Structural Networks for Brain Age Prediction

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Introduction

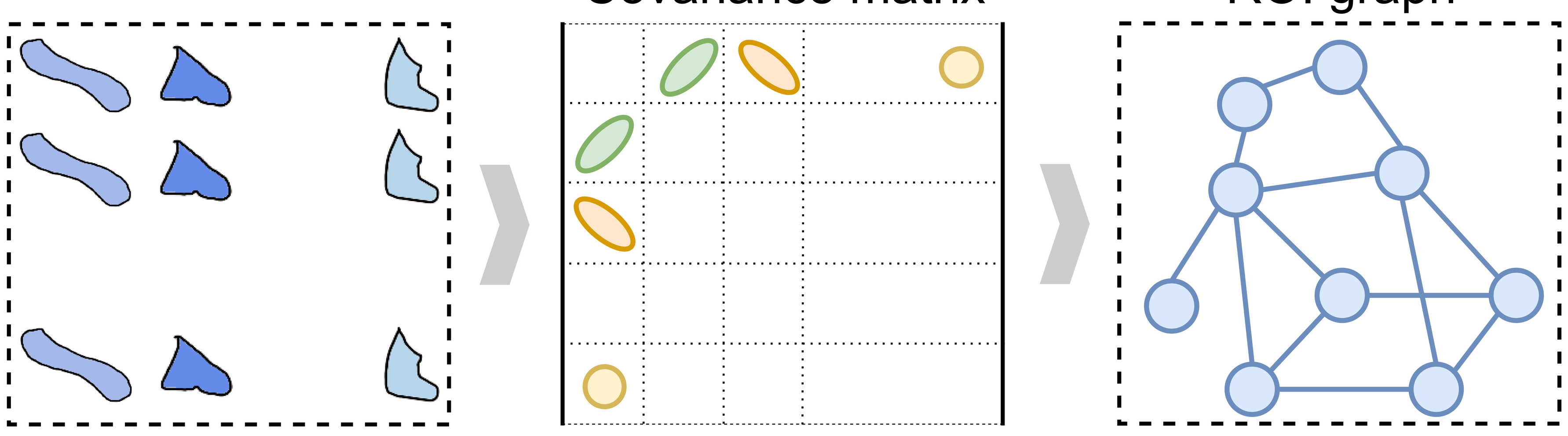
In this work we extend the definition of **structural covariance networks** with tools from Graph Signal Processing to define **ROI graphs** and explore the application of **Graph Neural Networks** (GNN) in this domain for **brain age prediction**. We also evaluate the role of permutation invariance and equivariance of GNN modules.

Structural Networks

Structural covariance networks are employed to examine co-variation through brain development of pairwise ROI morphology. A brain parcellation into ROIs is applied to the N sMRI scans to extract d morphological features, these are rearranged in a **N x d** matrix, the **d x d** correlation matrix is the **adjacency matrix** of the population **ROI graph**.

Brain parcellation

Volumes Matrix | Covariance matrix | ROI graph



Network Topology Inference

The correlation strategy can be replaced by more sophisticated algorithms, we consider (1) **Correlation-based neighborhood regression** and (2) **Graphical LASSO**:

