Meta OOD Learning for Continuously Adaptive OOD Detection

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Abstract: Out-of-distribution (OOD) detection is crucial to modern deep learning applications by identifying and alerting about the OOD samples that should not be tested or used for making predictions. Current OOD detection methods have made significant progress when in-distribution (ID) and OOD samples are drawn from static distributions. However, this can be unrealistic when applied to real-world systems which often undergo continuous variations and shifts in ID and OOD distributions over time. Therefore, for an effective application in real-world systems, the development of OOD detection methods that can adapt to these dynamic and evolving distributions is essential. In this paper, we propose a novel and more realistic setting called *continuously adaptive out-of-distribution* (CAOOD) detection which targets on developing an OOD detection model that enables dynamic and quick adaptation to a new arriving distribution, with insufficient ID samples during deployment time. To address CAOOD, we develop *meta OOD learning* (MOL) by designing a learning-to-adapt diagram such that a good initialized OOD detection model is learned during the training process. In the testing process, MOL ensures OOD detection performance over shifting distributions by quickly adapting to new distributions with a few adaptations. Extensive experiments on several OOD benchmarks endorse the effectiveness of our method in preserving both ID classification accuracy and OOD detection performance on continuously shifting distributions.

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