# A. Proof of Theorem 1

In the section, we provide a proof of Theorem 1. Different from the linear framework presented in (Yu et al., 2014), we prove the generalizability of the nonlinear model, especially the DNN based model. We will show that with the help of knowledge learned from past labels, the generalizability to model the new labels can be improved without compromising model accuracy. Given training data, the proposed DSLL learns a classifier  $\hat{W}$  by minimizing the *empirical risk*,

$$\hat{\mathcal{L}}(\mathbf{W}) = \frac{1}{n} \sum_{i=1}^{n} \ell(\mathbf{y}_i, f_i(\mathbf{x}_i^*, \mathbf{W})) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} \ell(y_i^j, f_i^j(\mathbf{x}_i^*, \mathbf{W})),$$

where  $\ell(\cdot)$  denotes the loss function;  $f_i^j(\boldsymbol{x}_i^*, \mathbf{W})$  is the predicted value of the *j*-th label corresponding to the *i*-th input data  $\boldsymbol{x}_i^*$ . And we can obtain

$$\hat{\mathbf{W}} = \operatorname*{arg\,min}_{\mathbf{W} \in \mathcal{W}} \hat{\mathcal{L}}(\mathbf{W}).$$

The goal of the proof is to show that the learned  $\hat{\mathbf{W}}$  is generalizable, i.e.,

$$\mathcal{L}(\hat{\mathbf{W}}) \leq \inf_{\mathbf{W} \in \mathcal{W}} \mathcal{L}(\mathbf{W}) + \epsilon,$$

where  $\mathcal{L}(\mathbf{W})$  is the *population risk* of a classifier, defined as:

$$\mathcal{L}(\mathbf{W}) = \mathop{\mathbb{E}}_{(\boldsymbol{x}^*, \boldsymbol{y}^{new})} \llbracket \ell(\boldsymbol{y}, f(\boldsymbol{x}^*, \mathbf{W})) \rrbracket = \mathop{\mathbb{E}}_{(\widetilde{\boldsymbol{x}}^*_i, \widetilde{\boldsymbol{y}}^{new}_i)} \left\| \frac{1}{n} \sum_{i=1}^n \ell(\widetilde{\boldsymbol{y}}^{new}_i, f_i(\widetilde{\boldsymbol{x}}^*_i, \mathbf{W})) \right\|$$

We perform our analysis in three setps:

- Step 1: By using McDiarmid's inequality (Sammut & Webb, 2010), the excess risk of the learned model can be bounded by the expected supremum deviation of empirical risks.
- Step 2: We bound the expected supremum deviation by application of Rademacher averages (Ledoux & Talagrand, 1991; Yu et al., 2014; Maurer, 2016).
- Step 3: Since we use diagonal sign matrix to denote ReLU activation (Definition 4.1), the network parameters corresponding to each input data can be expressed in the form of a matrix (Allen-Zhu et al., 2019). Then, we reduce the estimation of the Rademacher average to the estimation of the norm by matrix-based regularization techniques (Kakade et al., 2012; Maurer, 2016).

#### A.1. Bounding Excess Risk by Expected Supremum Deviation

We first investigate, by using McDiarmid's inequality (Sammut & Webb, 2010), that the excess risk  $\mathcal{L}(\hat{\mathbf{W}}) - \hat{\mathcal{L}}(\hat{\mathbf{W}})$  can be bounded by the expected supremum deviation of empirical risks,

$$\begin{split} \mathcal{L}(\hat{\mathbf{W}}) - \hat{\mathcal{L}}(\hat{\mathbf{W}}) &\leq \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \mathcal{L}(\mathbf{W}) - \hat{\mathcal{L}}(\mathbf{W}) \right\} \\ &= \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sup_{(\tilde{\boldsymbol{x}}_{i}^{*}, \tilde{\boldsymbol{y}}_{i}^{new})} \left[ \left[ \frac{1}{n} \sum_{i=1}^{n} \ell(\tilde{\boldsymbol{y}}_{i}^{new}, f_{i}(\tilde{\boldsymbol{x}}_{i}^{*}, \mathbf{W})) \right] \right] - \frac{1}{n} \sum_{i=1}^{n} \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\boldsymbol{x}_{i}^{*}, \mathbf{W})) \right\} \\ &\triangleq g((\boldsymbol{x}_{1}^{*}, \boldsymbol{y}_{1}^{new}), ..., (\boldsymbol{x}_{n}^{*}, \boldsymbol{y}_{n}^{new})). \end{split}$$

Since the decomposable loss function  $\ell(\boldsymbol{y}^{new}, f(\boldsymbol{x}^*, \mathbf{W})) = \sum_{j=m+1}^{m+k} \ell(\boldsymbol{y}^j, f^j(\boldsymbol{x}^*, \mathbf{W}))$  are bounded, the change in any  $(\boldsymbol{x}^*_i, \boldsymbol{y}^{new}_i)$  would induce a perturbation of  $g((\boldsymbol{x}^*_1, \boldsymbol{y}^{new}_1), ..., (\boldsymbol{x}^*_n, \boldsymbol{y}^{new}_n))$  at most  $\mathcal{O}(\frac{k}{n})$ . Then by applying McDiarmid's inequality, the sum of squared perturbations is bounded by  $\frac{2k^2}{n}$ , and thus the excess risk is bounded by a term related to the expectation of  $g((\boldsymbol{x}^*_1, \boldsymbol{y}^{new}_1), ..., (\boldsymbol{x}^*_n, \boldsymbol{y}^{new}_n))$ , the expected supremum deviation. Therefore, we have established that with

probability at least  $1 - \delta$ ,

$$\mathcal{L}(\hat{\mathbf{W}}) - \hat{\mathcal{L}}(\hat{\mathbf{W}}) \leq \mathbb{E}_{(\boldsymbol{x}_{i}^{*}, \boldsymbol{y}_{i}^{new})} \llbracket g((\boldsymbol{x}_{1}^{*}, \boldsymbol{y}_{1}^{new}), ..., (\boldsymbol{x}_{n}^{*}, \boldsymbol{y}_{n}^{new})) \rrbracket + \mathcal{O}\left(k\sqrt{\frac{\log \frac{1}{\delta}}{n}}\right).$$

Next, the upper bound of the expected supremum deviation will be investigated.

## A.2. Bounding Expected Supremum Deviation by Rademacher Averages

We now bound the expected supremum deviation by Rademacher averages (Ledoux & Talagrand, 1991; Yu et al., 2014; Maurer, 2016). We have

$$\begin{split} & \left\| \left\| g((\boldsymbol{x}_{1}^{*},\boldsymbol{y}_{1}^{new}), \dots, (\boldsymbol{x}_{n}^{*},\boldsymbol{y}_{n}^{new})) \right\| \\ &= \left\| \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{1}^{new})} \left\| \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \left( \sum_{(\tilde{\boldsymbol{x}}_{i}^{*},\tilde{\boldsymbol{y}}_{1}^{new})} \left\| \left[ \frac{1}{n} \sum_{i=1}^{n} \ell(\tilde{\boldsymbol{y}}_{i}^{new}, f_{i}(\tilde{\boldsymbol{x}}_{i}^{*}, \mathbf{W})) - \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\boldsymbol{x}_{i}^{*}, \mathbf{W})) \right] \right\| \right\} \right\| \\ &\leq \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{1}^{new})} \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \ell(\tilde{\boldsymbol{y}}_{i}^{new}, f_{i}(\tilde{\boldsymbol{x}}_{i}^{*}, \mathbf{W})) - \frac{1}{n} \sum_{i=1}^{n} \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\boldsymbol{x}_{i}^{*}, \mathbf{W})) \right\} \right\| \\ &= \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{i}^{new}), \epsilon_{i}} \left\| \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \epsilon_{i} \left( \ell(\tilde{\boldsymbol{y}}_{i}^{new}, f_{i}(\tilde{\boldsymbol{x}}_{i}^{*}, \mathbf{W})) - \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\boldsymbol{x}_{i}^{*}, \mathbf{W})) \right\} \right\| \\ &\leq \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{i}^{new}), (\tilde{\boldsymbol{x}}_{i}, \tilde{\boldsymbol{y}}_{i}^{new}), \epsilon_{i}} \left\| \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \epsilon_{i} \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\tilde{\boldsymbol{x}}_{i}^{*}, \mathbf{W})) \right\} \right\| \\ &+ \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{i}^{new}), (\tilde{\boldsymbol{x}}_{i}, \tilde{\boldsymbol{y}}_{i}^{new}), \epsilon_{i}} \left\| \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \epsilon_{i} \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\tilde{\boldsymbol{x}}_{i}^{*}, \mathbf{W})) \right\} \right\| \\ &= 2 \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{i}^{new}), \epsilon_{i}} \left\| \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \epsilon_{i} \ell(\boldsymbol{y}_{i}^{new}, f_{i}(\boldsymbol{x}_{i}, \mathbf{W})) \right\} \right\| \\ &= 2 \sum_{(\boldsymbol{x}_{i}^{*},\boldsymbol{y}_{i}^{new}), \epsilon_{i}} \left\| \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \epsilon_{i} \sum_{j=n+1}^{n+1} \ell(\boldsymbol{y}_{i}^{j}, f_{i}^{j}(\boldsymbol{x}_{i}^{*}, \mathbf{W})) \right\} \right\| \\ &\leq \frac{2C}{n} \sum_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \left\| \sup_{\boldsymbol{W}\in\mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+1} f_{i}^{j}(\epsilon_{i}^{j}\boldsymbol{x}_{i}^{*}, \mathbf{W}) \right\} \right\| = 2C\mathcal{R}_{n}(\mathcal{W}), \end{aligned}$$

