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Weakly Supervised Deep Learning for Disentangling Label and Measurement Noise Using Class-Specific Latent Maps

Deep learning (DL) models are significantly impacted by label and measurement noise, which can degrade performance. Label noise refers to wrong labels (Y) attached to samples, whereas measurement noise refers to the samples (X) that are corrupted due to issues during their acquisition. We present a generic approach for efficient learning in the presence of such noise, without relying on ground truth labels. Our approach is inspired by the work of Raymaekers et al. (2021) who introduced so-called "classmaps"for vizualizing classification results. The approach we introduce employs a weakly supervised learning paradigm, training a DL classifier on noisy datasets and using the predicted class for splitting the noisy dataset. A Variational Autoencoder (VAEs) is then used on each of the subsets of the data to create latent representations. By calculating the degree of outlyingness of each sample in the corresponding latent space, class-specific maps are generated that visually represent the different noise sources. This is particularly interesting because measurement noise can be disregarded, as it denotes poor-quality samples. In contrast, label noise can be presented to a labeller for verification, since those samples have a high probability of being mislabelled.
We will apply the approach using two different datasets. We will use the Fashion MNIST dataset for explaining the different steps of the framework, and a practical dataset of classifying insects on sticky plates to demonstrate the versatility and effectiveness of it.

Special/ Invited session

Classification

Both methodology and application

Keywords

Deep Learning, noisy data, efficient learning

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Track Classification: AI: Interpretability and Trustworthiness