Multi-Level Generative Models for Partial Label Learning with Non-random Label Noise

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Abstract

Partial label (PL) learning tackles the problem where each training instance is associated with a set of candidate labels that include both the true label and irrelevant noise labels. In this paper, we propose a novel multi-level generative model for partial label learning (MGPLL), which tackles the problem by learning both a label level adversarial generator and a feature level adversarial generator under a bi-directional mapping framework between the label vectors and the data samples. Specifically, MGPLL uses a conditional noise label generation network to model the non-random noise labels and perform label denoising, and uses a multi-class predictor to map the training instances to the denoised label vectors, while a conditional data feature generator is used to form an inverse mapping from the denoised label vectors to data samples. Both the noise label generator and the data feature generator are learned in an adversarial manner to match the observed candidate labels and data features respectively. Extensive experiments are conducted on synthesized and real-world partial label datasets. The proposed approach demonstrates the state-of-the-art performance for partial label learning.

1 Introduction

Partial label (PL) learning is a weakly supervised learning problem with ambiguous labels \([10; 21]\), where each training instance is assigned a set of candidate labels, among which only one is the true label. Since it is typically difficult and costly to annotate instances precisely, the task of partial label learning naturally arises in many real-world learning scenarios, including automatic face naming \([10; 21]\), and web mining \([13]\).

As the true label information is hidden in the candidate label set, the main challenge of PL lies in identifying the ground truth labels from the candidate noise labels. Intuitively, one basic strategy to tackle partial label learning is performing label disambiguation. There are two main groups of disambiguation-based PL approaches: the average-based disambiguation approaches and the identification-based approaches. For averaging-based disambiguation, each candidate label is treated equally in model induction and the final prediction is made by averaging the modeling outputs of all the candidate labels \([10; 3; 23]\). Without differentiating the informative true labels from the noise irrelevant labels, such simple averaging methods in general cannot produce satisfactory performance. Hence recent studies are mostly focused on identification-based disambiguation methods. Many identification-based disambiguation methods treat the ground-truth labels as latent variables and identify the true labels by employing iterative label refining procedures \([11; 22; 16]\). For example, the work in \([5]\) tries to estimate the latent label distribution with iterative label propagations and then induce a prediction model by fitting the learned latent label distribution. Another work in \([12]\) exploits a self-training strategy to induce label confidence values and learn classifiers in an alternative manner by minimizing the squared loss between the model predictions and the learned label confidence matrix. However, these methods suffer from the cumulative errors induced in either the separate label distribution estimation steps or the error-prone label confidence estimation process. Moreover, all these methods have a common drawback: they automatically assumed random noise in the label space—that is, they assume the noise labels are randomly distributed. However, in real world problems the appearance of noise labels are usually dependent on the target true labels. For example, when the object contained in an image is a “computer”, a noise label “TV” could be added due to a recognition mistake or image ambiguity, but it is less likely to annotate the object as “lamp” or “curtain”, while the probability of getting noise labels such as “tree” or “bike” is even smaller.

In this paper, we propose a novel multi-level adversarial generative model, MGPLL, for partial label learning. The MGPLL model comprises of conditional data generators at both the label level and feature level. The noise label generator directly models non-random appearances of noise labels conditioning on the true label by adversarially matching the candidate label observations, while the data feature generator models the data samples conditioning on the corresponding true labels by adversarially matching the observed data sample distribution. Moreover, a prediction network is incorporated to predict the denoised true label of each instance from its input features, which forms inverse mappings between labels and features, together with the data feature generator. The learning of the overall model corresponds to a minimax
adversarial game, which simultaneously identifies true labels of the training instances from both the observed data features and the observed candidate labels, while inducing accurate prediction networks that map input feature vectors to (denoised) true label vectors. To the best of our knowledge, this is the first work that exploits multi-level generative models to model non-random noise labels for partial label learning. We conduct extensive experiments on real-world and synthesized PL datasets. The empirical results show the proposed MGPLL achieves the state-of-the-art PL performance.

2 Related Work

Partial label learning is a weakly supervised classification problem in many real-world domains, where the true label of each training instance is hidden within a given candidate label set. The PL setting is different from the noise label learning, where the ground-truth labels on some instances are replaced by noise labels. The key for PL learning lies in how to disambiguate the candidate labels. Existing disambiguation-based approaches mainly follow two strategies: the average-based strategy and the identification-based strategy.

