华南理工大学
South China University of Technology

Learning Developmental Path Signature Features with Deep Learning Framework for Infant Cognitive Score Prediction

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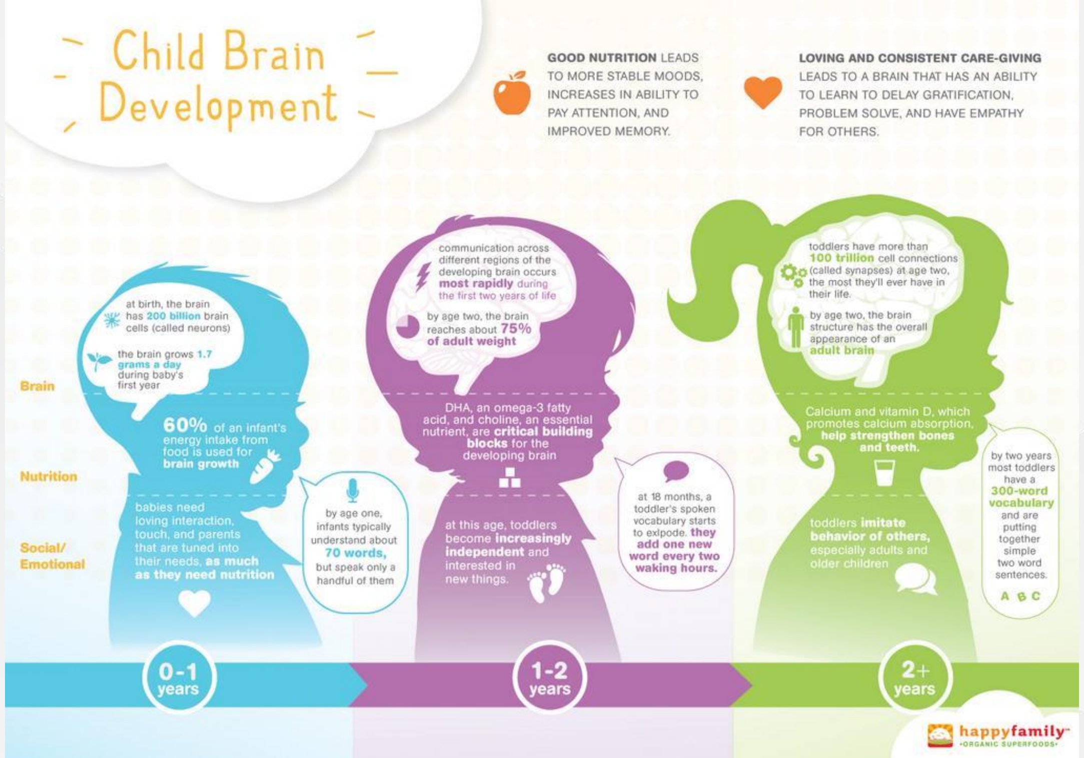
01

PART ONE

Background and Motivation

01/ Background and Motivation

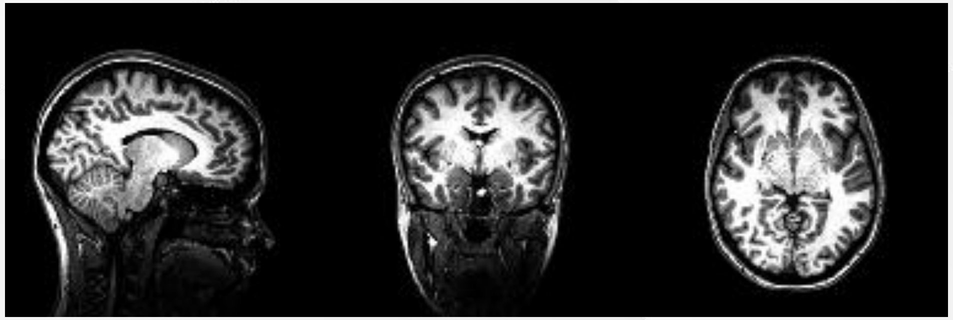
There is stunning rapid development of human brains during the infancy and toddler years.

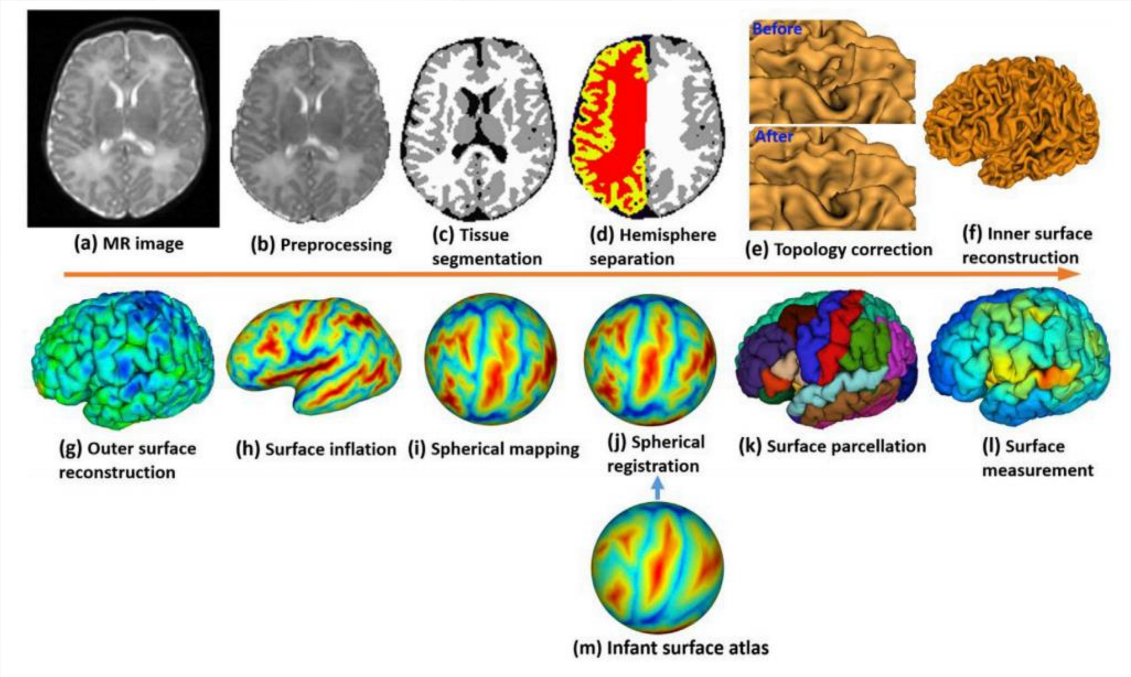


Li, G., Wang, L., Yap, P.T., Wang, F., Wu, Z., Meng, Y., Dong, P., Kim, J., Shi, F., Rekik, I.: Computational neuroanatomy of baby brains: A review. NeuroImage, 185, 906-925 (2019)

01/ Background and Motivation

With the advancement of magnetic resonance imaging (MRI) and image processing techniques, the early brain cortical structure and its development can be measured and studied.





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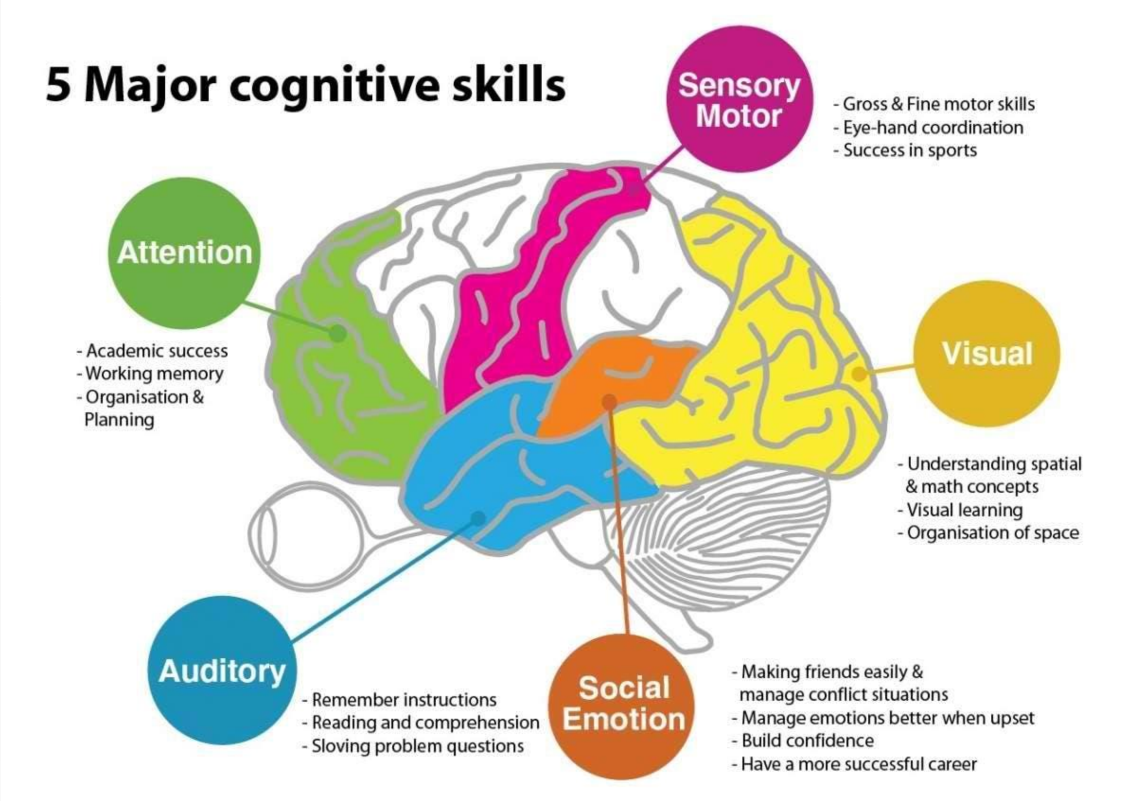
01/ Background and Motivation

Cognitive skills, (also called cognitive functions, cognitive abilities or cognitive capacities), are brain-based skills that encompass the domains of perception, attention, memory, learning, decision making and language abilities.



Braaten, E.B.: Mullen scales of early learning. The SAGE Encyclopedia of Intellectual and Developmental Disorders 34(4), 379-382 (2018)

01/ Background and Motivation

The Mullen Scales of Early Learning (MSEL) is designed to measure development in infants and preschoolers.

