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Title: Comprehensive comparative study of multi-label classification methods

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Summary

The article introduces the concept of multi-label classification (MLC) in predictive modeling, which goes beyond binary classification by predicting the presence or absence of multiple labels simultaneously for a given sample. This expanded approach is highly relevant in various domains, including image classification, gene function prediction, and text document classification, among others. Multi-label classification (MLC) models presents a powerful and versatile solution to tackle advanced classification problems across diverse fields by enabling the simultaneous prediction of multiple labels for a single sample. It distinguishes itself from multi-class classification (MCC) where only a single label is assigned to a sample from multiple classes, and from multi-target classification (MTC) where several targets are predicted, each taking one value from multiple classes. MLC offers a more comprehensive and flexible framework for handling complex classification scenarios.

The study focuses on MLC datasets primarily sourced from biology, text, and multimedia domains. Multimedia datasets include image and audio classification. Additional datasets from medicine and chemistry domains are included. The datasets vary in meta-features such as instance count, feature count, label count, label cardinality, and label density. The range of training examples spans from 174 to 17,190 instances, allowing for testing MLC methods' efficacy with varying data richness.

Overall, the paper presents an extensive comparative study of Multi-Label Classification (MLC) methods, providing both theoretical analysis and empirical evaluations. The study aims to map the landscape of MLC methods and offer guidelines for practitioners in selecting appropriate methods for their specific tasks. The theoretical analysis explores various aspects of the methods, including their inner workings, strengths, weaknesses, and their ability to handle label dependencies and high-dimensional label spaces. The methods are categorized into problem transformation and algorithm adaptation approaches. The empirical study is the largest conducted to date, involving 26 MLC methods trained on 42 datasets and evaluated using 18 performance measures and two efficiency criteria. The datasets cover diverse domains such as text, medicine, multimedia, bioinformatics, biology, and chemistry. The evaluation results identify the top-performing methods, such as RFPCT, RFDTBR, EBRJ48, AdaBoost.MH, and ECCJ48, based on their performance across the evaluation measures. The study also suggests avenues for future research, including exploring relationships between evaluation measures, meta learning with dataset properties, investigating deep learning methods for MLC, and improving label predictions through thresholding techniques.