The average-based strategy assumes that each candidate label contributes equally to model training, and then averages the outputs of all the candidate labels for final prediction. Following such a strategy, the discriminative learning methods [3, 23] distinguish the averaged model outputs based on all the candidate labels from the averaged outputs based on all the non-candidate labels. The instance-based learning methods [10, 7] on the other hand predict the label for a test instance by averaging the candidate labels from its neighbors. The simple average-based strategy however cannot produce satisfactory performance since it fails to take the difference among the candidate labels into account.

By considering the differences between candidate labels, the identification-based strategy has gained increasing attention due to its effectiveness of handling the candidate labels with discrimination. Many existing approaches following this strategy take the ground-truth labels as latent variables. Then, a prediction model is posed to learn the label confidence value of each candidate instance by averaging the candidate labels from its neighbors. As aforementioned, in real world partial

native optimization, the estimation error on confidence values can negatively impact the coupled partial label predictor. Moreover, all these existing methods have assumed random label noise by default, which however does not hold in many real world learning scenarios. This paper presents the first work that explicitly model non-random noise labels for partial label learning.

3 The Proposed Approach

Given a partial label training set \( S = \{(x_i, y_i)\}_{i=1}^n \), where \( x_i \in \mathbb{R}^d \) is a \( d \)-dimensional feature vector for the \( i \)-th instance, and \( y_i \in \{0, 1\}^L \) denotes the candidate label indicator associated with \( x_i \), which has multiple 1 values corresponding to the ground-truth label and the noise labels, the task is to learn a good multi-class prediction model. In real world scenarios, the irrelevant noise labels are typically not presented in a random manner, but rather correlated with the ground-truth label. In this section, we present a novel multi-level generative model for partial label learning, MGPLL. The model is illustrated in Figure 1. It models non-random noise labels using an adversarial conditional noise label generator \( G_n \) with a corresponding discriminator \( D_n \), and builds connections between the denoised label vectors and instance features using a label-conditioned feature level generator \( G_z \) and a label prediction network \( F \). The overall model learning problem corresponds to a minimax adversarial game, which conducts multi-level generator learning by matching the observed data in both the feature and label spaces, while boosting the correspondence relationships between features and labels to induce an accurate multi-class prediction model. Below we present the details of the two level generations, the prediction network, and the overall learning problem.

3.1 Conditional Noise Label Generation

The key challenge of partial label learning lies in the fact that ground-truth label is hidden among noise labels in the given candidate label set. As aforementioned, in real world partial

\begin{align*}
\text{Label Level} \quad & G_n(F(x), \varepsilon) \\
& \text{Feature Level} \quad G_z(z, \varepsilon)
\end{align*}

Figure 1: The proposed MGPLL model comprises five component networks: the conditional noise label generator, \( G_n \), which models noise labels conditioning on the truth label at the label level; the feature level conditional data generator, \( G_z \), generates data samples conditioning on the denoised label vectors; the discriminator, \( D_n \), tries to maximally separate the generated candidate label vectors from the observed real ones; the discriminator, \( D_z \), tries to maximally separate the generated samples from the real data; the prediction network, \( F \), predicts the denoised label vector for each training sample, and together with \( G_z \) forms bi-directional maps between the label and feature spaces.
In label learning problems, the appearances of noise labels are typically not random, but rather correlated with the ground-truth labels. Hence we propose a conditional noise label generation model to model the appearances of the target-label dependent noise labels and match the observed candidate label distribution in the training data through adversarial learning.

Specifically, given a noise value sampled from a uniform distribution $\epsilon \sim P_\epsilon$ and a one-hot label indicator vector $y$ sampled from a multinomial distribution $P_y$, we use a noise label generator $G_n(z, \epsilon)$ to generate a noise label vector conditioning on the true label $z$, which can be combined with $z$ to form a generated candidate label vector $\tilde{y}$, such that $\tilde{y} = G_n(z, \epsilon) \oplus z = \min(G_n(z, \epsilon) + z, 1)$. We then adopt the adversarial learning principle to learn such a noise label generation model by introducing a discriminator $D_n(y)$, which is a two-class classifier and predicts how likely a given label vector $y$ comes from the real data instead of generated data. By adopting the adversarial loss of the Wasserstein Generative Adversarial Network (WGAN) [1], our adversarial learning problem can be formulated as the following minimax optimization problem:

$$\min_{G_n} \max_{D_n} \mathcal{L}_{adv}(G_n, D_n) =$$

$$\mathbb{E}_{(x_i, y_i) \sim S} D_n(y_i) - \mathbb{E}_{z \sim P_z} D_n(G_n(z, \epsilon) \oplus z)$$

