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Synthia: multidimensional synthetic data generation in Python

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Summary

Synthetic data may be useful in several areas such as healthcare, finance, data science, and machine learning (Dahmen & Cook, 2019; Kamthe et al., 2021; Nowok et al., 2016; Patki et al., 2016). Copula-based data generation – probabilistic models that allow for the statistical properties of observed data to be modelled in terms of individual behavior and (inter-)dependences (Joe, 2014) – have shown potential for generating synthetic data in several different applications (Kamthe et al., 2021; Li et al., 2020; Meyer, Nagler, et al., 2021; Patki et al., 2016). Although copula-based data generation tools have been developed for tabular data – e.g. the Synthetic Data Vault project using Gaussian copulas and generative adversarial networks (Patki et al., 2016; Xu & Veeramachaneni, 2018), or the Synthetic Data Generation via Gaussian Copula (Li et al., 2020) – in computational sciences such as weather and climate, data often consist of large, labelled multidimensional datasets with complex dependencies.

Here we introduce Synthia, an open-source multidimensional synthetic data generator written in Python for xarray's (Hoyer & Hamman, 2017) labelled arrays and datasets with support for parametric and vine copulas models and functional principal component analysis (fPCA) – an extension of principal component analysis where data consist of functions instead of vectors (Ramsay & Silverman, 2005) – to allow for a wide range of data and dependent structures to be modelled. For efficiency, algorithms are implemented in NumPy (Harris et al., 2020) and SciPy (SciPy 1.0 Contributors et al., 2020) for Gaussian (parametric) copula and fPCA classes and rely on the C++ library vinecopulib (Nagler & Vatter, 2020b) through pyvinecopulib's (Nagler & Vatter, 2020a) bindings for fast computation of vines.

Recent applications include the generation of dependent (Meyer, Nagler, et al., 2021) and independent (Meyer, Hogan, et al., 2021) samples for improving the predictions of machine learning emulators in weather and climate applications. In this release we include examples and tutorials for univariate and multivariate synthetic data generation using copula and fPCA methods and look forward to enabling the generation of synthetic data in various scientific communities and for several different applications.

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