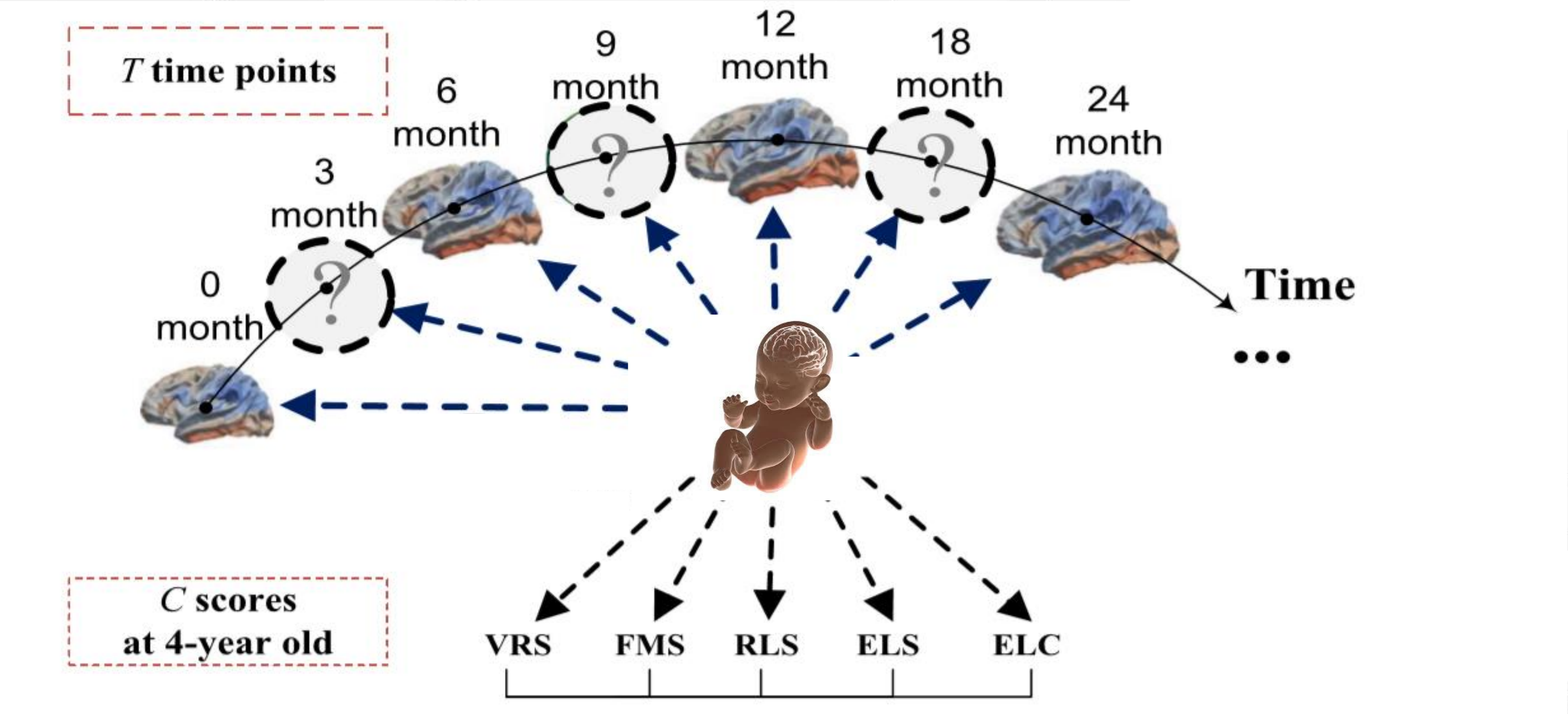
Usually, five cognitive scales are estimated including:

- Visual Receptive Scale (VRS)
- Fine Motor Scale (FMS)
- Expressive Language Scale (ELS)
- Receptive Language Scale (RLS)
- Early Learning Composite (ELC)

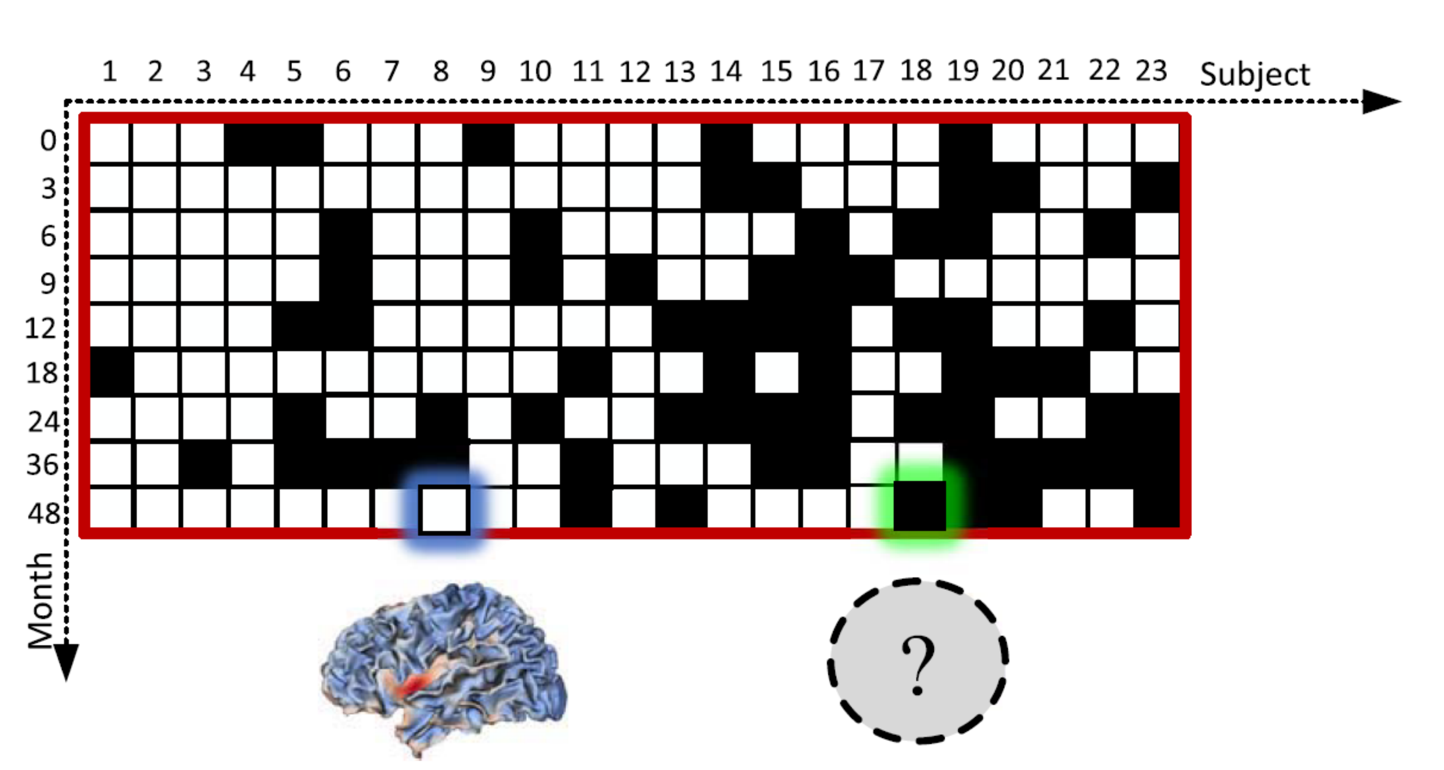
Braaten, E.B.: Mullen scales of early learning. The SAGE Encyclopedia of Intellectual and Developmental Disorders 34(4), 379-382 (2018)

01/ Background and Motivation

Our **research goal** is to understand the quantitative relationship between morphological features of infant cerebral cortex and cognitive skills with the *machine learning methods*.



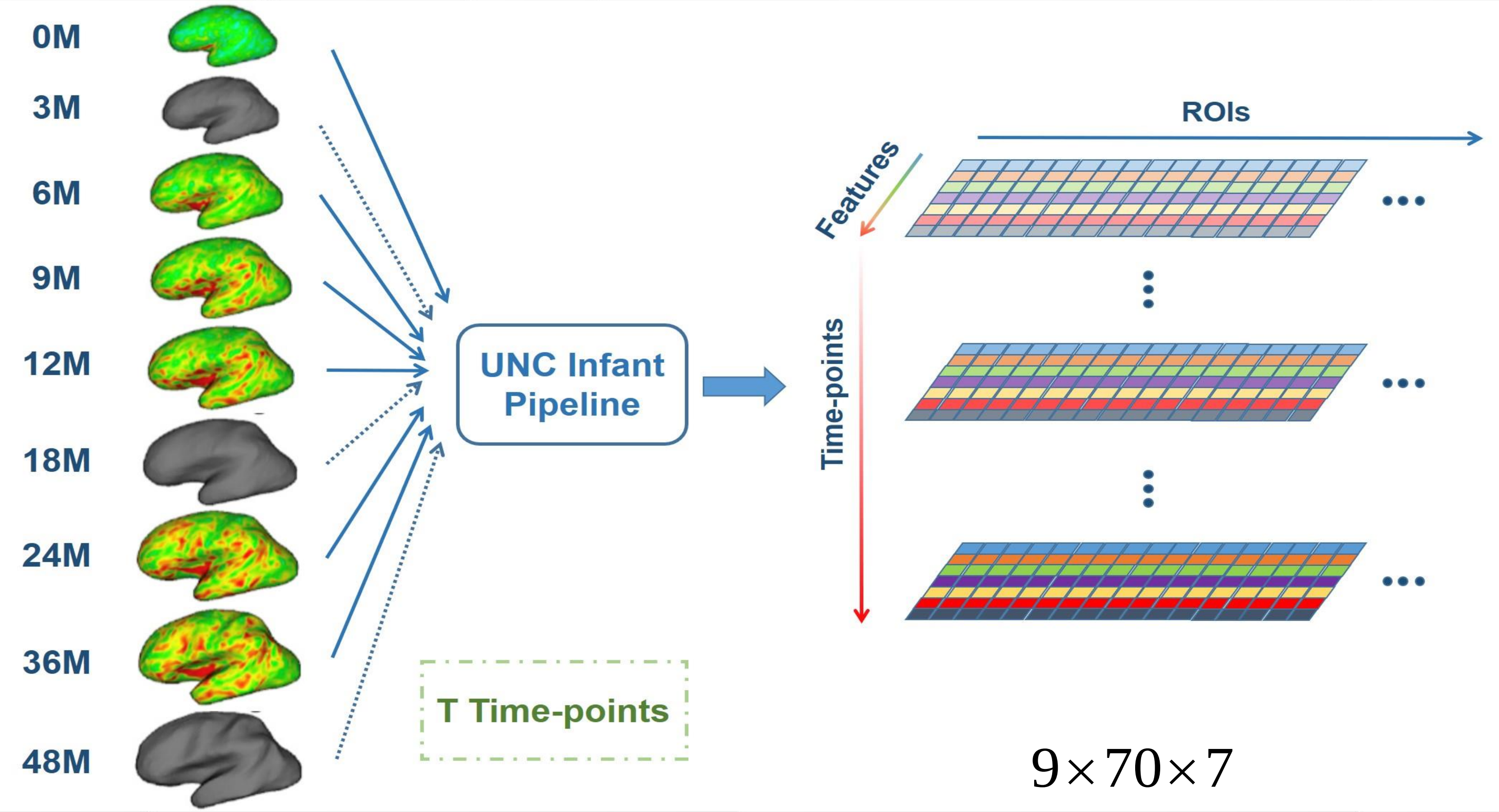
01/ Motivation and Challenges



Challenges:

1.Small data set: It is common in medical data analysis. Sometimes, there is a missing data issue as some participants (infants) can not show up at schedule.