where  $\epsilon_i$  is a Rademacher variable and  $\epsilon_i^j$  is an independent doubly indexed Rademacher sequence (Ledoux & Talagrand, 1991; Yu et al., 2014). Note that the first inequality employs Jensen inequality (Xi et al., 2020). The second inequality is based on the convexity of the supremum function. In the last inequality, we use the contraction inequality for Rademacher averages (see Maurer, 2016, corollary 4), and under the assumption that the loss  $\ell$  is bounded and C-Lipschitz.

#### A.3. Estimating the Rademacher Average

Now we estimate the Rademacher average (Maurer, 2016) to bound the following quantity:

$$\mathcal{R}_{n}(\mathcal{W}) \coloneqq \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \left[ \left[ \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} f_{i}^{j}(\epsilon_{i}^{j} \boldsymbol{x}_{i}^{*}, \mathbf{W}) \right\} \right] \right].$$

$$(2)$$

Before that, we have to express the nonlinear network in matrix form (Allen-Zhu et al., 2019). Note that the deep streaming label learning (DSLL) integrates three effective networks: Streaming Student  $W_S$ , Label Self-representation  $W_Y$  and Senior

Student  $\mathbf{W}_{\Delta}$ . These three networks constitute the DSLL model  $\mathbf{W}$  structurally, which is defined as  $\mathbf{W} = \mathbf{W}_{\Delta} \begin{bmatrix} \mathbf{W}_{S} \\ \mathbf{W}_{\mathcal{Y}} \end{bmatrix}$ . Specifically,  $\mathbf{W}$  consists of a fully connected network with the ReLU activation function in the hidden layers and the sigmoid activation function in the output layer.

ReLU 
$$\phi(x) = max(0, x)$$

sigmoid  $S(x) = \frac{1}{1 + e^{-x}}$ 

According to Definition 4.1, the neural network with ReLU can be expressed in the form of linear matrices corresponding to each input data, i.e.,

$$\hat{\boldsymbol{y}}_i = f_i(\boldsymbol{x}_i^*, \mathbf{W}) = \mathbf{B} \mathbf{D}_i^L \mathbf{W}_L, ..., D_i^1 \mathbf{W}_1 \mathbf{D}_i^0 \mathbf{A} \boldsymbol{x}_i^*,$$
(3)

where  $\mathbf{A} \in \mathbb{R}^{u_1 \times (d+m)}$  is the weight matrix for the input layer,  $\mathbf{W}_l \in \mathbb{R}^{u_{l+1} \times u_l}$  is the weight matrix for the *l*-th hidden layer,  $\mathbf{B} \in \mathbb{R}^{k \times u_L}$  is the weight matrix for the output layer, and  $u_l$  is the number of neurons in the hidden layer l.  $\mathbf{D}_i^l$  is diagonal sign matrix defined in Definition 4.1, which denotes the ReLU function of *l*-th layer corresponding to  $\boldsymbol{x}_i^*$ . We define the network matrix

$$\boldsymbol{w}_i = \mathbf{D}_i^L \mathbf{W}_L, ..., D_i^1 \mathbf{W}_1 \mathbf{D}_i^0 \mathbf{A},$$

where  $w_i$  is related to each input data  $x_i^*$  since different inputs correspond to different diagonal sign matrix  $\mathbf{D}_i^l$  to represent the effect of the nonlinear ReLU function. Then, Equation 3 can be rewrote:

$$\hat{\boldsymbol{y}}_i = f_i(\boldsymbol{x}_i^*, \mathbf{W}) = \mathbf{B}\boldsymbol{w}_i\boldsymbol{x}_i^*.$$

Note that  $\mathbf{B} \in \mathbb{R}^{k \times u_L}$  is the ouput matrix independent of input data  $x_i^*$ . Moreover,

-

$$\hat{y}_i^j = \mathbf{B}^j \boldsymbol{w}_i \boldsymbol{x}_i^*,$$

where  $\mathbf{B}^{j} \in \mathbb{R}^{1 \times u_{L}}$  denotes the *j*-th label component of output matrix,  $j \in [m + 1, ..., m + k]$ . Corresponding to  $\mathbf{W}_{S}$ ,  $\mathbf{W}_{Y}$ , and  $\mathbf{W}_{\Delta}$  above, we use  $w_{S_{i}}, w_{Y_{i}}, w_{\Delta_{i}}$  denote the networks parameters of streaming student, label mapping and senior student with respect to  $x_{i}^{*}$ . We define  $w_{\Delta_{i}} \coloneqq [w_{\Delta S_{i}}, w_{\Delta Y_{i}}]$  to denote the two components of  $w_{\Delta_{i}}$  corresponding streaming student and label mapping by column. Then, we have

$$\begin{aligned} \mathcal{R}_{n}(\mathcal{W}) &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{i} \boldsymbol{x}_{i}^{*} \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta_{i}} \left[ \boldsymbol{w}_{\mathcal{S}_{i}} \boldsymbol{x}_{i} \right] \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} c_{i}^{j} \mathbf{B}^{j} \left[ \boldsymbol{w}_{\Delta S_{i}}, \boldsymbol{w}_{\Delta y_{i}} \right] \left[ \frac{\boldsymbol{w}_{S_{i}} \boldsymbol{x}_{i}}{\boldsymbol{y}_{i}^{new}} \right] \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} c_{i}^{j} \mathbf{B}^{j} \left( \boldsymbol{w}_{\Delta S_{i}}, \boldsymbol{w}_{\Delta y_{i}} \mathbf{x}_{i} + \boldsymbol{w}_{\Delta y_{i}} \hat{\boldsymbol{y}}_{i}^{new} \right) \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} (c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta S_{i}} \boldsymbol{w}_{S_{i}} \boldsymbol{x}_{i} + c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta y_{i}} \left( (\hat{\boldsymbol{y}}_{i}^{new} - \boldsymbol{y}_{i}^{new}) + \boldsymbol{y}_{i}^{new} \right) \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} (c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta S_{i}} \boldsymbol{w}_{S_{i}} \boldsymbol{x}_{i} + c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta y_{i}} \left( (\hat{\boldsymbol{y}}_{i}^{new} - \boldsymbol{y}_{i}^{new}) + \boldsymbol{y}_{i}^{new} \right) \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} \left( c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta S_{i}} \boldsymbol{w}_{S_{i}} \boldsymbol{x}_{i} + c_{i}^{j} \mathbf{B}^{j} \boldsymbol{w}_{\Delta y_{i}} \left( \boldsymbol{\xi}_{i} + \boldsymbol{y}_{i}^{new} \right) \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sup_{\mathbf{W} \in \mathcal{W}} \left\{ \sum_{i=1}^{n} \sum_{j=m+1}^{m+k} \left( \mathbf{B}^{j}, \sum_{i=1}^{n} c_{i}^{j} \boldsymbol{w}_{\Delta S_{i}} \boldsymbol{w}_{i} \boldsymbol{x}_{i} \right) + \sum_{j=m+1}^{m+k} \left\langle \mathbf{B}^{j}, \sum_{i=1}^{n} c_{i}^{j} \boldsymbol{w}_{\Delta y_{i}} \left( \boldsymbol{\xi}_{i} + \boldsymbol{y}_{i}^{new} \right) \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}^{j}} \left\| \sum_{w \in \mathcal{W}} \left\{ \sum_{j=m+1}^{m+k} \left\langle \mathbf{B}^{j}, \sum_{i=1}^{n} c_{i}^{j} \boldsymbol{w}_{\Delta A_{i}} \boldsymbol{x}_{i} \right\} + \sum_{j=m+1}^{m+k} \left\langle \mathbf{B}^{j}, \sum_{i=1}^{n} c_{i}^{j} \boldsymbol{w}_{\Delta A_{i}} \left( \boldsymbol{\xi}_{i} + \boldsymbol{y}_{i}^{new} \right) \right\} \right\} \right\| \\ &= \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, c_{i}$$

