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Group Equivariant CNNs beyond Roto-Translations: B-Spline CNNs on Lie Groups

Group convolution neural networks (G-CNNs) can be used to improve classical CNNs by equipping them with the geometric structure of groups. Central in the success of G-CNNs is to lift feature maps to higher dimensional disentangled representations in which data characteristics are effectively learned, geometric data-augmentations are made obsolete, and predictable behavior under geometric transformations (equivariance) is guaranteed via group theory. Currently, however, the practical implementations of G-CNNs are limited to either discrete groups (that leave the grid intact) or continuous compact groups such as rotations (that enable the use of Fourier theory). In this talk I lift these limitations and propose a modular framework for the design and implementation of ***G-CNNs for arbitrary Lie groups***. In this approach the differential structure of Lie groups is used to expand convolution kernels in a generic basis of B-splines that is defined on the Lie algebra. This leads to a flexible framework that enables ***localized***, ***atrous***, and ***deformable convolutions*** in G-CNNs by means of respectively ***localized***, ***sparse*** and ***non-uniform*** B-spline expansions. The impact and potential of the approach is studied on two benchmark datasets: cancer detection in histopathology slides (PCAM dataset) in which rotation equivariance plays a key role and facial landmark localization (CelebA dataset) in which scale equivariance is important. In both cases, G-CNN architectures out-perform their classical 2D counterparts and the added value atrous and localized group convolutions is studied in detail.