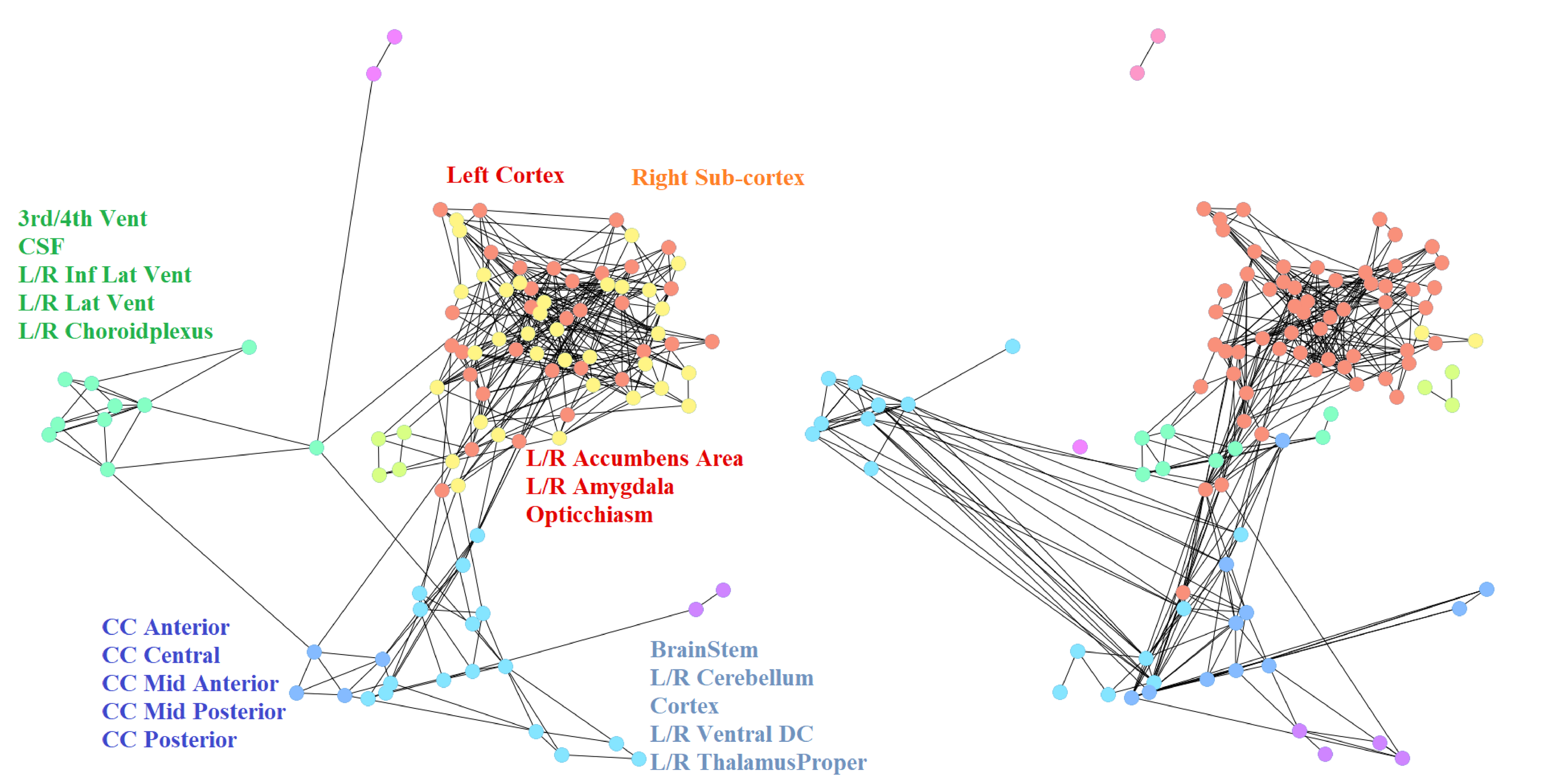
$$J_i = \left\| y_i - \sum_{j\neq i} w_{ij} \right\|_2^2 + \lambda \sum_{i\neq j} |w_{ij}| \qquad J(Q) = tr\{QR_x\} - log(detQ) + \lambda \|Q\|_1$$

Data

Subset of **N = 24106** subjects from the **UK Biobank**
Subjects are cognitively unimpaired, no mental disease, no trauma
Age 64.8 (7.50), **Female** 12406 (51.54%),
APOE Carriers 6755 (28.02%)

Network Topology Inference

We have **optimized** the value of the **sparsity hyperparameter** λ for every network inference strategy in terms of **small-world** properties of the obtained networks.



Cortical and sub-cortical regions create two (almost) independent communities. Cortical subnetwork splits into left and right side, whereas sub-cortex tend to also divide into smaller communities.