where  $\xi_i$  is the discrepancy between  $\hat{y}_i^{new}$  and  $y_i^{new}$ , which can be sufficiently small  $\mathbb{E}[\![\|\xi_i\|]\!] = \mathcal{O}(1)$  if the label representation performs accurately;  $w_{\Delta S_i} w_{S_i}$  is denoted by  $w_{S\Delta_i}$ .

Let F be a Hilbert-space, and let  $\mathcal{B}(F, \mathbb{R}^k)$  be the set of bounded transformation from F to  $\mathbb{R}^k$ . We denote  $||| \cdot |||$  as a norm of on  $\mathcal{B}(F, \mathbb{R}^k)$  with dual norm  $||| \cdot |||_*$ . Fix some real number  $\gamma$ , and define a class  $\mathcal{W}$  of functions from F to  $\mathbb{R}^k$  by

$$\mathcal{W} = \{ \boldsymbol{x} \to \mathbf{W}\boldsymbol{x} : \mathbf{W} \in \mathcal{B}(F, \mathbb{R}^k), |||\mathbf{W}||| \le \gamma \}.$$

Equation (4) can be rewrote as follow.

$$\mathcal{R}_{n}(\mathcal{W}) = \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{i}} \left[ \sup_{\mathbf{W} \in \mathcal{W}} \left\{ tr(H_{x}^{*}\mathbf{W}_{\mathcal{S}\Delta}) + tr(H_{y}^{*}\mathbf{W}_{\Delta\mathcal{Y}}) \right\} \right]$$

$$\leq \frac{1}{n} \mathop{\mathbb{E}}_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{i}} [\gamma|||H_{x}^{*}|||_{*} + \gamma|||H_{y}^{*}|||_{*}],$$
(5)

where  $H_x, H_y \in \mathcal{B}(F, \mathbb{R}^k)$  are the random transformations:

$$H_{x}: \quad v \to \left( \left\langle v, \sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{w}_{\mathcal{S}\Delta_{i}}^{j} \boldsymbol{x}_{i} \right\rangle, ..., \left\langle v, \sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{w}_{\mathcal{S}\Delta_{i}}^{j} \boldsymbol{x}_{i} \right\rangle \right),$$
  
$$H_{y}: \quad v \to \left( \left\langle v, \sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{w}_{\Delta \mathcal{Y}}^{j} \left( \xi_{i} + \boldsymbol{y}_{i}^{new} \right) \right\rangle, ..., \left\langle v, \sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{w}_{\Delta \mathcal{Y}}^{j} \left( \xi_{i} + \boldsymbol{y}_{i}^{new} \right) \right\rangle \right).$$

Bounding  $\mathbb{E} ||| \cdot |||_*$  depends on the nature of the norm  $||| \cdot |||$ . In Equation (5), we use the Hilbert-Schmidt or Frobenius norm, denoted  $|| \cdot ||_F$ , where

$$\frac{1}{n} \sum_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \|\gamma\| \|H_{\boldsymbol{x}}^{*}\|_{*}^{*} + \gamma\| \|H_{\boldsymbol{y}}^{*}\|_{*}^{*} \| \\
= \frac{1}{n} \sum_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \left[ \left[ \gamma \sqrt{\sum_{j=m+1}^{m+k} \left\|\sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{w}_{S\Delta_{i}} \boldsymbol{x}_{i}\right\|^{2}} + \gamma \sqrt{\sum_{j=m+1}^{m+k} \left\|\sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{w}_{\Delta\mathcal{Y}_{i}} \left(\xi_{i} + \boldsymbol{y}_{i}^{new}\right)\right\|^{2}} \right] \\
\leq \frac{1}{n} \sum_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \left[ \left[ \gamma \|\mathbf{W}_{S\Delta_{i}}\|_{F} \sqrt{\sum_{j=m+1}^{m+k} \left\|\sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{x}_{i}\right\|^{2}} + \gamma \|\mathbf{W}_{\Delta\mathcal{Y}_{i}}\|_{F} \sqrt{\sum_{j=m+1}^{m+k} \left\|\sum_{i=1}^{n} \epsilon_{i}^{j} \left(\xi_{i} + \boldsymbol{y}_{i}^{new}\right)\right\|^{2}} \right] \right] \\
= \frac{1}{n} \sum_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \left[ \left[ \gamma_{x} \sqrt{\sum_{j=m+1}^{m+k} \left\|\sum_{i=1}^{n} \epsilon_{i}^{j} \boldsymbol{x}_{i}\right\|^{2}} + \gamma_{y} \sqrt{\sum_{j=m+1}^{m+k} \left\|\sum_{i=1}^{n} \epsilon_{i}^{j} \left(\xi_{i} + \boldsymbol{y}_{i}^{new}\right)\right\|^{2}} \right] \\
\leq \frac{1}{n} \sum_{\boldsymbol{x}_{i}^{*}, \epsilon_{i}^{j}} \left[ \left[ \gamma_{x} \sqrt{k} \sum_{i=1}^{n} \|\boldsymbol{x}_{i}\|^{2} + \gamma_{y} \sqrt{k} \sum_{i=1}^{n} \|(\xi_{i} + \boldsymbol{y}_{i}^{new})\|^{2}} \right] .$$
(6)

In Equation (6), the first inequality applies the Cauchy-Schwarz inequality;  $\gamma_x$  and  $\gamma_y$  are real constant, which are the upper bounds of the norm of trained network parameters (Allen-Zhu et al., 2019); The second inequality estimates the Rademacher complexity for vector-valued classes (see Maurer, 2016, Section 4.2). Without loss of generality, we assume that  $\mathbb{E}[\|\boldsymbol{x}\|^2] \leq 1$ ,  $\mathbb{E}[\|\xi_i + \boldsymbol{y}_i^{new}\|^2] \leq 4k$ . This proves

$$\mathcal{R}_n(\mathcal{W}) \leq \sqrt{\frac{k}{n}} \left(\gamma_x + \gamma_y \sqrt{4k}\right),$$

which establishes Theorem 1.

## **B. Experimental Supplementary Material**

In this section, we provide more detailed experimental settings and results. Section B.1 presents definition of ten evaluation metrics and experimental settings. Section B.2 presents more extensive empirical evaluation for modeling new labels.

## **B.1. Evaluation Metrics and Settings.**

Given a test data set denoted by  $\mathcal{D} = \{(\boldsymbol{x}_1, \boldsymbol{y}_1), ..., (\boldsymbol{x}_n, \boldsymbol{y}_n)\}$ , where  $\boldsymbol{x}_i \in \mathcal{X} \subseteq \mathbb{R}^{d \times 1}$  is a real vector representing an input feature (instance) and  $\boldsymbol{y}_i \in \mathcal{Y} \subseteq \{0, 1\}^{m \times 1}$  is the corresponding output label vector  $(i \in [n], \text{ defined as } i \in \{1, ..., n\})$ . Moreover,  $y_i^j = 1$  if the *j*-th label is assigned to the instance  $\boldsymbol{x}_i$  and  $y_i^j = 0$  otherwise. For notational simplicity, we use  $Y_i^+$  to denote the index set of associated (non-associated) labels of  $\boldsymbol{y}_i$ . Formally,  $Y_i^+ = \{j | y_i^j = 1\}$  and  $Y_i^- = \{j | y_i^j = 0\}$ . With respect to *j*-th column of label matrix,  $Y_{\cdot j}^+ = \{i | y_i^j = 1\}$  denotes the index set of associated instance of the *j*-th label and  $Y_{\cdot j}^- = \{i | y_j^j = 0\}$  denotes the set of non-associated instances similarly. We use  $|\cdot|$  to represent the cardinality of a set.