Here the discriminator $D_n$ attempts to maximally distinguish the generated candidate label vectors from the observed candidate label indicator vectors in the real training data, while the generator $G_n$ tries to generate noise label vectors and hence candidate label vectors that are similar to the real data in order to maximally confuse the discriminator $D_n$. By playing a minimax game between the generator $G_n$ and the discriminator $D_n$, the adversarial learning is expected to induce a generator $G_n^*$ such that the generated candidate label distribution can match the observed candidate label distribution in the training data [3]. We adopted the training loss of WGAN here, as WGAN can overcome the mode collapse problem and have improved learning stability comparing to the standard GAN [1].

Note although the proposed generator $G_n$ is designed to model true-label dependent noise labels, it can be easily modified to model random noise label distributions by simply dropping the label vector input to have $G_n(\epsilon)$.

### 3.2 Prediction Network

The ultimate goal of partial label learning is to learn an accurate prediction network $F$. To train a good predictor, we need to obtain denoised labels on the training data. For a candidate label indicator vector $y$, if the noise label indicator vector $y_n$ is given, one can simply perform label denoising as follows to obtain the corresponding true label vector $z$:

$$z = y \oplus y_n = \max(y - y_n, 0)$$

(2)

Here the operator $\oplus$ is introduced to generalize the standard minus “-” operator into the non-ideal case, where the noise label indicator vector $y_n$ is not properly contained in the candidate label indicator vector.

The generator $G_n$ presented in the previous section provides a mechanism to generate noise labels and denoise candidate label sets, but requires true target label vector as input. We can use the outputs of the prediction network $F$ to approximate the target true label vectors of the training data for candidate label denoising purpose with $G_n$, while using the denoised labels as the prediction target for $F$. Specifically, with the noise label generator $G_n$ and predictor $F$, we can perform partial label learning by minimizing the following classification loss on the training data $S$:

$$\min_{F,G_n} \mathcal{L}_c(F, G_n) =$$

$$\mathbb{E}_{(x_i, y_i) \sim S} \ell_c(F(x_i), y_i \oplus G_n(F(x_i), \epsilon))$$

(3)

Although in the ideal case, the output vectors of $G_n$ and $F$ would be indicator label vectors, it is error-prone and difficult for neural networks to output discrete values. To pursue more reliable predictions and avoid overconfident outputs, $G_n$ and $F$ predict the probability of each class label being a noise label and ground-truth label respectively. Hence the loss function $\ell_c(\cdot, \cdot)$ in Eq.(3) above denotes a mean square error loss between the predicted probability of each label being the true label (through $F$) and its confidence of being a ground-truth label (through $G_n$).

### 3.3 Conditional Feature Level Data Generation

With the noise label generation model and the prediction network above, the observed training data in both the label and feature spaces are exploited to recognize the true labels and induce good prediction models. Next, we incorporate a conditional data generator $G_x(z, \epsilon)$ at the feature level to map (denoised) label vectors in the label space into instances in the feature space, aiming to further strengthen the mapping relations between data samples and the corresponding labels, enhance label denoising and hence improve partial label learning performance. Specifically, given a noise value $\epsilon$ sampled from a uniform distribution $P_\epsilon$ and a one-hot label vector $z$ sampled from a multinomial distribution $P_z$, $G_x(z, \epsilon)$ generates an instance in the feature space that is corresponding to label $z$. Hence given the training label vectors in $S$ denoised with $G_n$, the data generator $G_x$ is expected to regenerate the corresponding training instances in the feature space. This assumption can be captured using the following generation loss:

$$\mathcal{L}_g(F, G_n, G_x) = \mathbb{E}_{(x_i, y_i) \sim S} \ell_g(G_x(z_i, \epsilon_2), x_i)$$

(4)

where $z_i = y_i \oplus G_n(F(x_i), \epsilon_1)$ denotes the denoised label vector for the $i$-th training instance, and $\ell_g(\cdot, \cdot)$ is a mean square error loss function.

Moreover, by introducing a discriminator $D_x(x)$, which predicts how likely a given instance $x$ is real, we can deploy an adversarial learning scheme to learn the generator $G_x$ through the following minimax optimization problem with the WGAN loss:

$$\min_{G_x} \max_{D_x} \mathcal{L}_{adv}(G_x, D_x) =$$

$$\mathbb{E}_{(x_i, y_i) \sim S} D_x(x_i) - \mathbb{E}_{z \sim P_z} D_x(G_x(z, \epsilon))$$

(5)

By playing a minimax game between $G_x$ and $D_x$, this adversarial learning is expected to induce a generator $G_x^*$ that
Algorithm 1 Minibatch stochastic gradient descent.

