Abstract

Cosmic voids are the largest and least dense structures in the universe. Their properties have been shown to encode precious information about the laws and constituents of the Universe. However, due to the lack of robust theoretical frameworks, some aspects of cosmic voids still remain mysterious. In this work, we explore the relationship between void properties and the matter density parameter Ω_m, using graph neural networks (GNNs) and symbolic regression. We first model void data with graph neural networks and train the networks so that they can predict the value of Ω_m. During the training process, we use regularization techniques to encourage the sparsity of the model. After the model is trained, we use it to generate data, which is restricted to low-dimensional spaces compared to the original data and thus can reduce the search space for symbolic regression. Finally, we use symbolic regression to produce mathematical equations for a subpart of the GNNs and analyze the potential implication of the equations. This work relies on thousands of void catalogs from the `GIGANTES` dataset, where every catalog contains an average of 11,000 voids from a volume of 1 $(h^{-1}\text{Gpc})^3$. We focus on four properties of cosmic voids: position, ellipticity, density contrast, and radius, which accurately model voids. Our results provide an illustration for the use of combining deep learning and symbolic regression to explore cosmology with voids.