01/ Motivation and Challenges



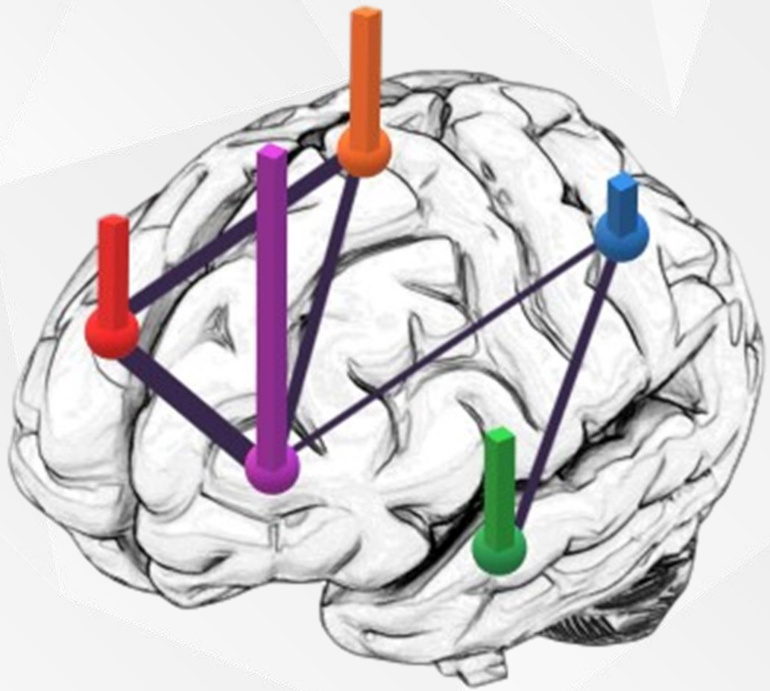
Challenges:

1. **Small data set**
2. **High dimensional features:** we process the data following an infant MRI computational pipeline. At each time points, we parcellate the cerebral cortex into 70 anatomically meaningful regions of interest (ROIs) and compute 7 different morphological cortical measurements.

01/ Motivation and Challenges

Challenges:

1. **Small data set**
2. **High dimensional features**
3. **Spatial pattern missing:** existing methods usually simply flatten brain morphological feature vectors at every time point into a **vector.** It obviously overlooks the potential connectivity among brain regions and longitudinal developmental information of early brain.



01/ Motivation and Challenges

In following works, we tried to:

- utilize **path signature features** as a set of compact and discriminative features to describe the grow trajectories of brain regions without introducing extra parameters, considering the **small data set** and **high dimensional features** issues;

- build a connectivity matrix based on the **path signature features** to illustrate the **spatial patterns** among brain regions, for a better understanding of the relationship between the cortical structure and cognition functions.

02

PART TWO

RELATED WORK

02/ Related Work

Early work mainly relies on statistical analysis

- Factor analysis and relate theories are used to qualitatively evaluate the impact of different cortical structure on cognition function and illustrate the highly correlation between the anatomical differentiation of white matter fiber and cognitive development.

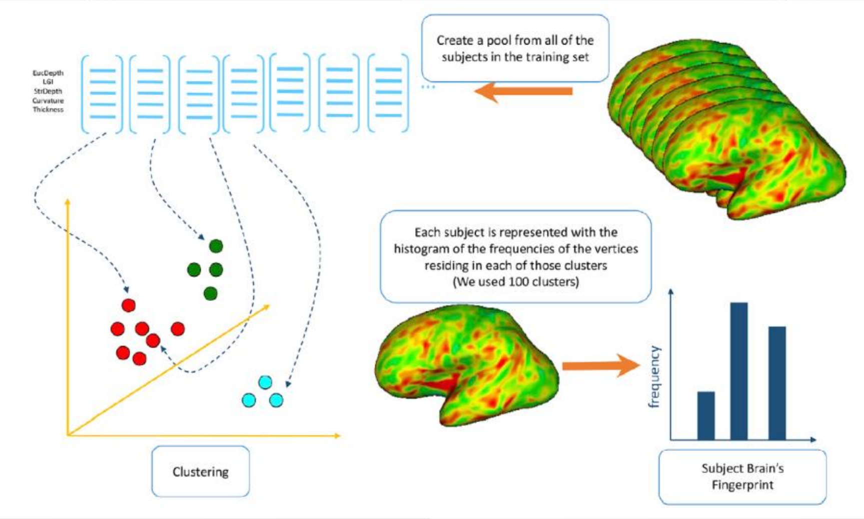
- Nevertheless, for the lack of quantitative formulation, they are incapable to predict the quantified cognitive scales directly.

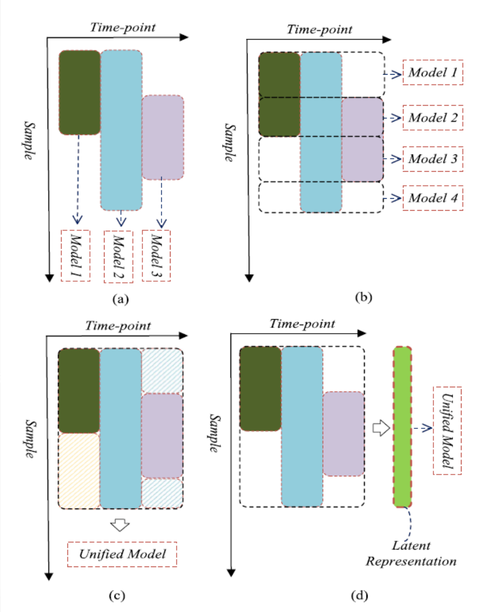
02 Related Work

Recent works involve more machine learning theories

[1] Bags-of-Words (BoW) based method was employed to slash the overlarge dimensionality of neuroimaging data.

[2] A nonlinear latent representation for each subject was generated by multi-view representation learning.





[1] Adeli, E., Meng, Y., Li, G., Lin, W., Shen, D.: Multi-task prediction of infant cognitive scores from longitudinal incomplete neuroimaging data. NeuroImage 185, 783{792 (2019)

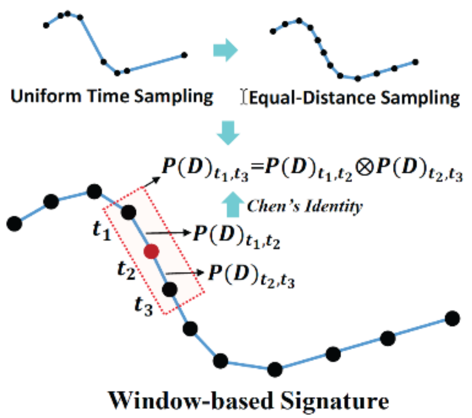
[2] Zhang, C., Adeli, E., Wu, Z., Li, G., Lin, W., Shen, D.: Infant brain development prediction with latent partial multi-view representation learning. IEEE Transactions on Medical Imaging 38(4), 909{918 (2019)

03

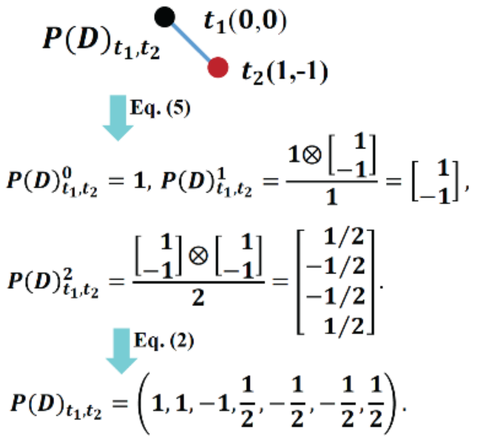
PART THREE

PATH SIGNATURE AND ITS APPLICATIONS

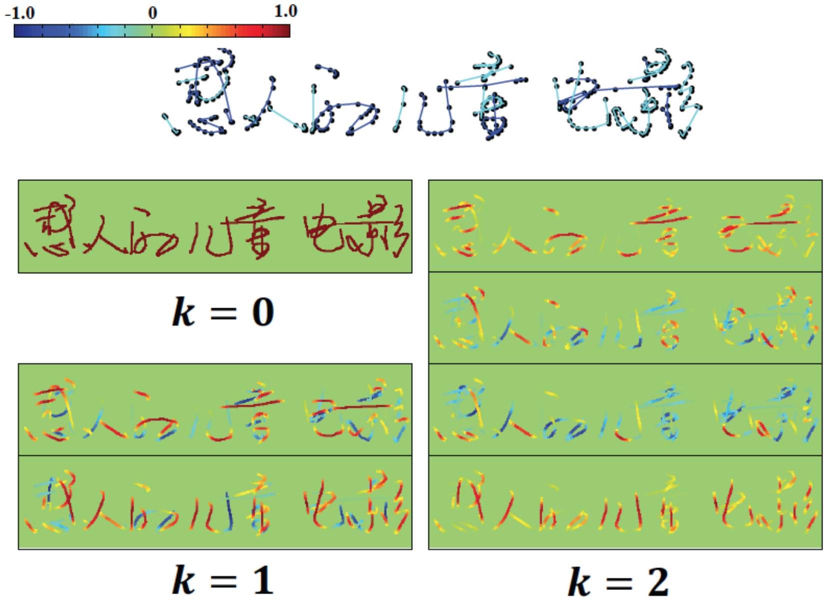
03 Path Signature Feature Maps



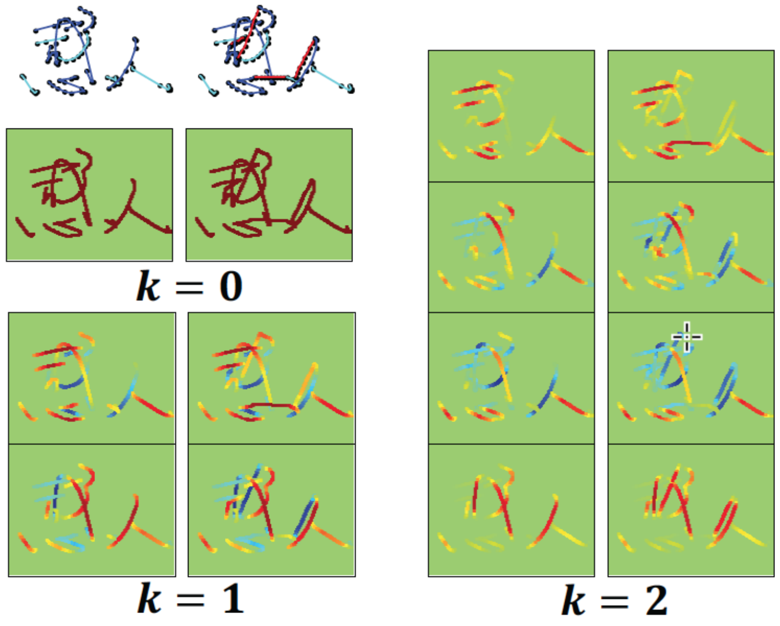
(a)