Table 4 summarizes the ten popular multi-label evaluation metrics used in this paper, which can be divided into bipartitionbased metrics, i.e., Hamming loss, macro-F1, micros-F1, and instance-F1, and ranking-based metrics, i.e., Precision@k, coverage, ranking loss, average precision (AP), macro-AUC, and micro-AUC (Wu & Zhou, 2017; Jain et al., 2016; Wang et al., 2019; Tsoumakas et al., 2010). We assume that  $H : \mathbb{R}^d \to \{0, 1\}^m$  is the multi-label classifier and predicts which labels an instance is associated with. H can be decomposed as  $\{h^1, ..., h^m\}$  and  $h^j(\mathbf{x}_i)$  represents the prediction of  $y_i^j$ . The results of H can be evaluated by bipartition-based metrics.  $F : \mathbb{R}^d \to \mathbb{R}^m$  is the multi-label predictor, whose predicted value could be regarded as the confidence of association.  $F = \{f^1, ..., f^m\}$  and  $f^j(\mathbf{x}_i)$  denotes the predicted value of  $y_i^j$ , which can be evaluated by ranking-based metrics. H can be induced from F by thresholding techniques. For example,  $h^j(\mathbf{x}_i) = \mathbb{1}\{f^j(\mathbf{x}_i) > t(\mathbf{x}_i)\}$ , where we use  $\mathbb{1}\{event\}$  to denote the indicator function for *event*. In the experiment, we simply use 0.5 as the threshold for the output of DSLL model.



Figure 3. Comparison of modeling new labels with different batch sizes by considering 50% labels as past labels. m indicates the number of new labels.

## **B.2.** Detailed Results with Emerging New Labels

- Figure 3 shows the macro-F1 and instance-F1 results for learning new labels with different batch sizes. Note that SLEEC, SML and SLL could not properly generate bipartite classification results, hence it is not possible to evaluate the results with the F1 scores.
- Table 5 shows the Coverage and Precision@1 results for learning new labels with different batch sizes.
- Table 6 shows the Average precision and macro-AUC results for learning new labels with different batch sizes. Note

	Table 4. Demittions of ten multi-faber performance measures.								
Measure	Formulation	Note							
Hamming loss	$hloss(H) = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} \mathbbm{1}\{h_{i}^{j} \neq y_{i}^{j}\}$	The fraction of misclassified labels.							
ranking loss	$rloss(F) = \frac{1}{n} \sum_{i=1}^{n} \frac{ S_{rank}^{i} }{ Y_{i}^{+}  Y_{i}^{-} } \\ S_{rank}^{i} = \{(u, v)   f_{u}(\boldsymbol{x}_{i}) \leq f_{v}(\boldsymbol{x}_{i}), (u, v) \in Y_{i}^{+} \times Y_{i}^{-} \}$	The average fraction of reversely or- dered label pairs of each instance.							
coverage	$coverage(F) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}\{\max_{j \in Y_{i}^+} rank_F(\boldsymbol{x}_i, j) - 1\}$	The number of more labels on average should include to cover all relevant labels							
average precision	$\begin{aligned} avgprec(F) &= \frac{1}{n} \sum_{i=1}^{n} \frac{1}{ Y_{i}^{+} } \sum_{j \in Y_{i}^{+}} \frac{ \mathcal{S}_{\text{precision}}^{ij} }{rank_{F}(\boldsymbol{x}_{i}, j)} \\ \mathcal{S}_{\text{precision}}^{ij} &= \{k \in Y_{i}^{+}   rank_{F}(\boldsymbol{x}_{i}, k) \leq rank_{F}(\boldsymbol{x}_{i}, j)\} \end{aligned}$	The average fraction of relevant labels ranked higher than one other relevant label.							
Precision@k	$\begin{aligned} Precision@k(F) &= \frac{1}{n} \sum_{i=1}^{n} \frac{ Y_{i\cdot}^+ \cap \top_k(f(\boldsymbol{x}_i)) }{k} \\ \top_k(f(\boldsymbol{x}_i)) &= \{j   f^j(\boldsymbol{x}_i) \in Top(f^1(\boldsymbol{x}_i),, f^m(\boldsymbol{x}_i)) \} \end{aligned}$	It is the fraction of correct predictions among the first $k$ predicted labels.							
macro-F1	$macro-FI(H) = \frac{1}{m} \sum_{j=1}^{m} \frac{2\sum_{i=1}^{n} y_{ij} h_{ij}}{\sum_{i=1}^{n} y_{ij} + \sum_{i=1}^{n} h_{ij}}$	F-measure averaging on each label.							
micro-F1	$\textit{micro-FI}(H) = \frac{2\sum_{j=1}^{m}\sum_{i=1}^{n}y_{ij}h_{ij}}{\sum_{j=1}^{m}\sum_{i=1}^{n}y_{ij} + \sum_{j=1}^{m}\sum_{i=1}^{n}h_{ij}}$	F-measure averaging on the prediction matrix.							
instance-F1	instance-FI(H) = $\frac{1}{n} \sum_{i=1}^{n} \frac{2 \sum_{j=1}^{m} y_{ij} h_{ij}}{\sum_{j=1}^{m} y_{ij} + \sum_{j=1}^{m} h_{ij}}$	F-measure averaging on each instance.							
macro-AUC	$macro-AUC(F) = \frac{1}{m} \sum_{j=1}^{m} \frac{ \mathcal{S}_{\text{macro}}^{j} }{ Y_{\cdot j}^{+}  Y_{\cdot j}^{-} }$ $\mathcal{S}_{\text{macro}}^{j} = \{(a, b) \in Y_{\cdot j}^{+} \times Y_{\cdot j}^{-} f_{j}(\boldsymbol{x}_{a}) \ge f_{j}(\boldsymbol{x}_{b})\}$	AUC averaging on each label. $S_{macro}$ is the set of correctly ordered instance pairs on each label.							
micro-AUC	$\begin{split} \textit{micro-AUC}(F) &= \frac{ \mathcal{S}_{\text{micro}} }{(\sum_{i=1}^{n}  Y_{i}^{+} ) \cdot (\sum_{i=1}^{n}  Y_{i}^{-} )} \\ \mathcal{S}_{\text{micro}} &= \{(a, b, i, j)   (a, b) \in Y_{\cdot i}^{+} \times Y_{\cdot j}^{-}, \ f_{i}(\boldsymbol{x}_{a}) \geq f_{j}(\boldsymbol{x}_{b}) \} \end{split}$	AUC averaging on prediction matrix. $S_{micro}$ is the set of correct quadruples.							

Table 4	Definitions of	f ten multi-label	performance measures
$1 a O C \tau$ .	Duminuons of	i ton muni-iaooi	periormance measures.

that due to the sparsity of text datasets, we could not use Average precision and macro-AUC to evaluate results on EURlex and Wiki10.

• Table 7 shows the Hamming loss results for learning new labels with different batch sizes. Note that SLEEC, SML and SLL could not properly generate bipartite classification results, hence it is not possible to evaluate the results with Hamming loss. In addition, due to the sparsity of text datasets, the performance of Hamming loss is homogenized on EURlex and Wiki10.