Acknokledgements

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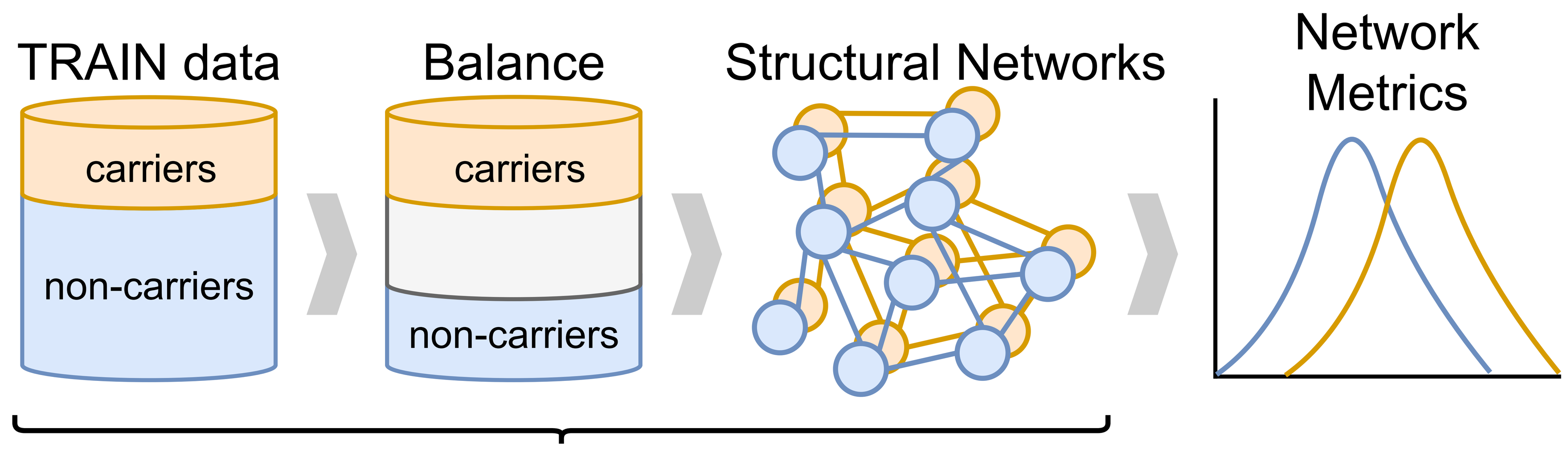
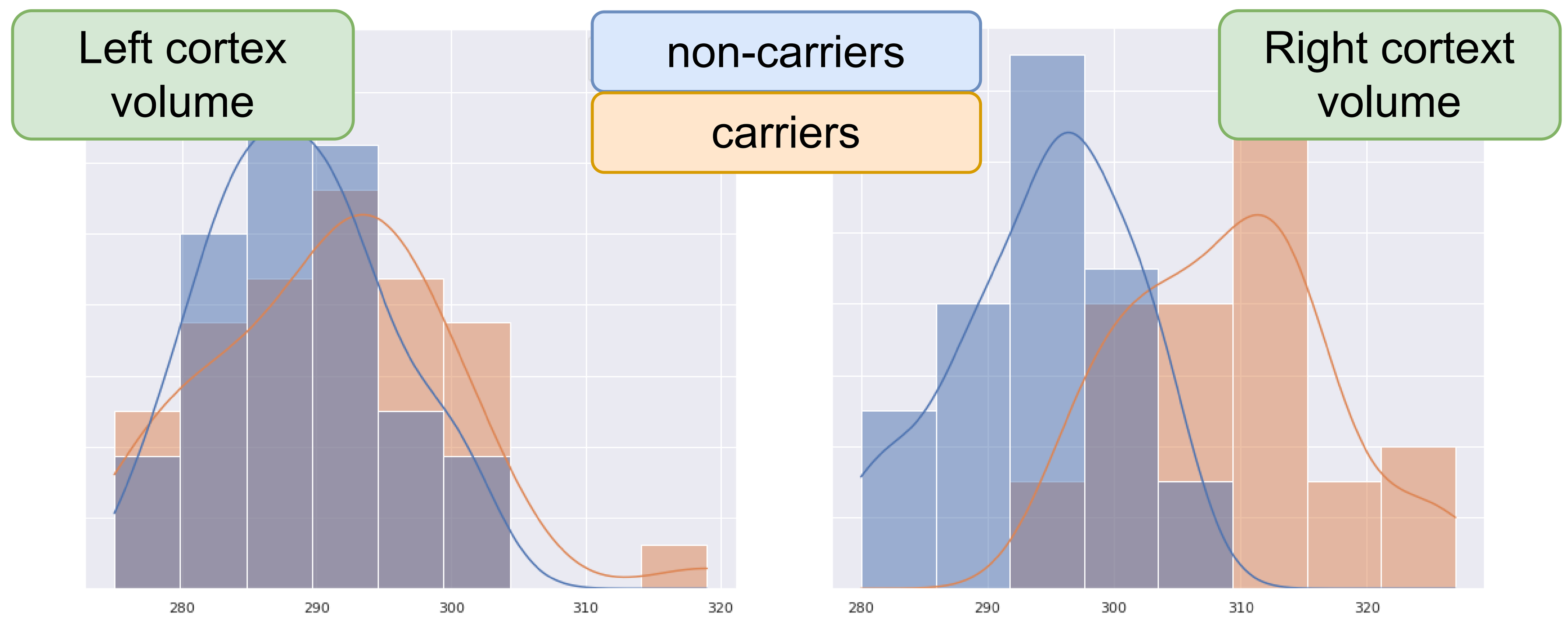
Group Structural Differences

