G^{2}NetPL: Generic Game-Theoretic Network for Partial-Label Image Classification

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Motivation

• Multi-label image classification aims to predict all possible labels in an image which it is expensive to annotate all the labels.
• To relieve the annotation burden of full labeling, partial-label learning is used.

Overview of G^{2}NetPL

In G^{2}NetPL, each unobserved label is associated with a soft pseudo label, which, together with the network, formulates a two-player non-zero-sum non-cooperative game.

Loss Functions

\[ \mathcal{L}_{\text{obs}}(\mathbf{y}, \mathbf{y}^\prime) = \sum_{j=1}^{n} |C_j(\mathbf{y}_j, F_j(\mathbf{y}_j)) + \lambda_j F_j(\mathbf{y}_j)(1 - F_j(\mathbf{y}_j))| \]
\[ \mathcal{L}_{\text{G^{2}NetPL}} = \mathcal{L}_{\text{obs}} + \mathcal{L}_{\text{uns}}. \]
\[ \mathcal{L}_{\text{uns}} = \sum_{j=1}^{n} \sum_{k=1}^{m_j} \mathcal{L}_k(\mathbf{y}_j, \mathbf{y}_k^0). \]

The pseudo labels will gradually build up their confidence during iterations.

Experiments

Table 1: Quantitative results (mAP) of multi-label image classification on four different datasets. Bold represents the highest mAP and underline represents the second-best among FSPL setting (Single positive and No negative).

| Observed Labels | End-to-End Setting |
|----------------|---------------------|
| LS [25]         | All                 |
| LS–LS           | All                 |
| AN [18]         | Single              |
| AN–LS [7]       | Single              |
| WSN [22]        | Single              |
| EPW [7]         | Single              |
| ROLE [7] (ours) | Single              |
| G^{2}NetPL      | Single              |

Comparison with Semi-supervised models:

Convergence of pseudo labels during the epochs:

1 or 0 mean strong indication, high confidence
0.5 means no information, low confidence