The loss function used in a conventional machine learning problem is generally specified as an easy fixed form, like L2 norm or L1 norm, which intrinsically assumes the noises contained in data are generated from a simple distribution, like an i.i.d. Gaussian or Laplacian. However, in practical scenarios with complex noise configurations, such modeling inclines to encounter the robustness issue, that is, such modeling manner tends to make the related learning algorithm sensitive to complex noises. In this talk, I will introduce some developments of our research team on noise/loss modeling, which aims to make a machine learning model capable of adaptively learning an appropriate loss function/noise distribution from data, so as to alleviate the robustness issue of generally machine learning regimes. Such loss/noise modeling paradigms have been used on multiple image/video/hyper-spectral image restoration tasks, and achieved state-of-the-art performance on hyper-spectral image denoising, online background subtraction on surveillance videos, low-dose CT image enhancement and video deraining. Such a fundamental regime is expected to inspire useful learning algorithms for more machine learning tasks.

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