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Title:
Equivariant and coordinate independent convolutional networks

Abstract:
Convolutional neural networks (CNNs) differ from generic fully connected networks in that they share synapse weights between different spatial locations. Weight sharing guarantees that CNNs process data in a position independent manner and generalize whatever they learn across space. This property is formally captured by the networks' ``translation equivariance'', i.e. by their property to commute with translations of their inputs.
The first part of this talk investigates how to construct generalized CNNs, which are equivariant under extended symmetry groups, including, for instance, rotations or reflections of images. Such networks generalize their inference over additional geometric transformations, which makes them more data efficient and robust in comparison to conventional CNNs.
In the second part, we discuss how convolutional networks can be generalized to process signals on Riemannian manifolds. Since manifolds do in general not admit canonical coordinates, the equations describing the neural network need to be coordinate independent. We argue that this results in a requirement on the convolution kernels to be equivariant under local gauge transformations. Convolutions with such kernels will automatically be equivariant under the manifolds' global symmetries (isometries).