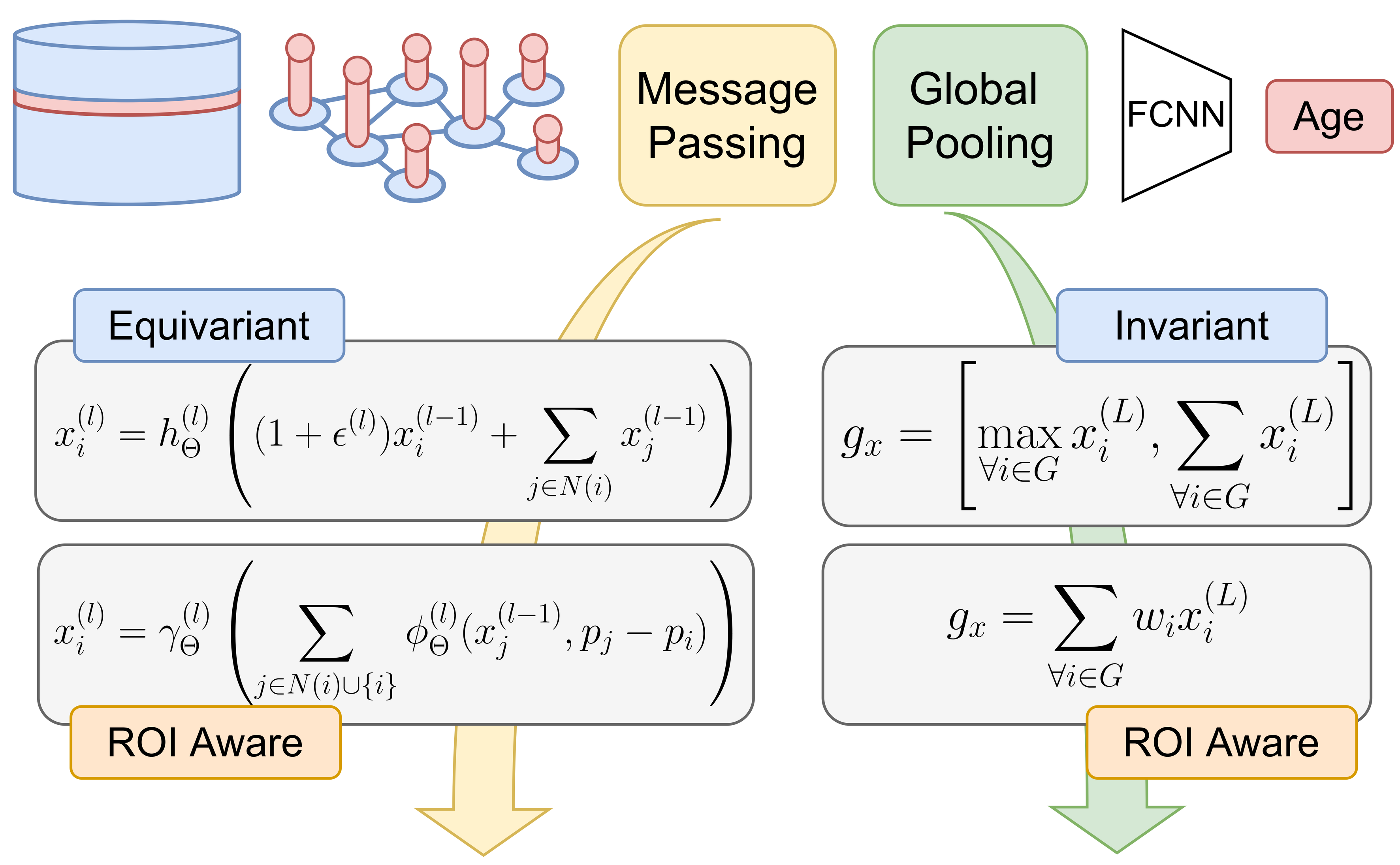
We have evaluated the differences of morphological brain development by quantifying network dissimilarities between the structural networks obtained with different subgroups of subjects. Concretely, our target variable has been **APOE** carriers vs non-carriers.





Brain Age Prediction

From now on, every subject is seen as a one-dimensional signal defined on the vertices of the ROI graph, whose values correspond to the volume of every ROI for that subject.



In order to evaluate the role of **permutation invariance / equivariance** in this scenario we implement all possible combinations of permutation equivariant - ROI aware message passing and permutation invariant - ROI aware global pooling.

Results

Model	Method	MAE	Pearson Correlation
FCNN	-	4.39 ± 0.04	0.70 ± 0.01
GNN *PE-PI*	Graphical LASSO	6.01 ± 0.09	0.29 ± 0.04
GNN *PE-PI*	Correlation-based	5.99 ± 0.06	0.30 ± 0.03
GNN *PE-RA*	Graphical LASSO	4.31 ± 0.11	0.69 ± 0.03
GNN *PE-RA*	Correlation-based	4.27 ± 0.07	0.70 ± 0.01
GNN *RA-PI*	Graphical LASSO	6.08 ± 0.12	0.26 ± 0.05
GNN *RA-PI*	Correlation-based	5.99 ± 0.09	0.30 ± 0.04
GNN *RA-RA*	Graphical LASSO	4.34 ± 0.04	0.69 ± 0.01
GNN *RA-RA*	Correlation-based	4.36 ± 0.06	0.69 ± 0.01

Conclusions

GNNs have been able to leverage the inductive bias of the structural networks and slightly improve the performance of a dense FCNN on the task of brain age prediction. We have seen that ROI aware global pooling is crucial to fit the task whereas ROI information during message passing seems to be of no relevance.