(b)



(c)

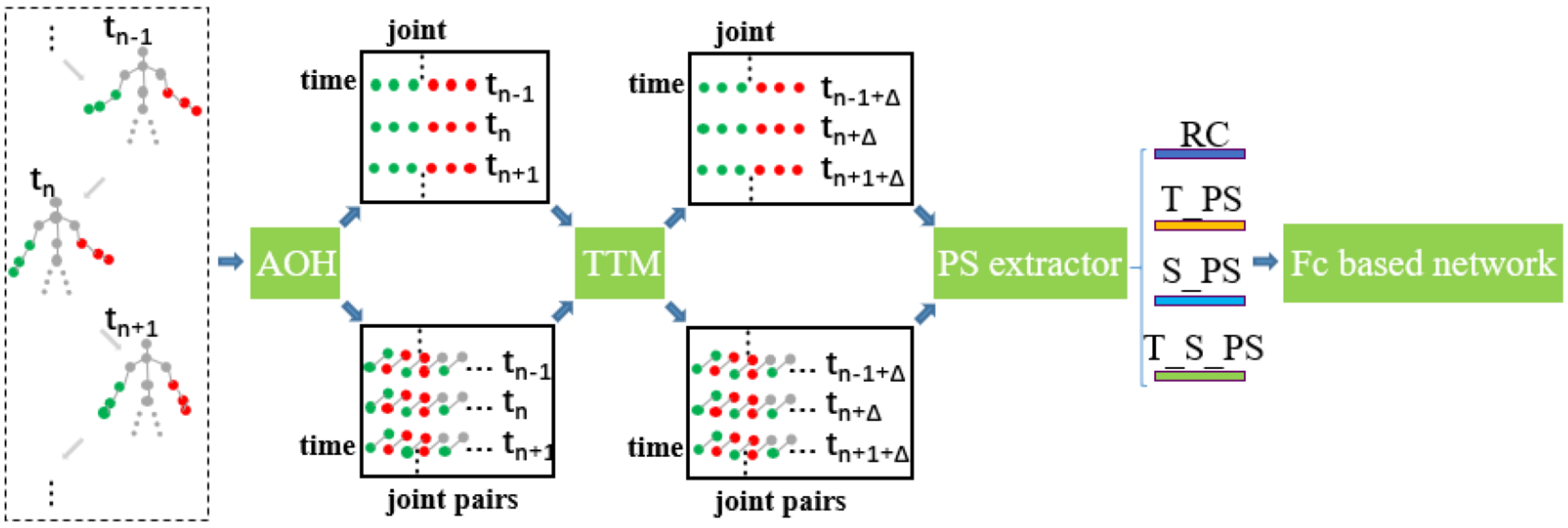


(d)

ZC Xie, ZH Shun, LW Jin, H Ni, T Lyons, IEEE TPAMI, 2018.

03 Path Signature

Hand gesture is defined on whole hand movement. Hand trajectory is considered as path.



Chenyang Li and Xin Zhang, "Skeleton-based Gesture Recognition Using Several Fully Connected Layers with Path Signature Features and Temporal Transformer Module" **AAAI 2019 (acceptance rate: 16.8%)**, https://arxiv.org/abs/1811.07081

03 Path Signature

Hand gesture is defined on whole hand movement. Hand trajectory is considered as path.

- **Feature types**: (path of signature is denoted as PS)
  - **Raw coordinates (RC):** the xyz coordinates of 6 joints on both hands.
  - **Temporal PS (T-PS):** the temporal dyadic PS over the evolution of each joint.
  - **Spatial PS (S-PS):** the PS of each pair of joint (spatial pathlet).
  - **Spatial-temporal PS (S-T-PS):** the PS of each dimension of spatial PS.

Chenyang Li, etc., "Skeleton-based Gesture Recognition Using Several Fully Connected Layers with Path Signature Features and Temporal Transformer Module" **AAAI 2019 (acceptance rate: 16.8%)**, https://arxiv.org/abs/1811.07081

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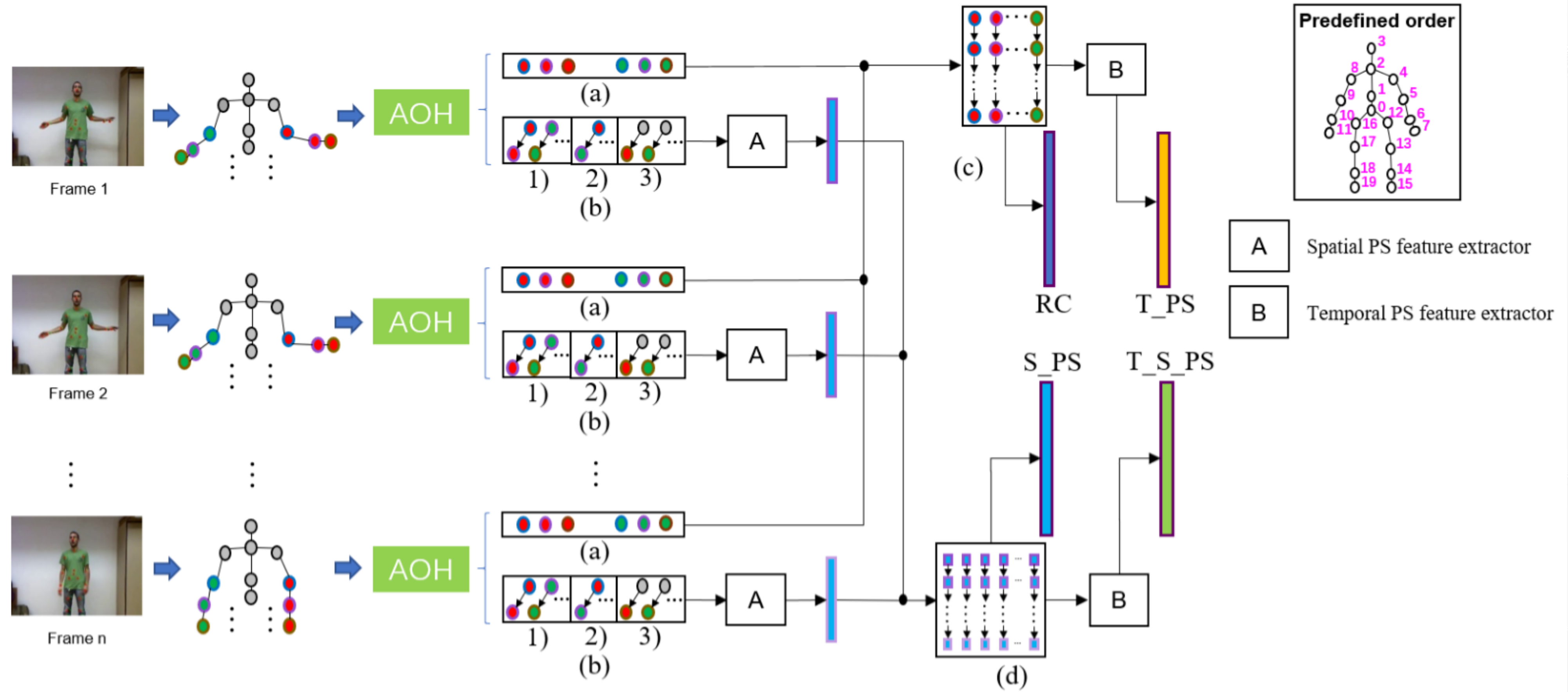

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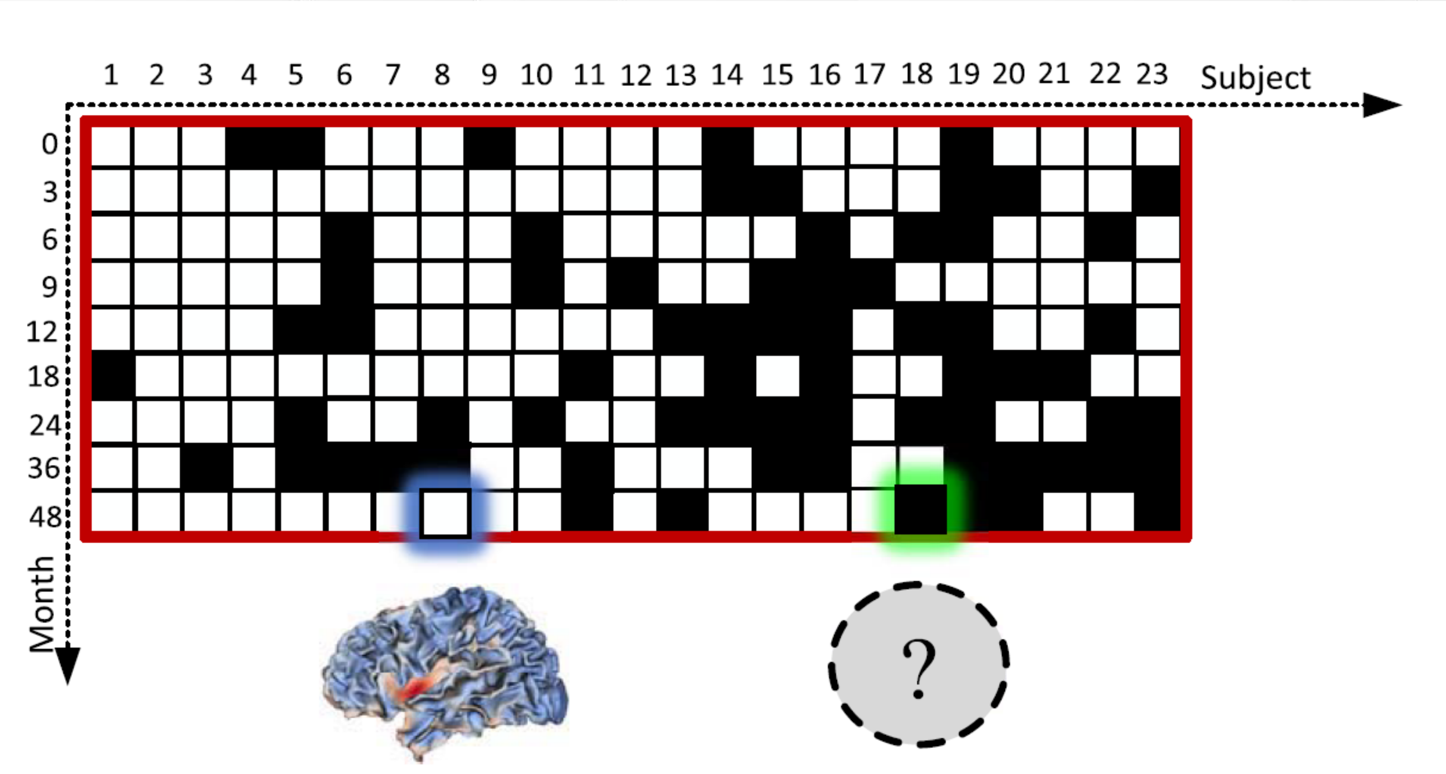
04