**Input:** $S$: the PL training set; $\alpha, \beta, \gamma$: the trade-off hyperparameters; $c$: the clipping parameter; $m$: minibatch size.

for number of training iterations do
    Sample a minibatch $B$ of $m$ samples from $S$.
    Sample $m$ noise values $\{\epsilon_i\}$ from a prior $P(\epsilon)$.
    Sample $m$ label vectors $\{z_i\}$ from a prior $P_z$.
    Update $D_n, D_x$ by ascending their stochastic gradients:
    $$\nabla_{\theta_{D_n, D_x}} \frac{1}{m} \sum_{i=1}^{m} \left\{ \left( D_n(y_i) - D_n(G_n(z_i, \epsilon_i) \oplus z_i) \right) + \alpha \left( D_x(x_i) - D_x(G_x(z_i, \epsilon_i)) \right) \right\}$$
    $$\theta_{D_n, D_x} \leftarrow \text{clip}(\theta_{D_n, D_x}, -c, c) \text{ (WGAN adjustment)}$$
    Sample $m$ noise values $\{\tau_i\}$ from a prior $P(\epsilon)$.
    Update $G_n, G_x, F$ by stochastic gradient descent:
    $$\nabla_{\theta_{G_n, G_x, F}} \frac{1}{m} \sum_{i=1}^{m} \left\{ \ell_c(F_G(x_i), y_i \oplus G_n(F_G(x_i), \epsilon_i)) - \alpha D_n(G_n(x_i, \epsilon_i) \oplus \tau_i) - \alpha D_x(G_x(z_i, \epsilon_i)) + \beta \ell(G_G(x_i, \epsilon_i) \oplus G_n(F_G(x_i), \epsilon_i), z_i) + \gamma \ell_c(F_G(z_i, \epsilon_i), z_i) \right\}$$
end for

Algorithm 2 can generate samples with the same distribution as the observed training instances. Hence the mapping relation from label vectors to samples induced by $G_x^*$ can also hold on the real training data, and should be consistent with the inverse mapping from samples to label vectors through the prediction network. Therefore, we can further consider an auxiliary classification loss on the generated data:

$$L_c(F, G_x) = \mathbb{E}_{x \sim P_x} \ell_c(F(G_x(z), \epsilon), z)$$

(6)

where $\ell_c(\cdot, \cdot)$ can be a cross-entropy loss between the label prediction probability vector and the sampled true label indicator vector.

### 3.4 Learning the MGPLL Model

By integrating the classification loss in Eq.(3), the adversarial losses in Eq.(1) and Eq.(5), the generation loss in Eq.(4) and the auxiliary classification loss in Eq.(6) together, MGPLL learning can be formulated as the following min-max optimization problem:

$$\min_{G_n, G_x, F} \max_{D_n, D_x} L_c(F, G_n) + L^{adv}_{adv}(G_n, D_n) + \alpha L^{adv}_{adv}(G_x, D_x) + \beta L_0(F, G_n, G_x) + \gamma L_c(F, G_x)$$

(7)

where $\alpha, \beta, \gamma$ are trade-off hyperparameters.

The training of the overall model corresponds to a minimax adversarial game. We develop a batch-based stochastic gradient descent algorithm to solve it by conducting minimization over $\{G_n, G_x, F\}$ and maximization over $\{D_n, D_x\}$ alternatively. The overall training algorithm is outlined in Algorithm 1.

### 4 Experiment

#### 4.1 Datasets

We conducted experiments on both controlled synthetic PL datasets and a number of real-world PL datasets.

The synthetic datasets are generated from four UCI datasets, ecoli, vehicle, segment and satimage, which have 8, 4, 7 and 7 classes, and 336, 846, 2310 and 6,345 examples, respectively. From each UCI dataset, we generated synthetic PL datasets using three controlling parameters $p, r, \epsilon$, following the controlling protocol in previous works [19, 20]. Among the three parameters, $p$ controls the proportion of instances that have noise candidate labels, $r$ controls the number of false positive labels, and $\epsilon$ controls the probability of a specific false positive label co-occurring with the true label. Under different parameter configurations, multiple PL variants can be generated from each UCI dataset. In particular, we considered two settings. In the first setting, we consider random noise labels with the following three groups of configurations: (I) $r = 1, p \in \{0.1, 0.2, \cdots, 0.7\}$; (II) $r = 2, p \in \{0.1, 0.2, \cdots, 0.7\}$; (III) $r = 3, p \in \{0.1, 0.2, \cdots, 0.7\}$. In the second setting, we consider the target label-dependent noise labels with the following configuration: (IV) $p = 1, r = 1, \epsilon \in \{0.1, 0.2, \cdots, 0.7\}$. In total, this provides us 112 (28 configurations $\times$ 4 UCI datasets) synthetic PL datasets.

