Designing Invariant and Equivariant Neural Networks

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Many tasks in machine learning (ML) require learning functions that are invariant or equivariant with respect to symmetric transformations of the data. For example, graph classification is invariant to permutations of its nodes, while recognizing the shape of a point cloud is invariant to both permutation and Euclidean motion of its points. Designing parameteric models (i.e., neural networks) that are *by construction* invariant or equivariant to symmetries of the data has been proven successful in many ML tasks involving data such as images, sets and point-clouds, and graphs. In designing invariant/equivariant neural network model there are few factors that should be taken into account: (i) The expressive/approximation power of the model; (ii) the computational and memory complexity of the model; (iii) the model's practical performance (inductive bias).

In this talk I will review two methodologies for designing invariant/equivariant networks: The *intrinsic method*, and the *extrinsic method*. The intrinsic method first characterizes invariant/equivariant primitive functions, such as linear transformations, and then composes these with non-linear activations to build the final parametric model. Extrinsic methods, on the other hand, apply symmetrization to general parametric functions. In the talk I will review some earlier works in this space, and provide an in-depth description of *Frame Averaging*, a recent symmetrization approach, that in some cases allows designing efficient and maximally expressive invariant/equivariant models.

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