Datasets #la	#labal	Coverage ↓												
Datasets	#label	BR	CC	RAKEL	ML-kNN	SLEEC	SML	SLL	BP-MLL	DNN-BCE	C2AE	DSLL		
	2	0.4826	0.4749	0.4553	0.4776	0.4057	0.4049	0.4128	0.4124	0.4062	0.4035	0.4013		
Datasets yeast MirFlickr Delicious EURlex	3	0.4217	0.4326	0.4097	0.4220	0.2846	0.2811	0.3341	0.2803	0.2788	0.2784	0.2777		
veast	4	0.5057	0.5172	0.5025	0.4981	0.3408	0.3384	0.4008	0.3424	0.3394	0.3408	0.3351		
<b>J</b> · · · · ·	5	0.5278	0.5429	0.5178	0.5186	0.3302	0.3259	0.4131	0.3335	0.3269	0.3291	0.3230		
	6	0.5676	0.5901	0.5549	0.5643	0.3595	0.3482	0.4340	0.3550	0.3571	0.3542	0.3499		
	3	0.4530	0.5721	0.4468	0.4570	0.4117	0 3013	0.3568	0.3435	0 3442	0.3334	0 3236		
	6	0.3983	0.5721	0.3916	0.4249	0.4117	0.3472	0.3308	0.2247	0.2216	0.3334	DSLL 0.4013 0.2777 0.3351 0.3230 0.3499 0.3236 0.2132 0.2153 0.2601 0.2663 0.1302 0.2512 0.3245 0.3189 0.0160 0.0270 0.0401 0.0461 0.0948 0.0635 0.1037 0.1317 0.1674 0.2125 DSLL 0.4820 0.5551 0.5442 0.5551 0.5442 0.5551 0.6035 0.6020 0.3099 0.3712 0.4904		
MirFlickr	0	0.3903	0.5815	0.3510	0.5212	0.3651	0.3472	0.2242	0.2247	0.2210	0.2213	0.2152		
WIIITHERI	12	0.5654	0.0909	0.4552	0.6372	0.3031	0.3230	0.2321	0.2342	0.2250	0.2207	0.2133		
	15	0.5817	0.8029	0.5733	0.6593	0.4954	0.4592	0.2862	0.2035	0.2809	0.2732	0.2663		
	100	0.4597	0.6027	0.5735	0.6002	0.1991	0.1572	0.2002	0.1510	0.1454	0.1400	0.12000		
	200	0.4387	0.0937	0.3420	0.0992	0.3084	0.2313	0.2208	0.1310	0.1434	0.1499	VE         DSLL           35         0.4013           84         0.2777           08         0.3351           91         0.3230           42         0.3499           34         0.2153           32         0.2601           81         0.2663           99         0.1302           83         0.2210           34         0.0160           25         0.0270           66         0.3245           90         0.3189           34         0.0160           25         0.0270           69         0.0401           70         0.0461           53         0.0948           13         0.0635           07         0.1037           441         0.1317           95         0.1674           83         0.2125		
Daliaiana	200	0.0147	0.00/3	0.7399	0.0034	0.4399	0.3093	0.3408	0.2401	0.2261	0.2365	0.2210		
Dencious	400	0.0957	0.9318	0.8500	0.9460	0.3400	0.4300	0.4329	0.3107	0.2634	0.2934	0.2512		
	400 500	0.738	0.90/9	0.88/1	0.9075	0.6044	0.3074	0.5147	0.3009	0.3277	0.3200	0.3245		
	200	0.1710	0.9762	0.9252	0.1022	0.0020	0.4004	0.0700	0.5808	0.4150	0.3390	0.01(0		
	200	0.1517	0.1350	0.1461	0.1823	0.0729	0.0813	0.0223	0.0932	0.0374	0.0234	0.0160		
FUDIan	400	0.2588	0.2211	0.2529	0.2978	0.1250	0.1023	0.0360	0.1176	0.0444	0.0325	0.0270		
EURIEX	600	0.3697	0.3242	0.3793	0.4280	0.1867	0.1439	0.0534	0.2127	0.0709	0.0669	0.0401		
	800	0.4457	0.3950	0.4839	0.5200	0.2317	0.1817	0.0080	0.1874	0.0812	0.0670	0.0461		
	1000	0.3408	0.4801	0.3679	0.0228	0.5102	0.2190	0.0988	0.3000	0.1076	0.1055	0.0948		
	1k	0.5116	0.4810	0.4577	0.5757	0.3551	0.2942	0.1222	0.2812	0.1413	0.0713	0.0635		
	2k	0.6751	0.6366	0.6251	0.7168	0.5469	0.3524	0.1954	0.4428	0.3217	0.1107	0.1037		
Wiki10	3k	0.7963	0.7573	0.7461	0.8188	0.6819	0.4835	0.3184	0.5405	0.3322	0.1441	0.1317		
	4k	0.8838	0.8477	0.8339	0.8922	0.7937	0.5126	0.3933	0.6152	0.3726	0.1795	0.1674		
	5k	0.9187	0.8868	0.8798	0.9226	0.8463	0.6424	0.4423	0.7134	0.4236	0.2083	0.2125		
Datasets	#label					Precision@	k (k=1)	$\uparrow$						
Dutusets	maoer	DD	00	DAVEL	MI _kNN	SLEEC	SMI	CLI	BP-MI I	DNN-BCE	CALE	234 0.0160 225 0.0270 569 0.0401 570 0.0461 553 0.0948 713 0.0635 107 0.1037 141 0.1317 795 0.1674 183 0.2125 AE DSLL 700 0.4844		
		BK	CC	KAKEL		BELLC	SIVIL	SLL	DI -IVILL	DIAIA-DCL	C2AE	DSLL		
	2	0.4046	0.4286	0.4493	0.4188	0.4689	0.4652	0.4515	0.4646	0.4689	0.4700	0.4844		
	23	0.4046 0.3119	0.4286	0.4493 0.3544	0.4188	0.4689 0.4591	0.4652 0.4478	0.4515 0.4253	0.4646 0.4678	0.4689 0.4719	0.4700 0.4722	0.4844 0.4820		
yeast	2 3 4	0.4046 0.3119 0.4449	0.4286 0.3195 0.4460	0.4493 0.3544 0.4427	0.4188 0.3272 0.4755	0.4689 0.4591 0.5420	0.4652 0.4478 0.5461	0.4515 0.4253 0.5158	0.4646 0.4678 0.5300	0.4689 0.4719 0.5420	0.4700 0.4722 0.5344	0.4844 0.4820 0.5551		
yeast	2 3 4 5	0.4046 0.3119 0.4449 0.3697	0.4286 0.3195 0.4460 0.3948	0.4493 0.3544 0.4427 0.4166	0.4188 0.3272 0.4755 0.4373	0.4689 0.4591 0.5420 0.5256	0.4652 0.4478 0.5461 0.5375	0.4515 0.4253 0.5158 0.4831	0.4646 0.4678 0.5300 0.5256	0.4689 0.4719 0.5420 0.5398	0.4700 0.4722 0.5344 0.5322	0.4844 0.4820 0.5551 0.5442		
yeast	2 3 4 5 6	BR           0.4046           0.3119           0.4449           0.3697           0.3904	0.4286 0.3195 0.4460 0.3948 0.4417	0.4493 0.3544 0.4427 0.4166 0.4558	0.4188 0.3272 0.4755 0.4373 0.4504	0.4689 0.4591 0.5420 0.5256 0.5333	0.4652 0.4478 0.5461 0.5375 <b>0.5437</b>	0.4515 0.4253 0.5158 0.4831 0.4798	0.4646 0.4678 0.5300 0.5256 0.5311	0.4689 0.4719 0.5420 0.5398 0.5213	0.4700 0.4722 0.5344 0.5322 0.5344	0.4844 0.4820 0.5551 0.5442 0.5420		
yeast	2 3 4 5 6 3	BR 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723	RAKEL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255	0.4652 0.4478 0.5461 0.5375 <b>0.5437</b> 0.3574	0.4515 0.4253 0.5158 0.4831 0.4798 0.4383	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729		
yeast	2 3 4 5 6 3 6	BR 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120 0.1906	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134	RAKEL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361           0.2189	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967	0.4652 0.4478 0.5461 0.5375 0.5437 0.3574 0.3553	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614		
yeast	2 3 4 5 6 3 6 9	BR 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120 0.1906 0.3908	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341	RAKEL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658	0.4652 0.4478 0.5461 0.5375 <b>0.5437</b> 0.3574 0.3353 0.3589	0.4515 0.4253 0.5158 0.4831 0.4798 0.4383 0.4402 0.5031	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511		
yeast MirFlickr	2 3 4 5 6 3 6 9 12	BK 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120 0.1906 0.3908 0.2780	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.3269 0.2813 0.4249 0.3980	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845	0.4652 0.4478 0.5461 0.5375 <b>0.5437</b> 0.3574 0.3353 0.3589 0.4053	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.5122 0.5122 0.5924	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035		
yeast MirFlickr	2 3 4 5 6 3 6 9 12 15	BK 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120 0.1906 0.3908 0.2780 0.2708	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826	0.4689 0.4591 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369	0.4652 0.4478 0.5461 0.5375 <b>0.5437</b> 0.3574 0.3553 0.3589 0.4053 0.3946	3LL           0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020		
yeast MirFlickr	2 3 4 5 6 3 6 9 12 15	BR 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120 0.1906 0.3908 0.2780 0.2708 0.0776	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.1263 0.1440 0.1783	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.3826	0.4689 0.4591 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914	0.4652 0.4478 0.5461 0.5375 0.5437 0.3574 0.3574 0.3553 0.3589 0.4053 0.3946 0.2962	3LL           0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5785           0.2967	0.4646 0.4646 0.5300 0.5256 0.5311 0.4580 0.4508 0.4508 0.5122 0.5924 0.5655 0.3052	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099		
yeast MirFlickr	$ \begin{array}{c} 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 9 \\ 12 \\ 15 \\ 100 \\ 200 \\ \end{array} $	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0553	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.1263 0.1440 0.1783 0.1991	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852 0.2251	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694	SML           0.4652           0.4478           0.5461           0.5375           0.5437           0.3574           0.3558           0.4053           0.3946           0.2962           0.3697	3LL           0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5785           0.2967           0.3704	0.4646 0.4646 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.6028 0.6028 0.6015 0.3091 0.3623	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712		
yeast MirFlickr	2 3 4 5 6 3 6 9 9 12 15 100 200 300	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0553           0.0333	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852 0.2251 0.2474	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672	SML           0.4652           0.4478           0.5461           0.5375           0.5437           0.3574           0.3553           0.3578           0.4053           0.3946           0.2962           0.3697           0.478	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904		
