Contrastive Machine Learning and Hyperparameter Optimization for Detecting Nuclear Material Transfers

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Abstract:

Semi-supervised machine learning techniques can alleviate the resource cost of curating training data to develop and deploy data analytical models in nuclear nonproliferation. Machine learning models that learn spectroscopic labeling information from gamma radiation measurements could aid in the detection and characterization of shielded radiological material transfers. Using a principled set of data augmentations designed for gamma radiation spectra, a contrastive machine learning model is trained via self-supervised learning to embed spectral features from unlabeled data in encoded representations. The label-invariant spectral augmentations enable the contrastive model to generate meaningful representations that emphasize fundamental characteristics in radiation detection measurements. A supervised classifier trained on these spectral representations estimates transfer type for a given spectrum and can distinguish between nuclear material transfers (byproducts or tracked nuclear material) with an accuracy of 80.30%. Model evaluation techniques like Principal Component Analysis and Integrated Gradients indicate that the contrastive framework uses learned spectral features in estimating the transfer type. Unlabeled data have demonstrated usefulness in training machine learning models for detection and characterization tasks. Furthermore, hyperparameter optimization finds a locally optimal model that maximizes accuracy among many degrees of freedom. This research established a methodology by which semi-supervised contrastive machine learning can be used as an analytical tool for nuclear nonproliferation applications.