Universidade de Pernambuco
Programa de Pós-Graduação em Engenharia da Computação (PPGEC)

Proposta de Dissertação de Mestrado

Área: Computação Inteligente

Título: Uncovering Algorithmic Fairness in Deep Learning–Based Imputation of Multivariate Clinical Time Series

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Descrição:

Multivariate time series (MTS) from healthcare data are often incomplete and irregular, which makes reliable clinical inference difficult [1-3]. In this healthcare setting, MTS are influenced by patients' clinical conditions and the natural progression of care, resulting in sparsity due to missing data and irregularity caused by asynchronous sampling. Because of their sparsity and irregularity, a key step in managing healthcare MTS is missing data imputation (MDI). State-of-the-art MDI techniques increasingly depend on deep learning models [4], such as Self-Attention-Based Imputation for Time Series (SAITS) [5], Bidirectional Recurrent Imputation for Time Series (BRITS) [6], Gaussian Process Variational Autoencoder (GPVAE) [7], Unsupervised Generative Adversarial Network (USGAN) [8], and Multidirectional Recurrent Neural Network (M-RNN) [9]. These methods can learn the approximate distribution of the underlying data from the observed data [3]. However, MDI in healthcare MTS is usually assessed only with aggregate efficiency metrics—such as mean absolute error (MAE)—while the algorithmic fairness of the underlying deep-learning models remains unexamined. Algorithmic fairness—especially in healthcare—cannot be ignored, as algorithms used for clinical inference and decision-making have the potential to cause harm [10-11]. Missing data is a major source of algorithmic unfairness. Although several fairness concepts have been proposed, they mainly address downstream classification tasks and often ignore fairness issues that arise during deep learning–based missing data imputation (MDI) [12-13]. This proposal's main goal is to assess both the algorithmic efficiency and fairness of cutting-edge deep learning models for MDI. This research will highlight the fairness aspects of deep learning models in MDI and stress the significance of imputation methods in healthcare MTS that focus on both efficiency and fairness in developing new deep-learning techniques for MDI.

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