yeast MirFlickr Delicious	2 3 4 5 6 9 12 15 100 200 300 400	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0333           0.0336	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852 0.2251 0.2474 0.2424	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.2914 0.3694 0.4672 0.5102	SML           0.4652           0.4478           0.5437           0.3574           0.3573           0.3574           0.3582	3LL           0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501		
yeast MirFlickr Delicious	2 3 4 5 6 9 12 15 100 200 300 400 500	BR           0.4046           0.3119           0.4449           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0333           0.0936           0.0424	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852 0.2251 0.2474 0.2424 0.2041	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3425	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171	0.4652 0.4478 0.5461 0.5375 <b>0.5437</b> 0.3574 0.3574 0.3574 0.3589 0.4053 0.3946 0.2962 0.3697 0.4798 0.5382 0.5216	3LL           0.4515           0.4253           0.5158           0.4283           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338 <b>0.50504</b>	0.4646 0.4678 0.5300 0.5256 0.5311 0.4588 0.4508 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140	$\begin{array}{c} 0.4689\\ 0.4719\\ 0.5420\\ 0.5398\\ 0.5213\\ 0.4508\\ 0.4575\\ 0.5305\\ 0.5972\\ 0.6001\\ \hline 0.2659\\ 0.3651\\ 0.4650\\ 0.5394\\ 0.5024\\ \end{array}$	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498		
yeast MirFlickr Delicious	2 3 4 5 6 3 6 9 9 12 15 100 200 300 400 500	BR 0.4046 0.3119 0.4449 0.3697 0.3904 0.3120 0.1906 0.3908 0.2780 0.2708 0.2708 0.0776 0.0553 0.0333 0.0936 0.0424 0.0501	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.2791 0.3463 0.3312	RAKEL           0.4493           0.3544           0.4493           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1042	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171	SML           0.4652           0.4478           0.5461           0.5375           0.5437           0.3574           0.3589           0.4053           0.3946           0.2962           0.3697           0.4798           0.5216           0.1601	0.4515           0.4553           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357	0.4689 0.4689 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394 0.5024	0.4700 0.4720 0.5344 0.5322 0.5344 0.4642 0.4558 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696		
yeast MirFlickr Delicious	2 3 4 5 6 3 6 9 9 12 15 100 200 300 400 500 200 0	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.0776           0.0333           0.0936           0.0424           0.0501           0.0649	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755	RAKEL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1042           0.1548	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357	SML           0.4652           0.4478           0.5461           0.5375           0.3574           0.3573           0.3574           0.3589           0.4053           0.3697           0.40798           0.5382           0.5216           0.1601	0.4515           0.4253           0.5158           0.4253           0.5158           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338 <b>0.5504</b> 0.1548           0.1548           0.2967	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132	$\begin{array}{c} 0.4689\\ 0.4719\\ 0.5420\\ 0.5398\\ 0.5213\\ \hline 0.4508\\ 0.4575\\ 0.5305\\ 0.5972\\ 0.6001\\ \hline 0.2659\\ 0.3651\\ 0.4650\\ 0.5394\\ 0.5024\\ \hline 0.1571\\ 0.2409 \end{array}$	0.4700 0.4720 0.5344 0.5322 0.5344 0.4642 0.4558 0.6028 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525		
yeast MirFlickr Delicious	2 3 4 5 6 9 9 12 15 100 200 300 400 500 200 400 600	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2708           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0853	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512	RAKEL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1042           0.1548	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3255	SML           0.4652           0.4478           0.5375           0.5375           0.3574           0.3573           0.3574           0.3599           0.4053           0.3946           0.2962           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.2352           0.3138	0.4646 0.4646 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394 0.5024 0.5024 0.1571 0.2409 0.3386	0.4700 0.4700 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3401	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497		
yeast MirFlickr Delicious EURlex	2 3 4 5 6 9 12 15 100 200 300 400 500 200 400 600 800	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0853           0.0943	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512 0.3037	RAKEL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2474           0.2424           0.2041           0.1042           0.1548           0.2132           0.2303	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590 0.1970	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3225 0.3711	SML           0.4652           0.4478           0.5375           0.5375           0.3574           0.3573           0.3574           0.3573           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3594           0.2962           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135           0.3958	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.2352           0.3138           0.5438	0.4646 0.4646 0.4678 0.5300 0.5256 0.5311 0.4588 0.4508 0.4508 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394 0.5024 0.5024 0.1571 0.2409 0.3386 0.3830	0.4700 0.4700 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3401 0.3983	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117		
yeast MirFlickr Delicious EURlex	2 3 4 5 6 9 12 15 100 200 300 400 500 200 400 600 800 800	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0943           0.1016	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512 0.3037 0.3546	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852 0.2251 0.2474 0.2424 0.2041 0.1042 0.1548 0.2132 0.2303 0.2985	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590 0.1970 0.2406	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3225 0.3711 0.4[29]	SML           0.4652           0.4478           0.5375           0.5375           0.3574           0.3573           0.3574           0.3573           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3575           0.4053           0.3946           0.2962           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135           0.3958           0.4363	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3388           0.5338           0.5504           0.1548           0.2352           0.3138           0.3657           0.42923	0.4646 0.4646 0.4678 0.5300 0.5256 0.5311 0.4588 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479 0.3874	$\begin{array}{c} 0.4689\\ 0.4719\\ 0.5420\\ 0.5398\\ 0.5213\\ \hline 0.4508\\ 0.4575\\ 0.5305\\ 0.5972\\ \hline 0.6001\\ \hline 0.2659\\ 0.3651\\ 0.4650\\ 0.5394\\ \hline 0.5024\\ \hline 0.1571\\ 0.2409\\ 0.3386\\ 0.3830\\ 0.4611\\ \hline \end{array}$	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3983 0.4732	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117 0.4854		
yeast MirFlickr Delicious EURlex	2 3 4 5 6 9 12 15 100 200 300 400 500 200 400 600 800 1000	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0943           0.0943           0.1016	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512 0.3037 0.3546 0.2269	0.4493 0.3544 0.4427 0.4166 0.4558 0.3361 0.2189 0.3937 0.3068 0.2765 0.1852 0.2251 0.2474 0.2424 0.2041 0.1042 0.1548 0.2132 0.2303 0.2985 0.2341	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590 0.1970 0.2406	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5171 0.1612 0.2357 0.3225 0.3711 0.1612 0.3255 0.3711	SML           0.4652           0.4478           0.5375           0.5375           0.3574           0.3573           0.3574           0.3573           0.3574           0.3575           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3575           0.4053           0.3946           0.2962           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135           0.3958           0.4363           0.3853	0.4515           0.4253           0.5158           0.4831           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.2352           0.3138           0.3657           0.4223           0.4122	0.4646 0.4646 0.4678 0.5300 0.5256 0.5311 0.4588 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479 0.3874 0.3004	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394 0.5024 0.1571 0.2409 0.3386 0.3830 0.4611 0.3758	0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3401 0.3983 0.4732 0.3626	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117 0.4854 0.4114		