PART FOUR

PROPOSED METHOD ONE: BRAIN-PS-NET

Published in MICCAI 2020, submitted to IEEE Trans on Medical Imaging

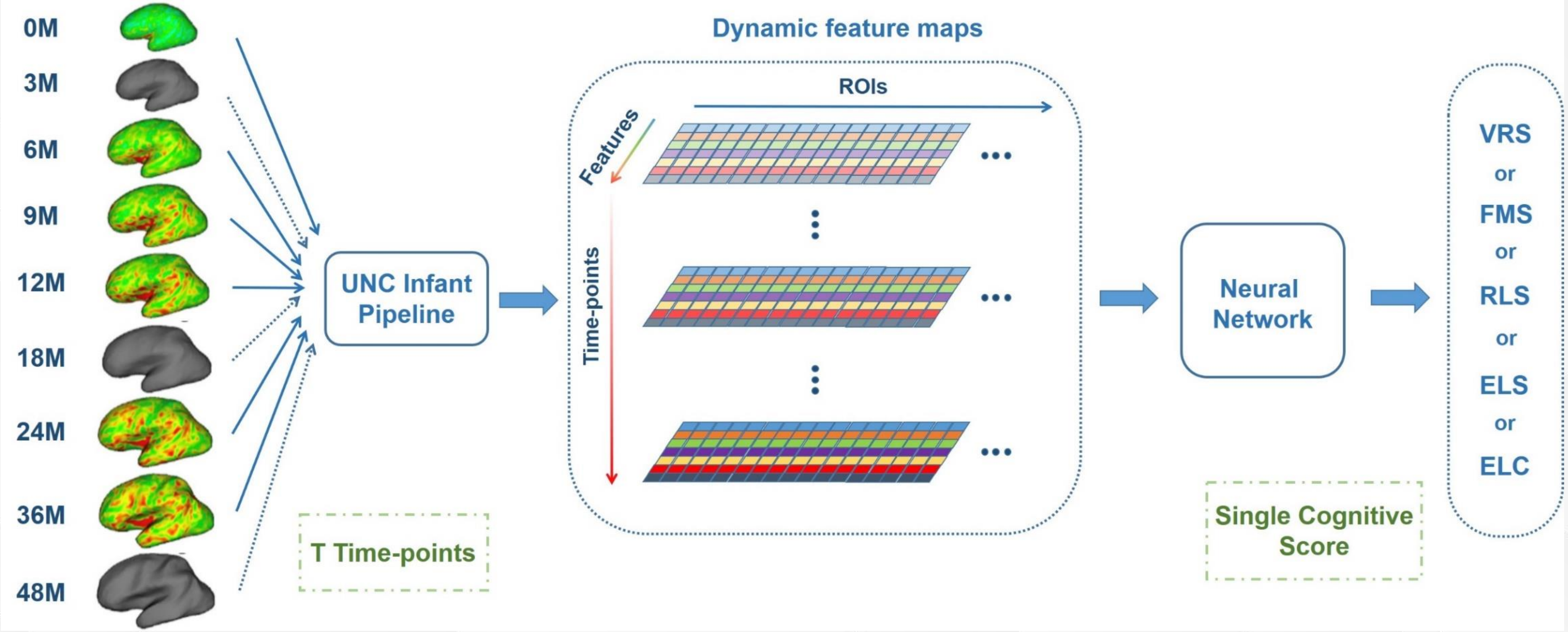
4.1 Dataset



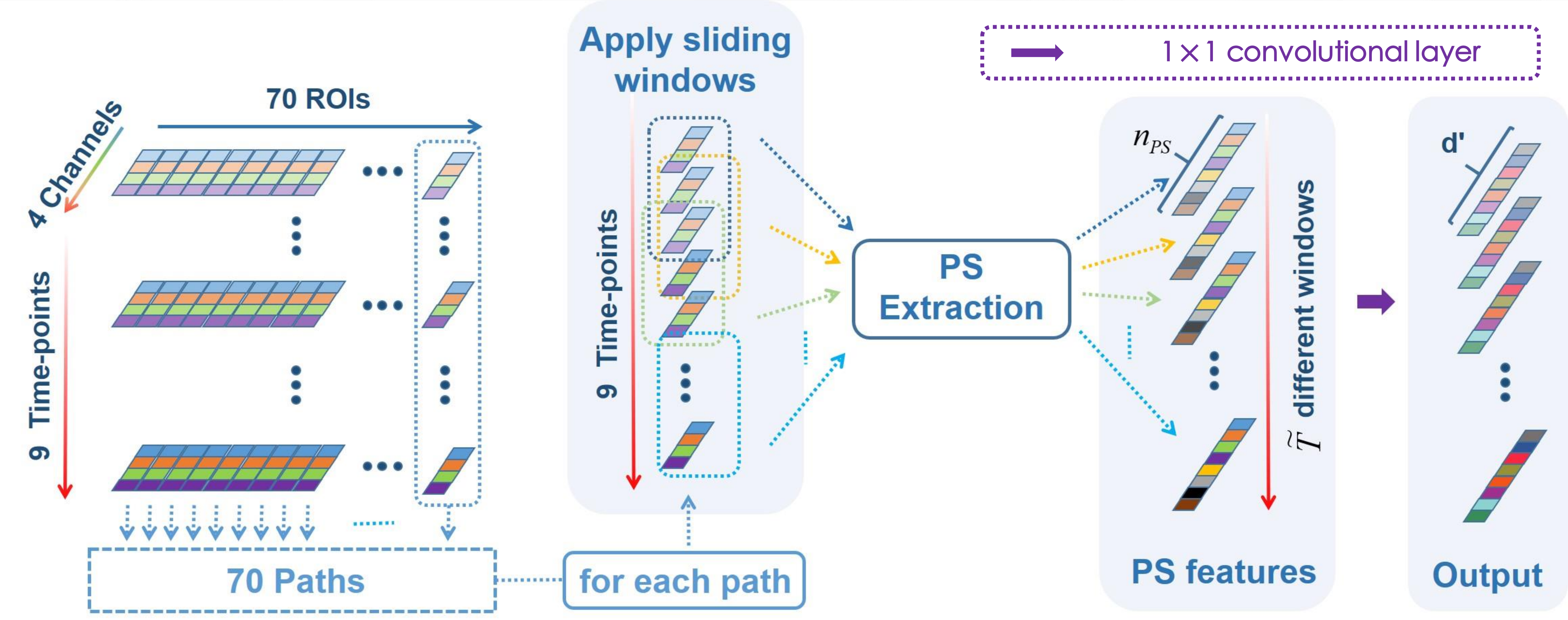
- We have 23 normal infants with their T1w and T2w MRI.
- Every subjects are supposed to have 9 scans at 0, 3, 6, 9, 12, 18, 24, 36 and 48 months after birth.
- At each time points, we parcellate the cerebral cortex into 70 anatomically meaningful regions of interest (ROIs) and compute 7 different morphological cortical measurements.

4.2 General Framework

- We formulate it as the neural network-based regression problem.
- We define the longitudinal data as the “temporal path”.
- We focus on feature extraction, selection and redundancy removal.

