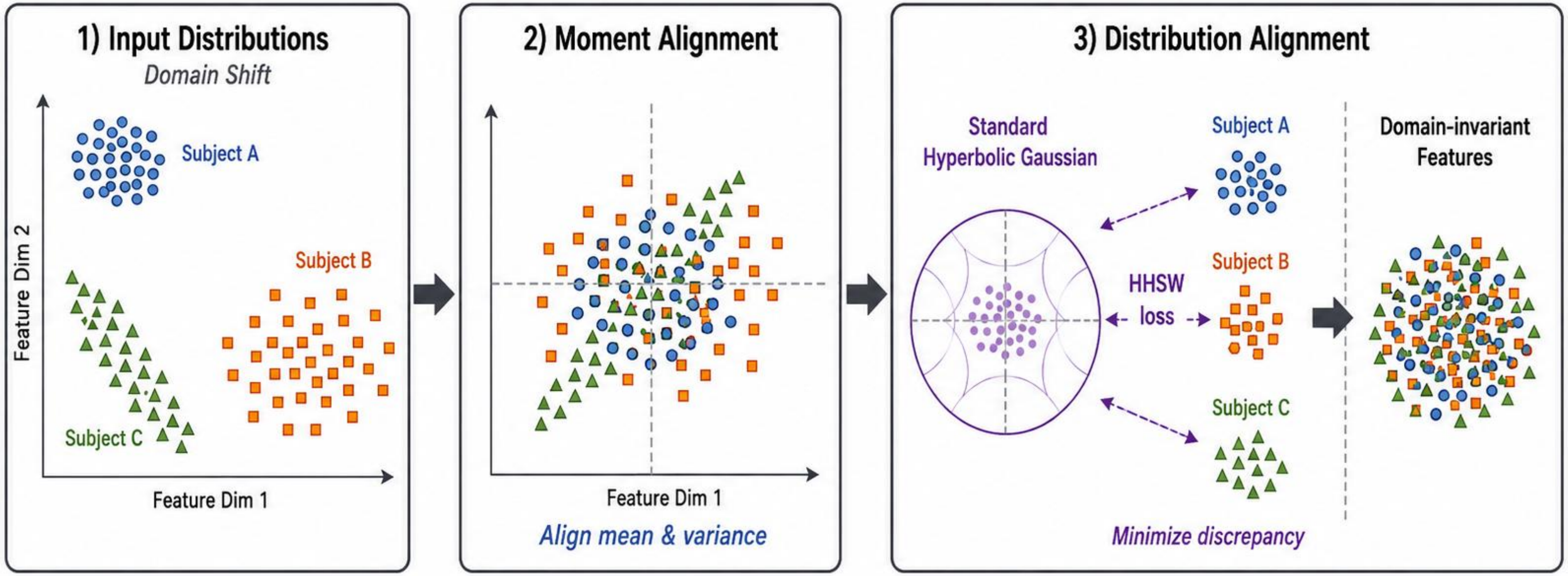
Figure 3: HEEGNet architecture.

03 **Domain Shift** : Hyperbolic geometry alone cannot remove subject variability



Hyperbolic structure helps, but domain alignment is still needed.

03 **Alignment**: Align subject-specific moments first, then distributions



Coarse alignment first, fine alignment second.