yeast MirFlickr Delicious EURlex	2 3 4 5 6 9 9 12 15 100 200 300 400 500 200 400 600 800 1000 1k	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0943           0.1016           0.2157           0.2142	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1440 0.1783 0.3312 0.3312 0.3312 0.1124 0.1755 0.2512 0.3037 0.3546 0.2269 0.2304	RAREL           0.4493           0.3544           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1548           0.2132           0.2303           0.2985	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590 0.1970 0.2406	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3225 0.3711 0.4129 0.3776 0.3478	3ML           0.4652           0.4478           0.5461           0.5375           0.3574           0.3573           0.3574           0.3574           0.3579           0.4053           0.3946           0.2962           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135           0.3958           0.4363           0.3853	0.4515           0.4515           0.4253           0.5158           0.4383           0.4798           0.4383           0.402           0.5031           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.2352           0.3138           0.3657           0.4132           0.3801	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479 0.3874 0.3094 0.3094	0.4689 0.4689 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394 0.5024 0.1571 0.2409 0.3386 0.3830 0.4611 0.3758 0.3284	0.4700 0.4700 0.5344 0.5322 0.5344 0.4642 0.4558 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3401 0.3983 0.4732 0.3626 0.3927	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117 0.4854 0.4143 0.4113		
yeast MirFlickr Delicious EURlex	2 3 4 5 6 9 9 12 15 100 200 300 400 500 200 400 600 800 1000 1k 2k	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0853           0.0943           0.1016           0.2157           0.2142	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512 0.3037 0.3546 0.2269 0.2304 0.2304	RAREL           0.4493           0.3544           0.4493           0.4493           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1042           0.1548           0.2303           0.2985           0.2341           0.2334	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590 0.1970 0.2406 0.1196 0.1261 0.1356	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3225 0.3711 0.4129 0.3776 0.3478 0.3965	SML           0.4652           0.4478           0.5461           0.5375           0.5437           0.3574           0.3573           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3589           0.4053           0.3946           0.2962           0.3697           0.4798           0.5216           0.1601           0.2474           0.3135           0.3958           0.4363           0.3853           0.3853           0.3853	0.4515           0.4253           0.5158           0.4253           0.5158           0.4253           0.4253           0.4253           0.4383           0.4798           0.4383           0.402           0.5031           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.2352           0.3138           0.3657           0.4132           0.4132	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479 0.3874 0.3094 0.3171 0.3253	$\begin{array}{c} 0.4689\\ 0.4719\\ 0.5420\\ 0.5398\\ 0.5213\\ 0.4508\\ 0.4575\\ 0.5305\\ 0.5972\\ 0.6001\\ \hline 0.2659\\ 0.3651\\ 0.4650\\ 0.5394\\ 0.5024\\ \hline 0.1571\\ 0.2409\\ 0.3386\\ 0.3830\\ 0.4611\\ \hline 0.3758\\ 0.3284\\ 0.3623\\ \hline \end{array}$	0.4700 0.4700 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3401 0.3983 0.4732 0.3626 0.3927 0.4076	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117 0.4854 0.4143 0.4143 0.413 0.413		
yeast MirFlickr Delicious EURlex Wiki10	2 3 4 5 6 9 9 12 15 100 200 300 400 500 200 400 500 200 400 500 200 400 500 1000 1000	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2780           0.2708           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0853           0.0943           0.1016           0.2157           0.2142	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512 0.3037 0.3546 0.2269 0.2304 0.2291 0.2304	RAKEL           0.4493           0.3544           0.4493           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1042           0.1548           0.2303           0.2985           0.2341           0.2334           0.2541	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3825 0.3372 0.0636 0.1031 0.1590 0.1970 0.2406	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3225 0.3711 0.4129 0.3776 0.3478 0.3965	3ML           0.4652           0.4478           0.5461           0.5375           0.3574           0.3573           0.3574           0.3574           0.3574           0.3574           0.3574           0.3589           0.4053           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135           0.3958           0.4363           0.3853           0.3909           0.4087	0.4515           0.4253           0.5158           0.4253           0.5158           0.4253           0.4253           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.3704           0.4893           0.5338           0.5504           0.1548           0.3657           0.4223           0.4132           0.3801           0.4123	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479 0.3874 0.3094 0.3171 0.3253 0.3464	$\begin{array}{c} 0.4689\\ 0.4719\\ 0.5420\\ 0.5398\\ 0.5213\\ 0.4508\\ 0.4575\\ 0.5305\\ 0.5972\\ 0.6001\\ 0.2659\\ 0.3651\\ 0.4650\\ 0.5394\\ 0.5024\\ \hline 0.1571\\ 0.2409\\ 0.3386\\ 0.3830\\ 0.4611\\ \hline 0.3758\\ 0.3284\\ 0.3623\\ 0.3514\\ \hline \end{array}$	0.4700 0.4700 0.4722 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6028 0.6028 0.6028 0.6028 0.6028 0.6028 0.6028 0.6028 0.6028 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.3983 0.4732 0.3626 0.3927 0.4076	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117 0.4854 0.4143 0.4113 0.413 0.413		
yeast MirFlickr Delicious EURlex Wiki10	2 3 4 5 6 9 9 12 15 100 200 300 400 500 200 400 600 200 400 600 800 1000 1k 2k 3k 4k 5k	BR           0.4046           0.3119           0.4449           0.3697           0.3904           0.3120           0.1906           0.3908           0.2708           0.0776           0.0553           0.0333           0.0936           0.0424           0.0501           0.0649           0.0853           0.0943           0.1016           0.2157           0.2142           0.2133           0.2142	0.4286 0.3195 0.4460 0.3948 0.4417 0.1723 0.0134 0.3341 0.1263 0.1440 0.1783 0.1991 0.2791 0.3463 0.3312 0.1124 0.1755 0.2512 0.3037 0.3546 0.2269 0.2304 0.2491 0.2573 0.2922	RAKEL           0.4493           0.3544           0.4493           0.4427           0.4166           0.4558           0.3361           0.2189           0.3937           0.3068           0.2765           0.1852           0.2251           0.2474           0.2041           0.1042           0.1548           0.2303           0.2985           0.2341           0.2341           0.2541           0.2766	0.4188 0.3272 0.4755 0.4373 0.4504 0.3269 0.2813 0.4249 0.3980 0.3826 0.1805 0.2232 0.3108 0.3425 0.3372 0.0636 0.1031 0.1590 0.1970 0.2406 0.1196 0.1261 0.1356 0.1548 0.1750	0.4689 0.4591 0.5420 0.5256 0.5333 0.3255 0.2967 0.3658 0.3845 0.4369 0.2914 0.3694 0.4672 0.5102 0.5171 0.1612 0.2357 0.3225 0.3711 0.4129 0.3776 0.3478 0.3965 0.4149	SML           0.4652           0.4478           0.5375           0.5375           0.3574           0.3573           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3574           0.3589           0.4053           0.3946           0.2962           0.3697           0.4798           0.5382           0.5216           0.1601           0.2474           0.3135           0.3958           0.4363           0.3853           0.3958           0.4087           0.4087           0.4184	0.4515           0.4253           0.5158           0.4383           0.4798           0.4383           0.4402           0.5031           0.5842           0.5785           0.2967           0.3704           0.4893           0.5338           0.5504           0.1548           0.3657           0.4223           0.4132           0.3801           0.4123           0.4034	0.4646 0.4678 0.5300 0.5256 0.5311 0.4580 0.4508 0.5122 0.5924 0.5655 0.3052 0.3706 0.4386 0.5268 0.5140 0.1357 0.2132 0.2750 0.3479 0.3874 0.3094 0.3171 0.3253 0.3464 0.3581	0.4689 0.4719 0.5420 0.5398 0.5213 0.4508 0.4575 0.5305 0.5972 0.6001 0.2659 0.3651 0.4650 0.5394 0.5024 0.1571 0.2409 0.3386 0.3830 0.4611 0.3758 0.3284 0.3623 0.3514 0.3614	0.4700 0.4700 0.5344 0.5322 0.5344 0.4642 0.4558 0.5386 0.6028 0.6015 0.3091 0.3623 0.4898 0.5130 0.5278 0.1641 0.2516 0.3401 0.3983 0.4732 0.3626 0.3927 0.4076 0.4265 0.4388	0.4844 0.4820 0.5551 0.5442 0.5420 0.4729 0.4614 0.5511 0.6035 0.6020 0.3099 0.3712 0.4904 0.5501 0.5498 0.1696 0.2525 0.3497 0.4117 0.4854 0.4143 0.4113 0.4335 0.4503		