We used five real-world PL datasets that are collected from several application domains, including FG-NET [15] for facial age estimation, Lost [3], Yahoo! News [9] for automatic face naming in images or videos, MSRCv2 [4] for object classification, and BirdSong [2] for bird song classification. The characteristics of the real-world PL datasets are summarized in Table 1.

| Dataset      | #Example | #Feature | #Class | avg.#CLs |
|--------------|----------|----------|--------|----------|
| FG-NET       | 1,002    | 262      | 78     | 7.48     |
| Lost         | 1,122    | 108      | 16     | 2.23     |
| MSRCv2       | 1,758    | 48       | 23     | 3.16     |
| BirdSong     | 4,998    | 38       | 13     | 2.18     |
| Yahoo! News  | 22,991   | 163      | 219    | 1.91     |

### 4.2 Comparison Methods

We compared the proposed MGPLL approach with the following PL methods, each configured with the suggested parameters according to the respective literature:

- **PL-KNN** [10]: A k-NN based method which makes prediction with weighted voting.
- **PL-SVM** [14]: A maximum-margin based method which maximizes the classification margin between candidate and non-candidate class labels.
- **CLPL** [3]: A convex optimization based method for partial label learning.
- **PALOC** [19]: An ensemble method which trains multiple binary classifiers with the one-vs-one decomposition strategy and makes prediction by consulting all binary classifiers.
Table 2: Win/tie/loss counts of pairwise t-test (at 0.05 significance level) between MGPLL and each comparison approach.

|                      | MGPLL vs – |       |       |       |
|----------------------|------------|-------|-------|-------|
|                      | SURE       | PALOC | CLPL  | PL-SVM|
| varying \( p \)      |            |       |       |       |
| varying \( p = 1 \)  | 18/7/3     | 22/6/0| 24/4/0| 24/4/0|
| varying \( p = 2 \)  | 16/9/3     | 19/9/0| 21/7/0| 22/6/0|
| varying \( p = 3 \)  | 14/12/2    | 18/10/0| 20/8/0| 23/5/0|
| varying \( \epsilon \) | 15/13/0    | 18/10/0| 18/10/0| 21/7/0|
| Total                | 63/41/8    | 77/35/0| 83/29/0| 90/22/0|

- MGPLL: A self-training based method which learns a confidence matrix of candidate labels with a maximum infinity norm regularization and trains the prediction model over the learned label confidence matrix.

4.3 Implementation Details

The proposed MGPLL model has five component networks, all of which are designed as multilayer perceptrons with Leaky ReLu activation for the middle layers. The noise label generator is a four-layer network with sigmoid activation in the output layer. The conditional data generator is a five-layer network with tanh activation in the output layer, while batch normalization is deployed in its middle three layers. The predictor is a three-layer network with softmax activation in the output layer. Both the noise label discriminator and the data discriminator are three-layer networks without activation in the output layer. The RMSProp optimizer is used in our implementation and the mini-batch size \( m \) is set to 32. We selected the hyperparameters \( \alpha, \beta, \gamma \) from \{0.001, 0.01, 0.1, 1, 10\} based on the classification loss value \( \mathcal{L}_c \) in the training objective function; that is, we chose their values that lead to the smallest training \( \mathcal{L}_c \) loss.

4.4 Results on Synthetic PL Datasets

We conducted experiments on two types of synthetic PL datasets generated from the UCI datasets, with random noise labels and target label-dependent noise labels, respectively. For each PL dataset, ten-fold cross-validation is performed and the average test accuracy results are recorded. First we study the comparison results over the PL datasets with target label-dependent noise labels under the PL configuration setting IV. In this setting, a specific label is selected as the coupled label that co-occurs with the ground-truth label with probability \( \epsilon \), and any other label can be randomly chosen as a noisy label with probability \( 1 - \epsilon \). Figure 2 presents the comparison results for the configuration setting IV, where \( \epsilon \) increases from 0.1 to 0.7 (with 100% partially labeled examples \( p = 1 \)) and one false positive candidate label \( r = 1 \).

