LIGHTWEIGHTING CONVOLUTIONAL NEURAL NETWORKS BY HYPERCOMPLEX PARAMETERIZATION

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ABSTRACT

Hypercomplex neural networks have proved to reduce the overall number of parameters while ensuring valuable performances by leveraging the properties of Clifford algebras. Recently, hypercomplex linear layers have been further improved by involving efficient parameterized Kronecker products. In this paper, we define the parameterization of hypercomplex convolutional layers to develop lightweight and efficient large-scale convolutional models. Our method grasps the convolution rules and the filters organization directly from data without requiring a rigidly predefined domain structure to follow. The proposed approach is flexible to operate in any user-defined or tuned domain, from 1D to nD regardless of whether the algebra rules are preset. Such a malleability allows processing multi-dimensional inputs in their natural domain without annexing further dimensions, as done, instead, in quaternion neural networks for 3D inputs like color images. As a result, the proposed method operates with $1/n$ free parameters as regards its analog in the real domain. We demonstrate the versatility of this approach to multiple domains of application by performing experiments on various image as well as audio datasets in which our method outperforms real and quaternion-valued counterparts.

1 KEYWORDS

Hypercomplex Neural Networks, Lightweight Neural Networks, Quaternion Neural Networks, Parameterized Hypercomplex Convolutions, Hypercomplex Representation Learning

2 ONE-SENTENCE SUMMARY

We propose a hypercomplex parameterization of convolutional layers which lightweightens and outperforms real and quaternion-valued neural networks in different application domains.