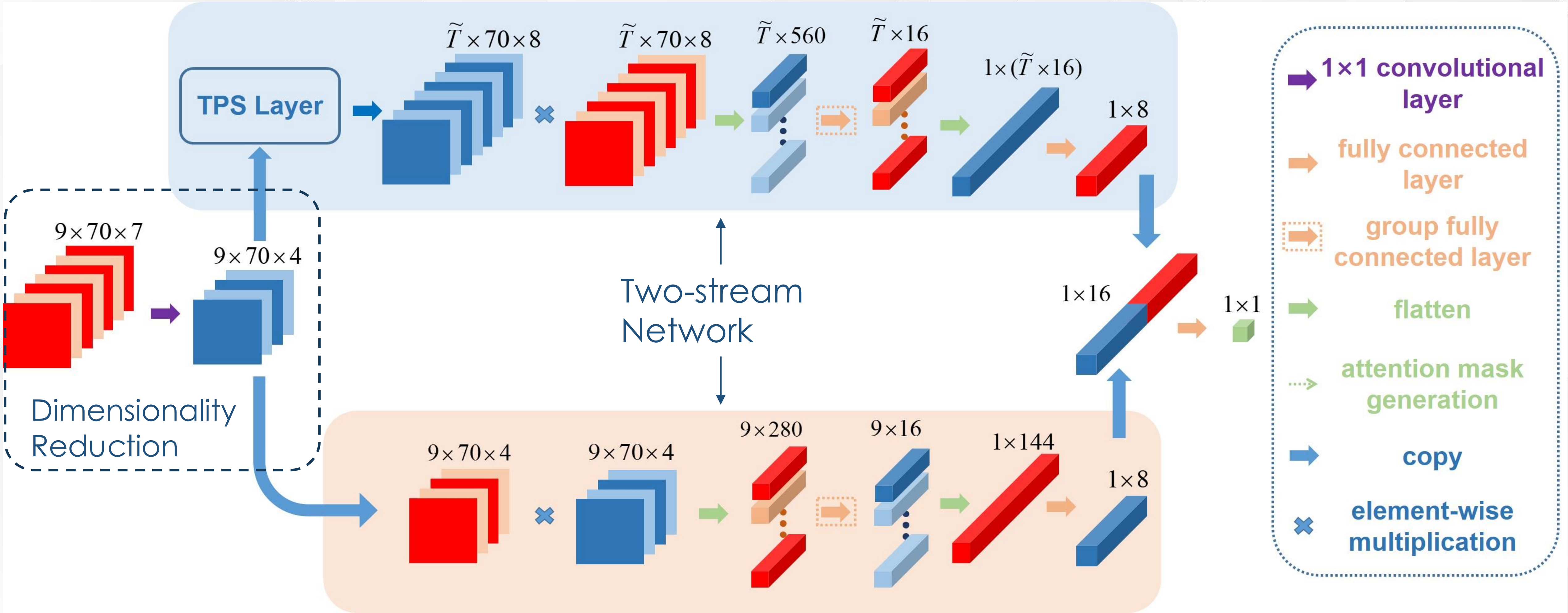


4.3/ Temporal Path Signature Layer

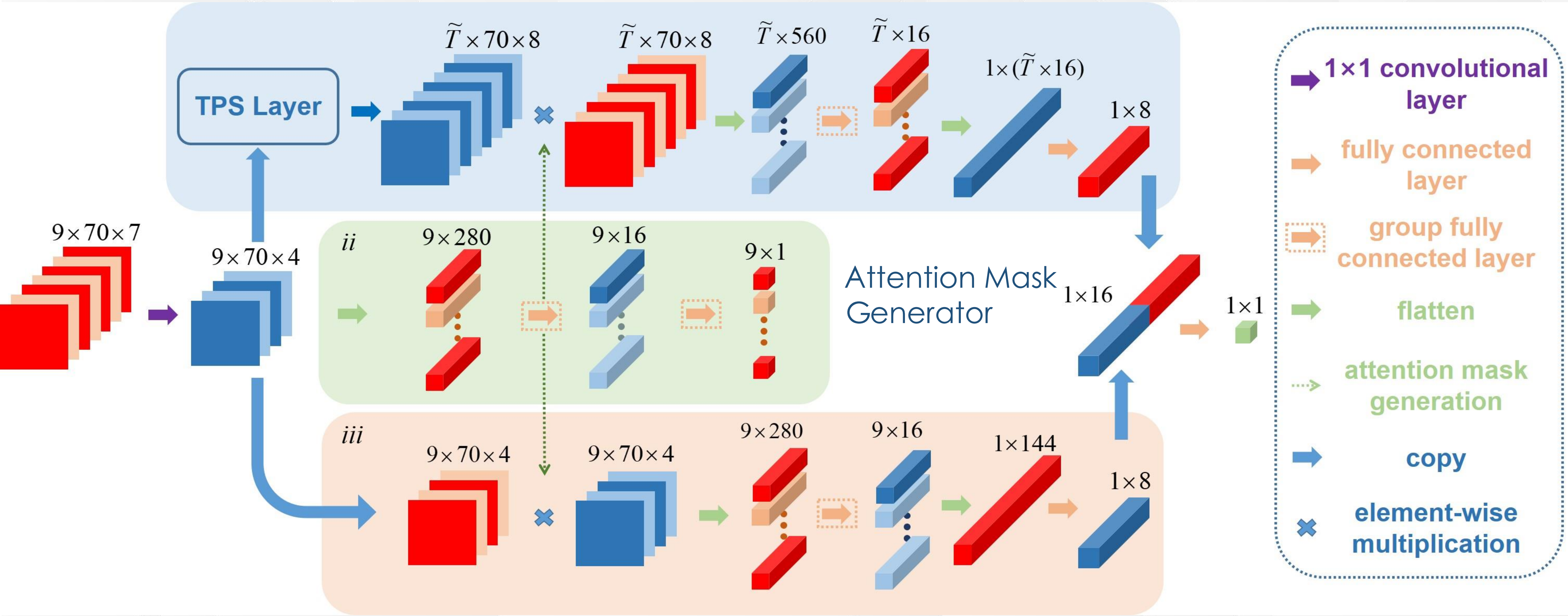


Why do we use longitudinal data as the path? Why not others?

4.4 BrainPSNet



4.4 BrainPSNet



4.5 Experiment: PS Parameters

We compared the performance of our model (1) different sliding window sizes with a fixed k = 2; (2) different truncated level with fixed window size W=4.

	VRS	FMS	RLS	ELS	ELC	AVE
$W=3$	0.085	0.091	0.115	0.050	0.076	0.084
$W=4$	0.067	0.076	0.084	0.049	0.060	0.067
$W=5$	0.079	0.072	0.088	0.050	0.073	0.072
$W=6$	0.081	0.093	0.081	0.048	0.074	0.075
$W=7$	0.085	0.076	0.088	0.063	0.075	0.077

	VRS	FMS	RLS	ELS	ELC	AVE
$k=1$	0.061	0.075	0.083	0.041	0.076	0.067
$k=2$	0.067	0.076	0.084	0.049	0.060	0.067
$k=3$	0.078	0.093	0.070	0.051	0.083	0.075
$k=4$	0.096	0.088	0.077	0.052	0.080	0.078

We set W=4 and k=2 in this work.

4.5 Experiment: Ablation Study

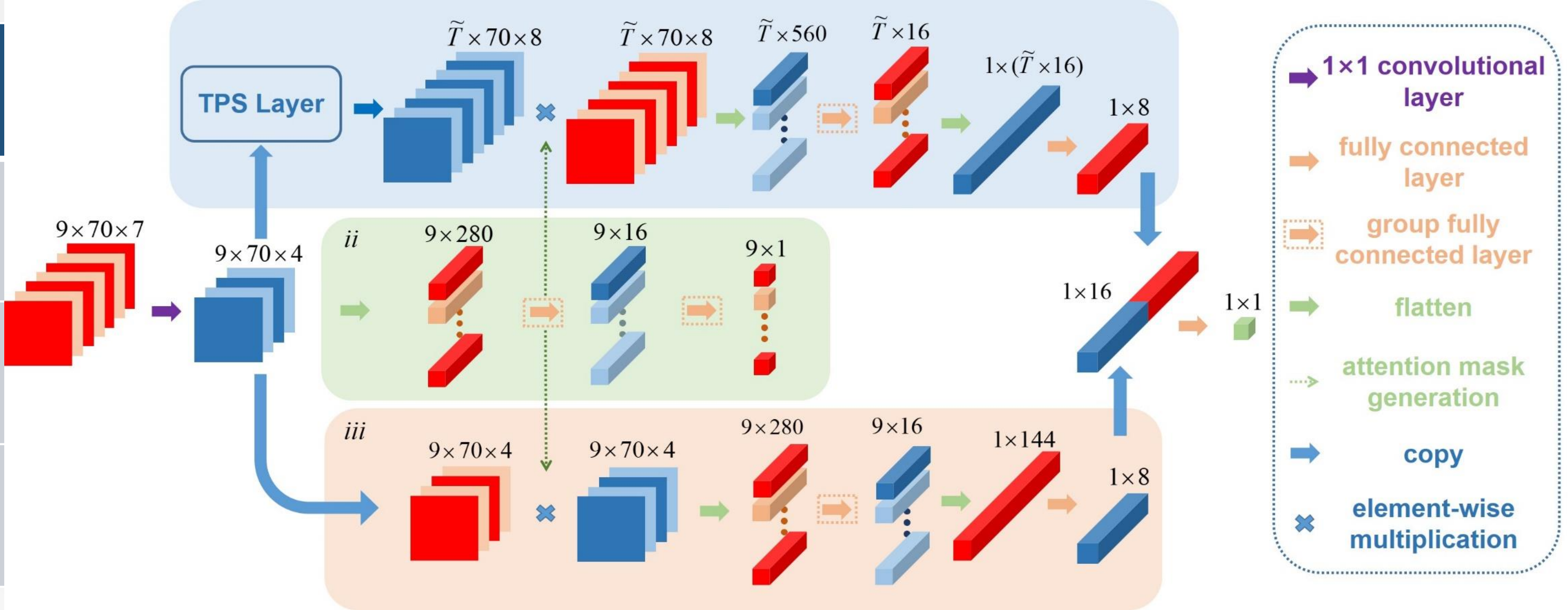
The ablation study shows that path signature features and attention module both bring improvements to the final estimation result (in terms of RMSE).

	VRS	FMS	RLS	ELS	ELC		AVE
w/o TPS	0.059	0.100	0.103	0.066	0.089		0.084
w/o Attention	0.092	0.108	0.162	0.077	0.103		0.108
Proposed	**0.046**	**0.075**	**0.095**	**0.063**	**0.057**		**0.067**

4.5 Experiment: Effect of TPS

Performance comparison between the TPS layer and other sequential feature extraction models. In the last column, we calculate the total time cost for 1200 epochs of our method with different substitutes.

