

**Multi-Label Learning with Global and Local Label Correlation**

**Abstract:**

It is well-known that exploiting label correlations is important to multi-label learning. Existing approaches either assume that the label correlations are global and shared by all instances; or that the label correlations are local and shared only by a data subset. In fact, in the real-world applications, both cases may occur that some label correlations are globally applicable and some are shared only in a local group of instances. Moreover, it is also a usual case that only partial labels are observed, which makes the exploitation of the label correlations much more difficult. That is, it is hard to estimate the label correlations when many labels are absent. In this paper, we propose a new multi-label approach GLOCAL dealing with both the full-label and the missing-label cases, exploiting global and local label correlations simultaneously, through learning a latent label representation and optimizing label manifolds. The extensive experimental studies validate the effectiveness of our approach on both full-label and missing-label data.

**Existing System:**

In multi-label learning, human labelers may sometimes ignore labels they do not know or of little interest. Thus, some labels may be missing from the training set. To address this problem, there have been attempts to recover the missing labels by exploiting label correlations. For example, as labels are correlated, one can assume the label correlation matrix and/or instance-label mapping matrix to

have internal linear dependence structure and thus lowrank (i.e., its rank is smaller than its size).

A common approach to encourage this low-rank assumption during inference is by using the nuclear-norm regularizer. However, optimization may be computationally expensive. A more direct approach to enforce this lowrank assumption on the label matrix is by approximating it as a product of two smaller matrices

**Proposed System:**

We propose a new approach called “Multi-Label Learning with GLObal and loCAL Label Correlation” (GLOCAL), which simultaneously recovers the missing labels, trains the linear classifiers, explores and exploits both global and local label correlations. Classifier outputs are encouraged to be similar on highly positively correlated labels, and dissimilar on highly negatively correlated labels. We do not assume the presence of external knowledge sources specifying the label correlations. Instead, these correlations are learned simultaneously with the latent label representations and instance-label mapping.