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3D Molecular Representations Based on the Wave Transform for Convolutional Neural Networks

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Abstract

© 2018 American Chemical Society. Convolutional neural networks (CNN) have been successfully used to handle three-dimensional data and are a natural match for data with spatial structure such as 3D molecular structures. However, a direct 3D representation of a molecule with atoms localized at voxels is too sparse, which leads to poor performance of the CNNs. In this work, we present a novel approach where atoms are extended to fill other nearby voxels with a transformation based on the wave transform. Experimenting on 4.5 million molecules from the Zinc database, we show that our proposed representation leads to better performance of CNN-based autoencoders than either the voxel-based representation or the previously used Gaussian blur of atoms and then successfully apply the new representation to classification tasks such as MACCS fingerprint prediction.

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Keywords

3D convolutional neural networks, autoencoders, wave transform, wavelets

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