Methods	Time
Transformer	578s
LSTM	2147s
TPS Layer	405s

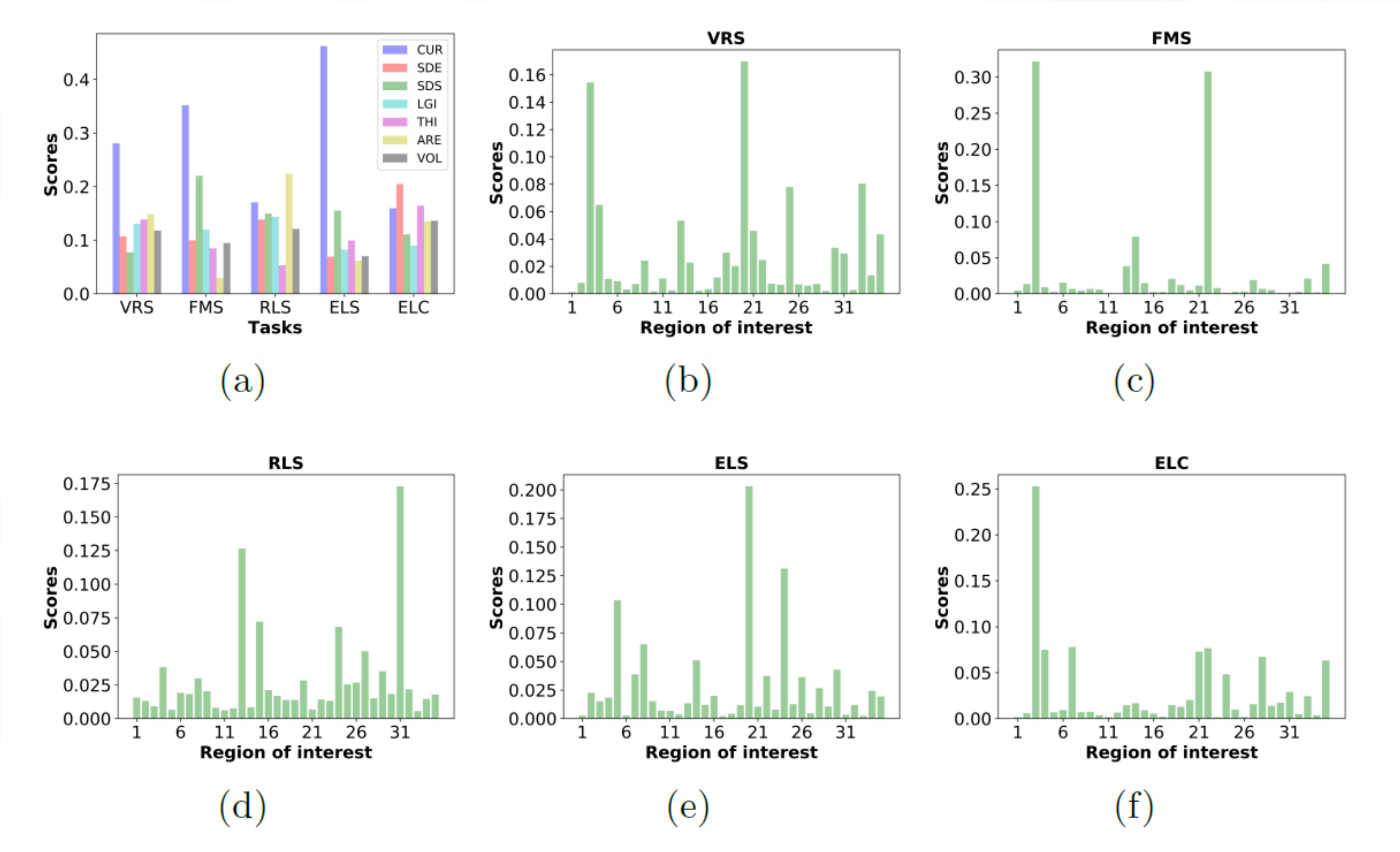


4.5 Experiment: SOTA Comparison

Performance comparison of BrainPSNet (in terms of RMSE)

	VRS	FMS	RLS	ELS	ELC		AVE
TrMTL (2009, ICML)	0.279	0.276	0.192	0.217	0.136		0.220
MtJFS (2007, NIPS)	0.276	0.273	0.189	0.214	0.134		0.217
NN	0.219	0.259	0.165	0.196	0.182		0.204
RMTL (2011, ACM-KDD)	0.146	0.200	0.178	0.188	0.137		0.170
LPMvRL (2019, IEEE TMI)	0.162	0.189	0.139	0.165	0.138		0.158
Proposed method	**0.046**	**0.075**	**0.095**	**0.063**	**0.057**		**0.067**

4.6 Brain Region Analysis



Most cognitive skills strongly related to the **cortical curvature feature**, and other features have various importance.

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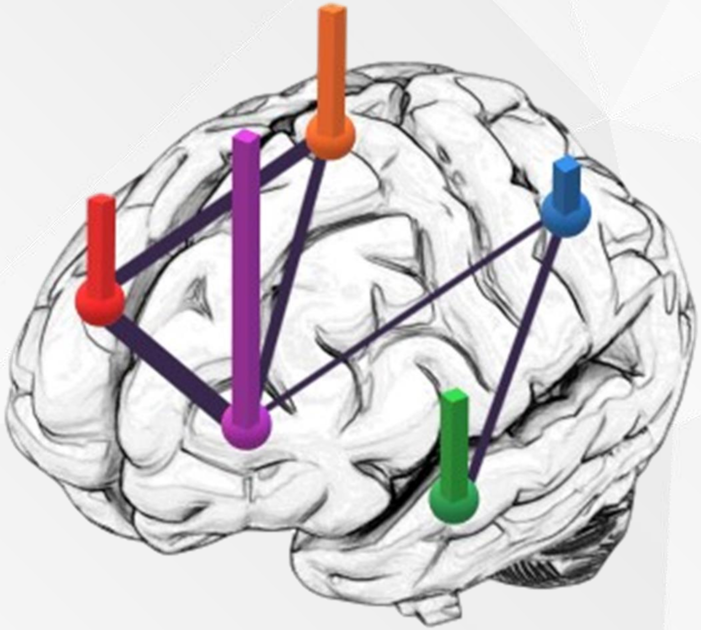
PART Five

PROPOSED METHOD TWO: PS-GCN

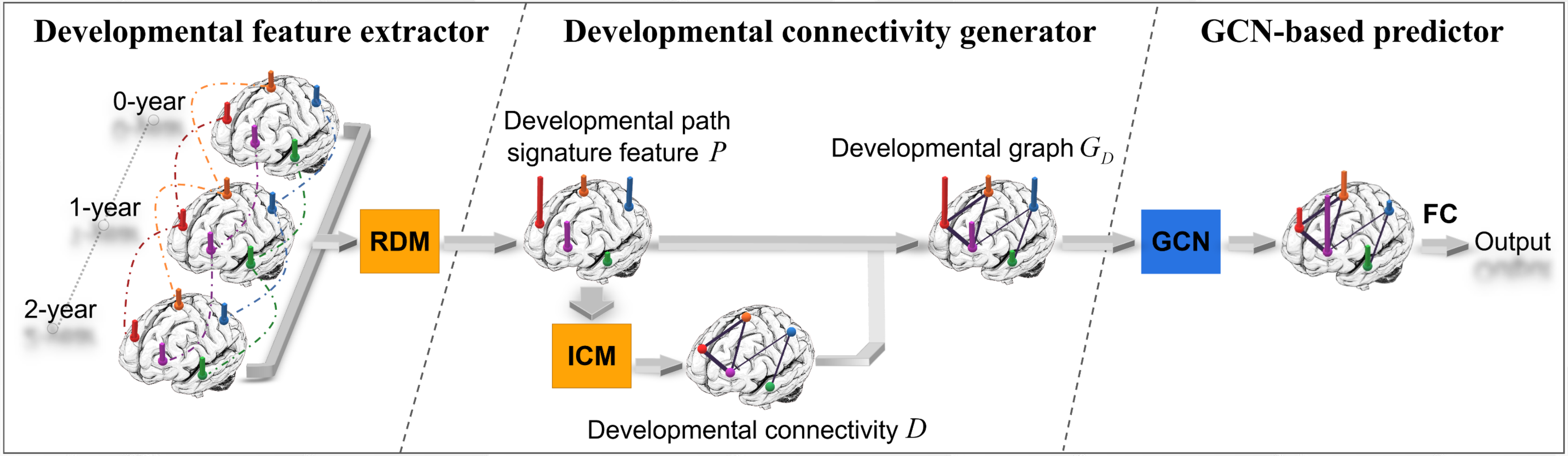
5.1/ Motivation



- **Brain has a spatial connectivity relationship.**
- **Infant brain developmental has region-wise similarities.**
- Our goal is to learn the brain developmental connectivity with path signature features.

5.2 General Framework

- Region-wise Development Module (RDM) is used to extract path signature features P of the input longitudinal brain structural data.
- Inter-region Connectivity Module (ICM) is proposed to learn the relationship D between brain region pairs.
- A GCN-based predictor is used to predict the cognitive score.



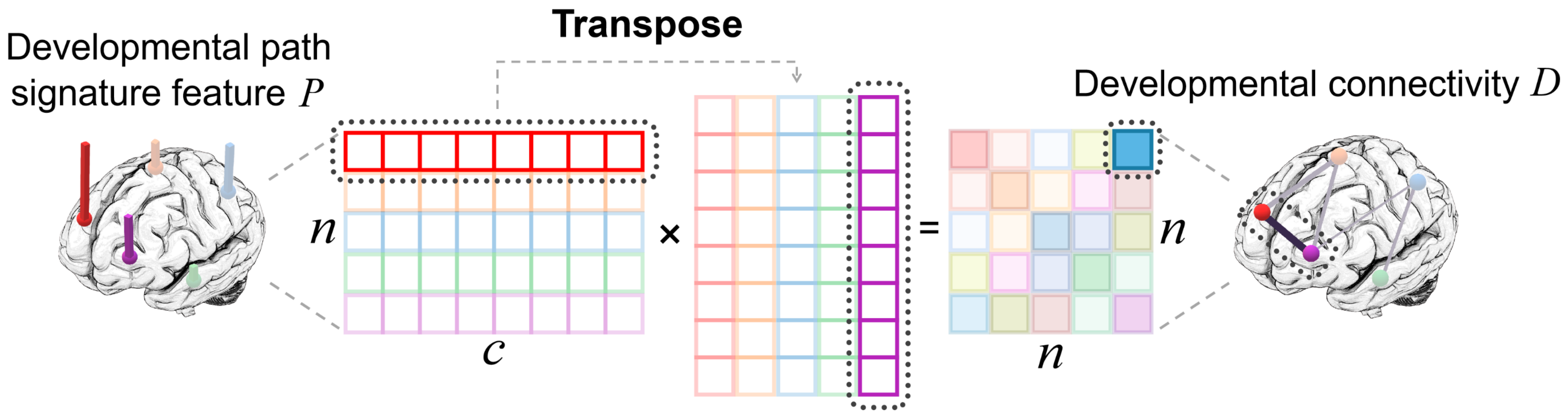
5.3 Region-wise Development Module

Compared to the traditional PS extraction, we introduce several sets of learnable parameters to have a deep interation between path signature methods and deep learning.

$$P_i = \mathbf{w_3} \cdot [ReLU(Conv(\mathbf{w_1} \cdot X_i))||(\mathbf{w_2} \cdot Sig_k(\mathbf{w_1} \cdot X_i))]$$

- X_i : the growth trajectory of the i^{th} brain region.
- P_i : the development descriptor for the growth pattern of the i^{th} brain region.
- w_1: introduced to embed the input path into a suitable low-dimensional feature space.
- w_2: introduced to fuse the multi-fold iterated intergrals.
- w_3: introduced to combine the extracted path signature features with input.