*Table 5.* Comparison of modeling new labels with different batch sizes by considering 50% labels as past labels. #label denotes the number of new labels.  $\downarrow(\uparrow)$  means the smaller (larger) the value is, the performance will be the better.

*Table 6.* Comparison of modeling new labels with different batch sizes by considering 50% labels as past labels. #label denotes the number of new labels.  $\downarrow(\uparrow)$  means the smaller (larger) the value is, the performance will be the better.

Datasets	#label					Average	precision $\uparrow$					
Dutusets	muoor	BR	CC	RAKEL	ML- $kNN$	SLEEC	SML	SLL	<b>BP-MLL</b>	DNN-BCE	C2AE	DSLL
	2	0.4307	0.4475	0.4504	0.4427	0.5162	0.5315	0.5350	0.5049	0.5486	0.5550	0.5719
	3	0.3206	0.3030	0.3042	0.2998	0.3510	0.4113	0.3847	0.4010	0.3832	0.4172	0.4230
yeast	4	0.3787	0.3606	0.3573	0.3504	0.3824	0.4412	0.4576	0.4424	0.4543	0.4741	0.4811
	5	0.3273	0.3086	0.3075	0.3073	0.3418	0.3718	0.4032	0.3834	0.3948	0.4294	0.4341
	6	0.3111	0.2895	0.2970	0.2985	0.3319	0.3593	0.3825	0.3857	0.3934	0.3922	0.3961
	3	0.3832	0.2791	0.3580	0.3432	0.2836	0.3251	0.4602	0.5238	0.5278	0.6314	0.6341
	6	0.2370	0.1715	0.2365	0.2129	0.1717	0.2435	0.3366	0.3587	0.3978	0.4143	0.4558
MirFlickr	9	0.2391	0.1599	0.2444	0.2111	0.1718	0.2519	0.3840	0.3738	0.3986	0.4307	0.4925
	12	0.2529	0.1711	0.2611	0.2243	0.1837	0.2373	0.4118	0.3876	0.4507	0.4517	0.4952
	15	0.2408	0.1594	0.2460	0.2117	0.1764	0.2391	0.4056	0.3861	0.4566	0.4660	0.4985
	100	0.0408	0.0595	0.0631	0.0531	0.0684	0.0631	0.1180	0.1028	0.1183	0.1553	0.1563
	200	0.0393	0.0580	0.0599	0.0512	0.0699	0.0707	0.1128	0.0994	0.1250	0.1420	0.1428
Delicious	300	0.0394	0.0612	0.0608	0.0524	0.0717	0.0689	0.1193	0.1220	0.1561	0.1596	0.1604
	400	0.0405	0.0584	0.0563	0.0528	0.0724	0.0774	0.1164	0.1113	0.1363	0.1514	0.1520
	500	0.0439	0.0622	0.0559	0.0580	0.0760	0.0819	0.1224	0.1290	0.1107	0.1634	0.1631
Detecate	#labal					macro	-AUC ↑					
Datasets	#1abe1	BR	CC	RAKEL	ML-kNN	SLEEC	SML	SLL	BP-MLL	DNN-BCE	C2AE	DSLL
	2	0.6507	0.6486	0.6567	0.6555	0.6791	0.6963	0.7140	0.6974	0.7248	0.7235	0.7542
	3	0.6269	0.5991	0.6040	0.6037	0.6167	0.6314	0.7292	0.7188	0.7349	0.7453	0.7525
yeast	4	0.6358	0.6270	0.6271	0.6225	0.6259	0.6711	0.7428	0.6902	0.7381	0.7541	0.7641
•	5	0.6302	0.6013	0.6051	0.6103	0.6421	0.6698	0.7219	0.6140	0.6765	0.7475	0.7536
	6	0.6275	0.5887	0.6026	0.6083	0.6325	0.6472	0.7090	0.7010	0.7122	0.7377	0.7354
	3	0.6625	0.5035	0.6522	0.6111	0.5185	0.5614	0.7151	0.7471	0.7472	0.7966	0.8063
	6	0.7088	0.5015	0.6854	0.5729	0.5093	0.5751	0.7666	0.7834	0.8013	0.8069	0.8114
MirFlickr	9	0.7414	0.5028	0.7202	0.5789	0.5307	0.5853	0.8059	0.8125	0.8238	0.8369	0.8636
	12	0.7284	0.5020	0.7080	0.5804	0.5302	0.5825	0.8007	0.8001	0.8110	0.8305	0.8423
	15	0.7290	0.5018	0.7066	0.5788	0.5379	0.5919	0.8077	0.8085	0.8276	0.8336	0.8420
	100	0.6260	0.5338	0.6271	0.5376	0.6806	0.6894	0.7331	0.7592	0.7383	0.7718	0.8109
	200	0.6249	0.5339	0.6187	0.5355	0.6805	0.6912	0.7279	0.7388	0.7633	0.7506	0.7941
Delicious	300	0.6229	0.5358	0.6203	0.5361	0.6850	0.7015	0.7280	0.7472	0.7543	0.7844	0.8093
	400	0.6185	0.5335	0.6179	0.5360	0.6863	0.6931	0.7309	0.7178	0.7720	0.7549	0.7991
	500	0.6211	0.5364	0.6200	0.5391	0.6885	0.6997	0.7335	0.7411	0.7290	0.7616	0.8021

Datasets	#label	Hamming loss ↓							
Dutubets		BR	CC	RAKEL	ML-kNN	<b>BP-MLL</b>	DNN-BCE	C2AE	DSLL
	2	0.319	0.2579	0.2557	0.2797	0.2721	0.2612	0.2557	0.2534
	3	0.2399	0.1767	0.1765	0.1912	0.1854	0.1759	0.1756	0.1852
yeast	4	0.2568	0.1979	0.2067	0.2143	0.2037	0.1955	0.1971	0.1927
	5	0.2580	0.1788	0.1893	0.1954	0.1889	0.1830	0.1830	0.1804
	6	0.2681	0.1845	0.1827	0.1950	0.1818	0.1832	0.1821	0.1879
	3	0.3807	0.2744	0.2708	0.3066	0.2487	0.2447	0.2262	0.2175
	6	0.3201	0.1695	0.1689	0.1946	0.1542	0.1441	0.1477	0.1393
MirFlickr	9	0.2749	0.1553	0.1555	0.1642	0.1459	0.1373	0.1277	0.1203
	12	0.2839	0.1679	0.1691	0.1718	0.1523	0.1355	0.1351	0.1294
	15	0.2845	0.1569	0.1579	0.1627	0.1482	0.1179	0.1305	0.1261
	100	0.4042	0.0140	0.0142	0.0155	0.0357	0.0154	0.0158	0.0146
	200	0.4069	0.0131	0.0135	0.0144	0.0321	0.0140	0.0141	0.0139
Delicious	300	0.4035	0.0156	0.0164	0.0176	0.0458	0.0172	0.0160	0.0153
	400	0.4103	0.0167	0.0179	0.0178	0.0401	0.0174	0.0172	0.0166
	500	0.4139	0.0173	0.0199	0.0181	0.0411	0.0174	0.0175	0.0170
	200	0.0095	0.0016	0.0013	0.0013	0.0018	0.0012	0.0012	0.0012
	400	0.0069	0.0014	0.0012	0.0011	0.0023	0.0010	0.0010	0.0010
EURlex	600	0.0077	0.0015	0.0013	0.0010	0.0024	0.0010	0.0010	0.0010
	800	0.0074	0.0014	0.0013	0.0011	0.0023	0.0010	0.0011	0.0011
	1000	0.0078	0.0015	0.0013	0.0012	0.0021	0.0010	0.0010	0.0010
	1k	0.0010	0.0011	0.0010	0.0010	0.0010	0.0011	0.0011	0.0010
	2k	0.0007	0.0008	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007
Wiki10	3k	0.0007	0.0008	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007
	4k	0.0007	0.0008	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007
	5k	0.0007	0.0008	0.0007	0.0006	0.0007	0.0008	0.0007	0.0007

*Table 7.* Comparison of modeling new labels with different batch sizes by considering 50% labels as past labels. #label denotes the number of new labels.  $\downarrow(\uparrow)$  means the smaller (larger) the value is, the performance will be the better.