Learning from Complementary-Label Learning

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Abstract

Complementary-label learning (CLL) is a weakly supervised paradigm for multi-class classification in which each instance is annotated only with the classes it does not belong to, reducing annotation effort while introducing indirect supervision and label noise. Although unbiased risk estimators and specialized loss functions have established CLL's theoretical underpinnings, its real-world applicability remains limited by a lack of comprehensive empirical validation and effective noise-handling techniques. We begin by diagnosing the gaps between CLL's theoretical promise and practical use, pinpointing the barriers that prevent real-world deployment. Next, we demonstrate CLL's acute sensitivity to noisy supervision and present general strategies for mitigating complementary-label noise, supported by benchmarking results from our open-source toolkit with standardized implementations and evaluation protocols. Finally, we outline promising research directions to boost scalability, strengthen robustness under severe noise, and pave the way for practical CLL applications.