03 **Generalization** : Geometry and domain alignment work together

Model	SFUDA	VEP (n=67)	Emotion (n=168)	Intracranial (n=37)	Overall (n=272)
EEGNet	w/o	35.7±15.5 •	38.1±27.0 •	55.4±9.1 •	39.9±23.6 •
	EA	55.8±20.8 •	73.8±22.3 •	59.1±11.2 •	67.4±22.3 •
	STMA	30.3±8.9 •	70.7±20.5 •	51.2±5.9 •	58.1±24.0 •
EEGConformer	w/o	29.1±9.1 •	83.2±16.9 •	55.5±7.0 •	66.1±27.2 •
	EA	46.1±23.1•	82.8±16.8 •	61.7±13.1 •	70.9±24.1 •
	STMA	27.8±7.0 •	78.2±15.9 •	53.1±5.2 •	62.4±25.2 •
ATCNet	w/o	33.3±15.4 •	17.5±11.7 •	57.5±9.0 •	26.9±18.5 •
	EA	52.2±21.4•	54.1±15.5 •	57.1±9.0 •	54.0±16.5 •
	STMA	39.4±15.6 •	56.4±16.3 •	54.2±5.7 •	51.9±16.7 •
TSLANet	w/o	24.4±14.1 •	35.5±12.9 •	55.1±9.3 •	35.5±15.7 •
	EA	37.3±28.1 •	44.8±18.1 •	54.9±10.4 •	44.3±20.8 •
	STMA	20.5±5.4 •	49.6±15.1 •	54.1±6.2 •	43.0±17.9 •
SchirrmeisterNet	w/o	40.2±27.5 •	51.9±22.4 •	56.9±7.7 •	49.7±23.1 •
	EA	35.7±24.7 •	79.0±16.4 •	65.0±10.2	66.5±25.7 •
	STMA	33.1±16.8 •	64.2±16.7 •	53.9±5.5 •	55.2±20.4 •
FBCNet	w/o	22.8±8.0 •	28.5±19.5 •	61.1±10.6 •	31.6±20.2 •
	EA	38.8±28.4 •	51.3±20.7 •	61.3±11.0 •	49.6±22.9 •
	STMA	21.6±5.4 •	33.0±20.9 •	53.0±6.8 •	32.9±19.2 •
HEEGNet *(proposed)*	DSMDBN	**79.6±19.8**	82.8±16.6	58.4±9.6	78.7±18.6
	DSMDBN+EA	77.4±12.6	**86.7±12.5**	**66.7±12.5**	**81.7±14.4**

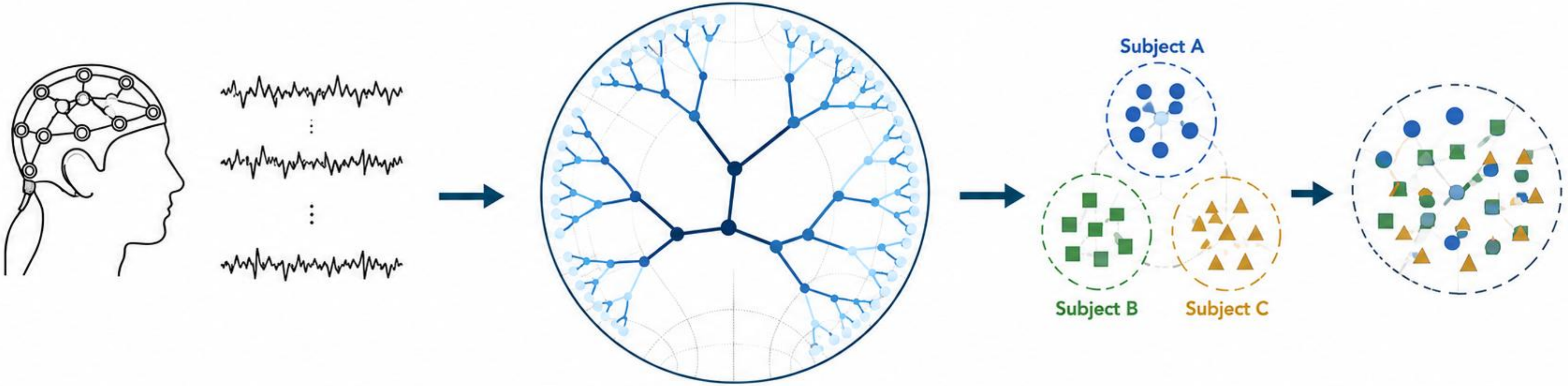
Conclusion

03 Conclusion : EEG may need the right geometry

1. EEG Geometry

2. Hyperbolic Representation

3. Domain Alignment



EEG representations show tree-like structure

Hyperbolic space provides a useful inductive bias

Geometry works best with subject-specific alignment

HEEGNet = Hyperbolic Representation + Domain Alignment

The key question is not only how to learn EEG features, but what geometry those features should live in.

Thank You

2026.08.18

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