Figure 2: Test accuracy of each comparison method changes as \( \epsilon \) (co-occurring probability of the coupling label) increases from 0.1 to 0.7 (with 100% partially labeled examples \( p = 1 \)) and one false positive candidate label \( r = 1 \).

|                      | SURE       | PALOC   | CLPL   | PL-SVM  |
|----------------------|------------|---------|--------|---------|
| varying \( \epsilon \) |            |         |        |         |
| \( \epsilon = 0.1 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |
| \( \epsilon = 0.2 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |
| \( \epsilon = 0.3 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |
| \( \epsilon = 0.4 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |
| \( \epsilon = 0.5 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |
| \( \epsilon = 0.6 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |
| \( \epsilon = 0.7 \) | 74.1%      | 75.0%   | 74.1%  | 73.0%   |

Table 2: Win/tie/loss counts of pairwise t-test (at 0.05 significance level) between MGPLL and each comparison approach.

4.5 Results on Real-World PL Datasets

We compared the proposed MGPLL method with the comparison methods on five real-world PL datasets. For each dataset, ten-fold cross-validation is conducted, while the mean test ac-
The objective function of MGPLL contains five loss terms: classification loss, adversarial loss at the label level, adversarial loss at the feature level, generation loss and auxiliary classification loss. To assess the contribution of each part, we conducted an ablation study by comparing MGPLL with the following ablation variants: (1) CLS-w/o-adv, which drops the adversarial loss at the label level. (2) CLS-w/o-advx, which drops the adversarial loss at the feature level. (3) CLS-w/o-g, which drops the generation loss. (4) CLS-w/o-aux, which drops the auxiliary classification loss. (5) CLS, which only uses the classification loss by dropping all the other loss terms. The comparison results are reported in Table 4.

Table 4: Comparison results of MGPLL and its five ablative variants.

| Dataset          | MGPLL ± std | CLS-w/o-adv ± std | CLS-w/o-advx ± std | CLS-w/o-g ± std | CLS-w/o-aux ± std | CLS ± std |
|------------------|-------------|--------------------|--------------------|----------------|-------------------|-----------|
| FG-NET           | 0.079 ± 0.024 | 0.061 ± 0.024 | 0.072 ± 0.020 | 0.068 ± 0.029 | 0.076 ± 0.022 | 0.057 ± 0.016 |
| FG-NET(MAE3)     | 0.468 ± 0.027 | 0.430 ± 0.029 | 0.451 ± 0.032 | 0.436 ± 0.038 | 0.456 ± 0.033 | 0.420 ± 0.042 |
| FG-NET(MAE5)     | 0.626 ± 0.022 | 0.583 ± 0.055 | 0.605 ± 0.031 | 0.591 ± 0.045 | 0.612 ± 0.047 | 0.570 ± 0.034 |
| Lost             | 0.798 ± 0.033 | 0.623 ± 0.037 | 0.754 ± 0.032 | 0.687 ± 0.026 | 0.782 ± 0.043 | 0.609 ± 0.040 |
| MSRCv2           | 0.533 ± 0.021 | 0.472 ± 0.030 | 0.480 ± 0.038 | 0.497 ± 0.031 | 0.526 ± 0.036 | 0.450 ± 0.037 |
| BirdSong         | 0.748 ± 0.020 | 0.728 ± 0.010 | 0.732 ± 0.011 | 0.716 ± 0.011 | 0.742 ± 0.024 | 0.674 ± 0.016 |
| Yahoo! News      | 0.678 ± 0.008 | 0.645 ± 0.008 | 0.675 ± 0.009 | 0.648 ± 0.014 | 0.671 ± 0.012 | 0.610 ± 0.015 |

5 Conclusion

In this paper, we proposed a novel multi-level generative model, MGPLL, for partial label learning. MGPLL uses a conditional label level generator to model target label dependent non-random noise label appearances, which directly performs candidate label denoising, while using a conditional feature level generator to generate data samples from denoised label vectors. Moreover, a prediction network is in-
corporated to predict the denoised true label of each instance from its input features, which forms inverse mappings between labels and features, together with the data feature generator. The adversarial learning of the overall model simultaneously identifies true labels of the training instances from both the observed data features and the observed candidate labels, while inducing accurate prediction networks that map input feature vectors to (denoised) true label vectors. We conducted extensive experiments on real-world and synthesized PL datasets. The proposed MGPLL model demonstrates the state-of-the-art PL performance.

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