5.3 Inter-region Connectivity Module



We calculate the cosine similarity of pairs of brain regions by multiplying feature matrices

5.4 Experiment: Ablation Study

- We have 110 normal infants with their T1w and T2w MRI.
- Every subject only has 3 scans at 0, 1, 2 years of age.
- Evaluation of adjacent matrices and node features for GCN backbone (average RMSE of five Mullen Scales)

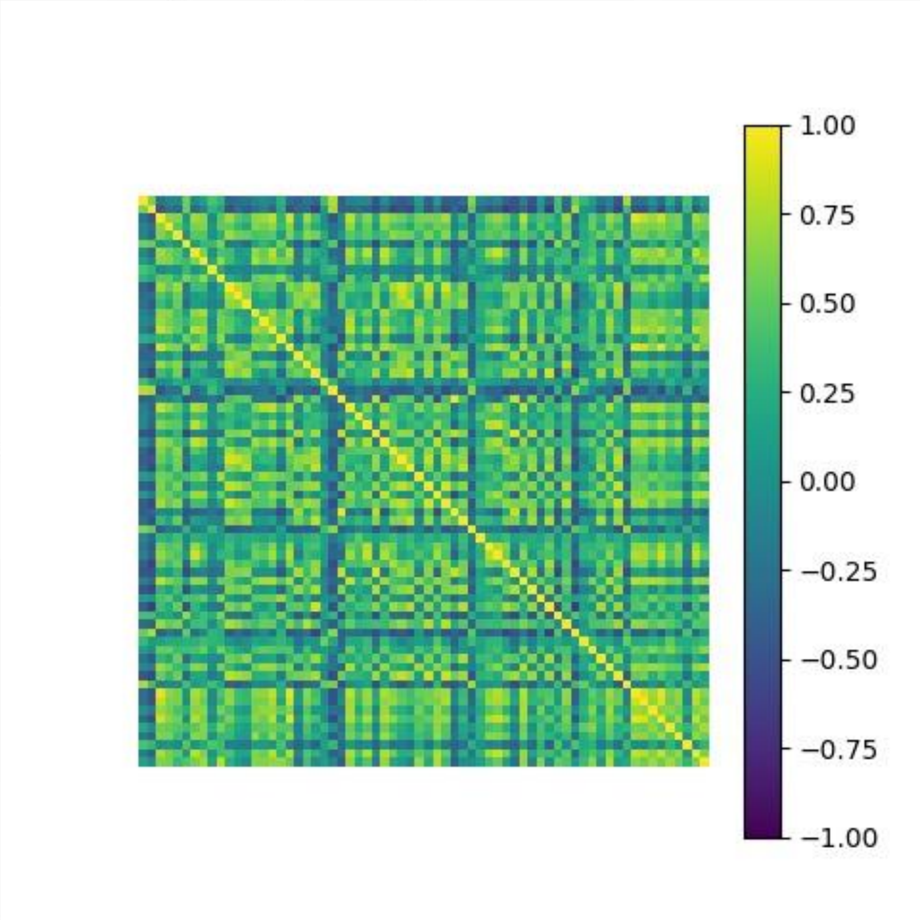
Adjacent Matrix / Node Feature	Pearson	RawData-ICM	RDM-ICM
Raw data	0.1807	0.1697	0.1662
Developmental PS feature	0.1741	0.1668	**0.1648**

5.4 Experiment: SOTA Comparison

Performance comparison of PSGCN (in terms of RMSE)

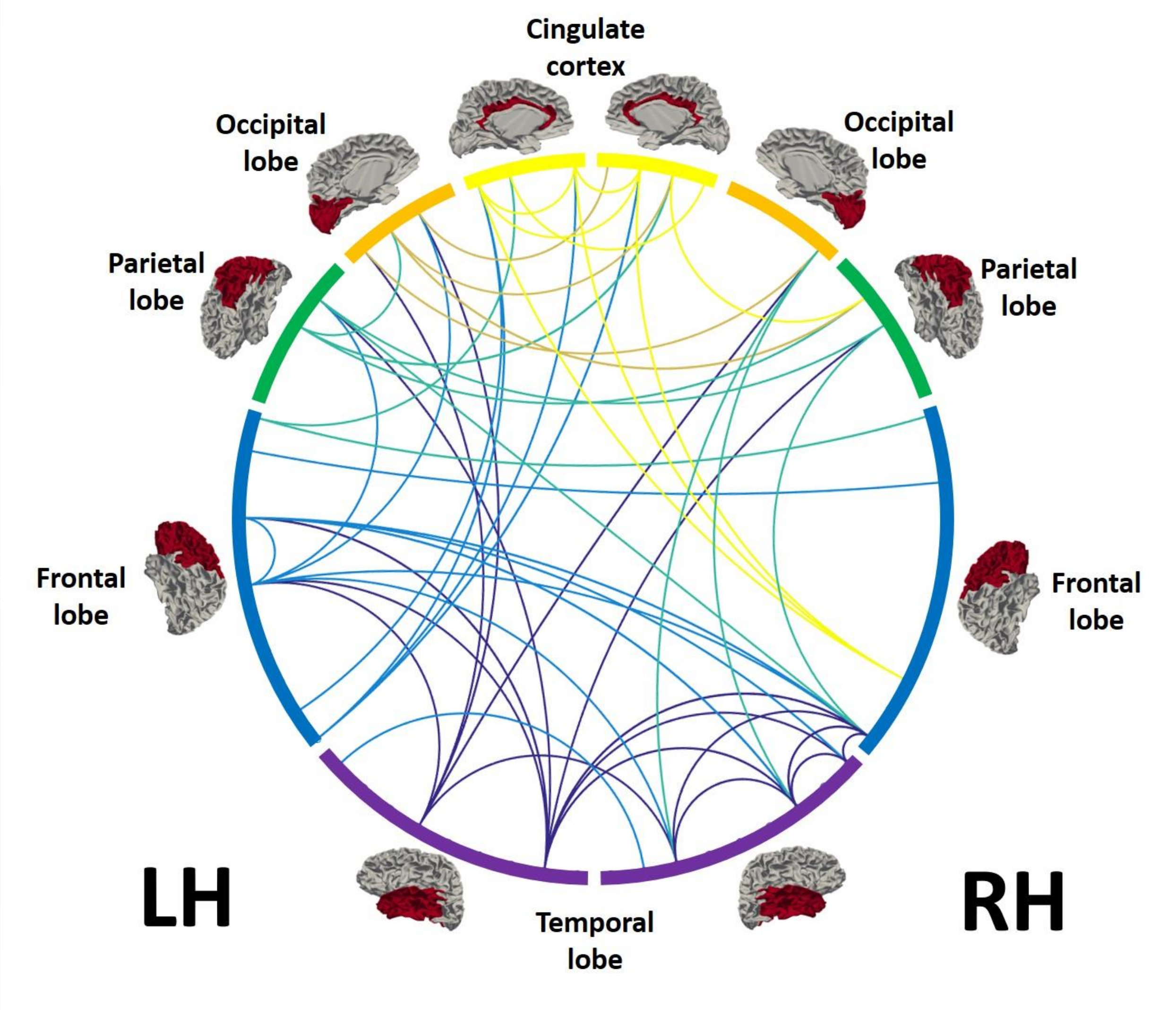
	VRS	FMS	RLS	ELS	ELC		AVE
KNN	0.1877	0.1943	0.1680	0.1848	0.1766		0.1877±0.022
SVR	0.1864	0.1987	0.1691	0.1788	0.1814		0.1829±0.022
RF	0.1892	0.1945	0.1665	0.1801	0.1824		0.1825±0.022
GRU	0.1788	0.1889	0.1637	**0.1732**	0.1715		0.1747±0.017
LSTM	0.1770	0.1859	0.1674	0.1761	0.1673		0.1747±0.017
GCN	0.1855	0.1951	0.1679	0.1794	0.1757		0.1807±0.018
GAT	0.1783	0.1946	0.1760	0.1770	0.1597		0.1757±0.020
Proposed method	**0.1621**	**0.1845**	**0.1501**	0.1743	**0.1531**		**0.1648±0.018**

5.5 Brain Region Analysis



The learned Brain Region Developmental Connectivity shows a phenomenon of modularization, indicating that brain regions in the same area have similar function.

5.5 Brain Region Analysis



By showing the top 3% connections in the left figure, most of the connections are concentrated in **temporal lobe** and **frontal lobe**. The brain regions with the strongest connections are **precuneus cortex**, **transverse temporal cortex** and **cuneus cortex**, which are all involved in vision or language.

06

PART SIX

SUMMARY

06 SUMMARY AND FUTURE WORK

Summary

1. We propose two novel model, BrainPSNet and PSGCN, to predict cognitive scores using longitudinal cortical features during infancy and reach the state-of-the-art result.
2. In BrainPSNet, the path signature feature is introduced to explore hidden anatomical and geometric properties of the cortical developmental trajectories.
3. Further, in PSGCN, we constructed structural brain connectivity by calculating developmental similarities between brain regions.

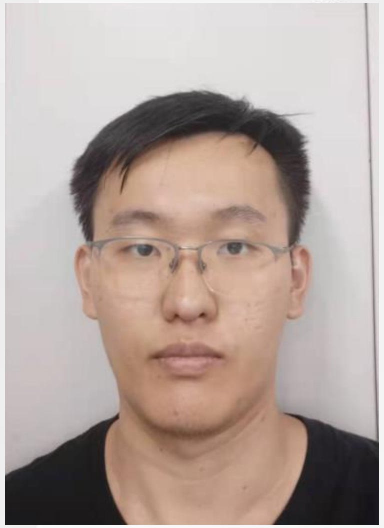
Future work

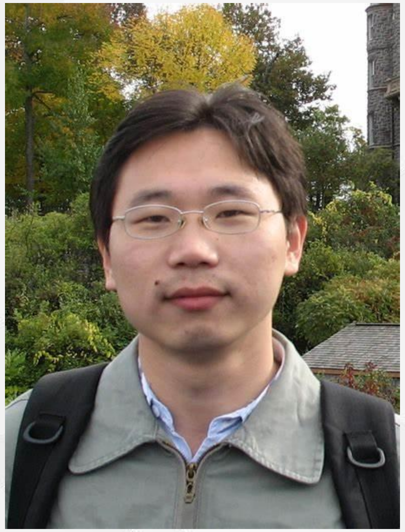
1. Further brain region selection strategy might be helpful.
2. Different temporal path or spatial path could be considered.
3. More complex brain connectivity should be explored.

06/ ACKNOWLEDGEMENT

The BrainPSNet is accepted by MICCAI 2020 as "Infant Cognitive Scores Prediction With Multi-stream Attention-based Temporal Path Signature Features" . The PS-GCN is under review of MICCAI 2021.

They are joint works with my graduate students **Yu Li, Jiale Cheng and Dr. Hao Ni** from UCL, **Dr. Gang Li** from UNC.



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THANK YOU!

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