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Title: Deep Convolution Neural Network sharing for the multi-label images classification

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Summary

The article delves into the application of deep learning, more specifically deep neural networks to tackle multi-label classification problems. It has been used mainly for image classification problems. The article introduces two major categories of multi-label classification methods: problem transformation and algorithm adaptation.

In problem transformation, the multi-label dataset is transformed into a single-label dataset using various operations like copy, select-max, and ignore. One commonly employed method in this category is Binary Relevance, which trains individual binary classifiers for each label.

Algorithm adaptation methods directly manipulate multi-label data to make predictions using specific learning algorithms.

Problem transformation and algorithm adaptation are two categories that provide frameworks for effectively addressing multi-label classification tasks. These approaches offer diverse strategies to tackle challenges related to multi-label datasets and optimize the prediction process. In this article, a new approach using a Multi-Branch Neural Network (MBNN) is introduced for multi-label classification. The authors address the challenges of transforming the problem into binary classification and identifying relevant label classes.

To address the challenge of limited training data in multi-label classification tasks, we can apply the "Divide and Conquer" principle within multi-task learning (MTL). MTL allows us to tackle multiple problems simultaneously, leveraging the learning process to overcome difficulties across tasks. Initially, the model learns parameters from source tasks, which serve as feature extractors. These learned parameters are then used to train the model on the target task using its specific datasets. By utilizing MTL and the Divide and Conquer principle, we can effectively handle multi-label classification tasks with limited training data.

Transfer learning is a highly effective technique in deep learning for multi-label classification. It overcomes the limitations of limited labeled training data and resource-intensive processes. By leveraging knowledge from previous tasks, transfer learning significantly improves performance on new tasks. In image classification, it involves utilizing a pre-trained neural network through fine-tuning or feature extraction.

This article introduces a new approach for multi-label classification by utilizing deep multitask learning. The proposed classifier is compared against established deep learning classifiers such as ResNet50, InceptionV3, and VGG16. The evaluation of the classifiers includes a comprehensive analysis of performance measures like precision, recall, F1-score, and average precision. To assess the significance of performance differences, the study employs rigorous statistical tests, including the Friedman test and Nemenyi post-hoc test.

The Friedman test serves as a valuable tool in determining substantial variations in classifier performance across multiple datasets, providing insights into the comparative effectiveness of the classifiers under examination. Nemenyi post-hoc test determines statistical significance between classifier pairs by calculating a critical difference threshold based on average ranks, indicating the minimum difference needed for classifiers to be considered significantly different.

The proposed approach achieves performance comparable to standard classifiers, with soft parameter sharing and multi-feature networks outperforming hard parameter sharing with multi-output networks. The study emphasizes the benefits of utilizing pre-trained layers, transfer learning techniques, and larger source data for training classification models. Future work should focus on exploring more efficient network architectures, incorporating attention mechanisms, and utilizing additional datasets to advance multi-label classification. Analyzing the impact of various learning parameters is crucial, including learning rate, optimizer, batch size, and epoch, with a wider range of values. These efforts aim to enhance classifier performance and interpretability.