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# Permutation equivariant structurefunction mapping

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Predicting the brain's function given its structure (structure-function mapping<sup>12</sup>) is no easy task. In this work, we observe the problem through the lens of a permutation equivariant graph neural network (PE-GNN).

### **Key finding:**

A PE-GNN achieves performance similar to a naive mean-estimator even though information on parcel-ordering is discarded during the modelling procedure.

## Why structure-function mapping?

Brain structure-function mapping addresses the problem of predicting the brain's functional connectivity measured through (rs-fMRI) from the structural connectivity measured through (dMRI). The modelling procedure is built on two main assumptions:

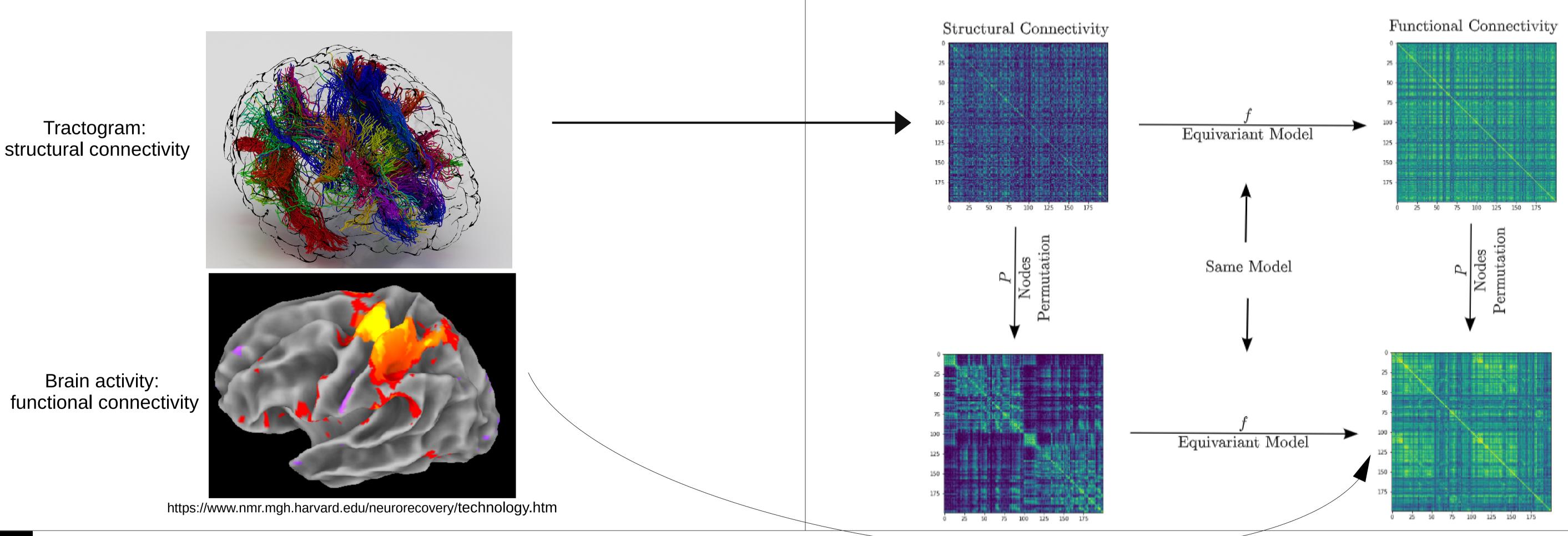
- 1. Given the structure of a subject, it should be possible, at least partially, to predict his function.
- 2. The structure and function of specific sub-regions of the brain are matched across all subjects.

# Why a permutation equivariant model?

Assume that X is a  $n \times n$  matrix and P is an arbitrary  $n \times n$ permutation matrix. Then a function  $f: \mathbb{R}^{n \times n} \to \mathbb{R}^{n \times n}$  is permutation equivariant if

$$f(PXP^T) = Pf(X)P^T$$

Modelling the relation between structure and function by incorporating permutation equivariance ensures that the model behaves similarly for all parcel-orderings, and therefore relaxes the second assumption.

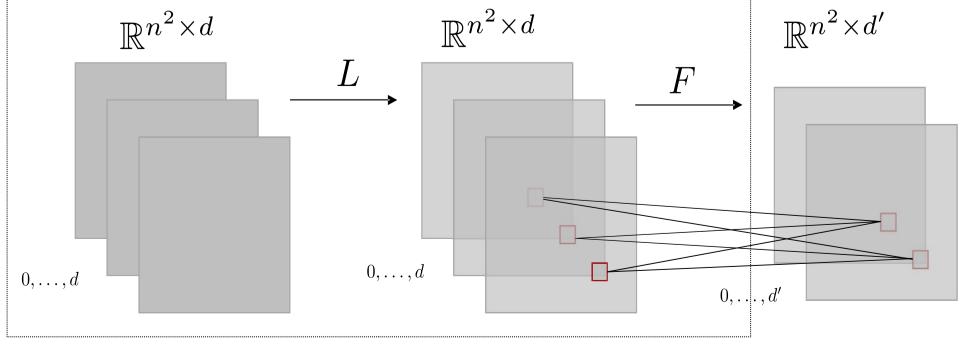


# Methods

This work considers dMRI and rs-fMRI of 1050 young and healthy adults from the Human Connectome Project<sup>3</sup>. For each subject, we derived a pair of structural and functional connectivity matrices. Two parcellations of the brain are considered; one containing 68 parcels (Desikan-Killiany), and one containing 200 parcels (Gallardo<sup>4</sup>).

### Architecture

The architecture consists of 3 equivariant modules. The most important components in each module are the linear equivariant layers (L)<sup>5</sup>, and the 2D convolution with a  $1\times1$ kernel size (F) as seen below.



The **PE-GNN** is compared, using 10-fold cross-validation, to the mean functional connectivity matrix, which is used as a reference estimator of the functional connectivity<sup>1</sup>. We compute this predictor on both the training data (M-FC) and a second version of the training data where the rows and columns have been randomly permuted (PM-FC).

Number of parcels	PE-GNN	PM-FC	M-FC
68 200		$0.0750 \pm 0.0017$ $0.0489 \pm 0.0017$	

The mean squared error (MSE) plus-minus the standard-deviation obtained from a 10-fold cross validation for each estimator. Each estimator is tested for atlases containing 68 and 200 parcels respectively.

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