



# A Locally Adaptive Multi-Label $k$ -Nearest Neighbor Algorithm

Dengbao Wang<sup>1</sup>, Jingyuan Wang<sup>1</sup>, Fei Hu<sup>1</sup>, Li Li<sup>1</sup>(✉), and Xiuzhen Zhang<sup>2</sup>

<sup>1</sup> College of Computer and Information Science, Southwest University,  
Chongqing, China  
lily@swu.edu.cn

<sup>2</sup> School of Computer Science and Information Technology, RMIT University,  
Melbourne, Australia

**Abstract.** In the field of multi-label learning, ML- $k$ NN is the first lazy learning approach and one of the most influential approaches. The main idea of it is to adapt  $k$ -NN method to deal with multi-label data, where maximum a posteriori rule is utilized to adaptively adjust decision boundary for each unseen instance. In ML- $k$ NN, all test instances which get the same number of votes among  $k$  nearest neighbors have the same probability to be assigned a label, which may cause improper decision since it ignores the local difference of samples. Actually, in real world data sets, the instances with (or without) label  $l$  from different locations may have different numbers of neighbors with the label  $l$ . In this paper, we propose a locally adaptive Multi-Label  $k$ -Nearest Neighbor method to address this problem, which takes the local difference of samples into account. We show how a simple modification to the posterior probability expression, previously used in ML- $k$ NN algorithm, allows us to take the local difference into account. Experimental results on benchmark data sets demonstrate that our approach has superior classification performance with respect to other  $k$ NN-based algorithms.

## 1 Introduction

### 1.1 Background

Multi-Label classification has received considerable attention over the past several years. In multi-label classification, each instance in the dataset is associated with a set of labels, and the task of multi-label classification problem is to output a label set whose size is unknown for each test instances. Multi-label problems are ubiquitous in the real world, for example, in image categorization, each image can be associated with multiple labels, such as *sea*, *desert* and *mountain* [1]; in text categorization, each text may belong to a set of topics, such as *economics*, *poetry* and *health* [2]; in bioinformatics, a gene may be related to multiple functions, such as *metabolism* and *protein synthesis* [3].

Formally, let  $\mathcal{X} = \mathcal{R}^d$  denote the  $d$ -dimensional feature space and  $\mathcal{Y} = \{0, 1\}^L$  be the label space with  $L$  possible labels, then the goal of multi-label classifier

is to learn a function  $\mathbf{f}: \mathcal{X} \mapsto \mathcal{Y}$ . Given a multi-label dataset  $\mathcal{D}$ , we can divide it into feature space  $\mathcal{X}$  and label space  $\mathcal{Y}$ . An instance  $x_i$  is associated with a subset of labels  $Y_i \subseteq \mathcal{Y}$  (finite set of labels), and a multi-label dataset is composed of  $m$  examples  $(x_1, Y_1), (x_2, Y_2), \dots, (x_n, Y_n)$  [4].

Given a multi-label learning task, it can be transformed into other well-established learning tasks. This category of approaches is formally defined as *Problem Transformation* method. In this way, we can decompose a multi-label problem into multiple single-label problems, and each single-label problems can be tackled by a binary classifier. Thus, the multi-label classification function can be represented in another form  $\mathbf{f} = \{f_1, f_2, \dots, f_L\}$  in this way. Problem Transformation is widely used in multi-label learning problems for its greater flexibility [8, 9, 11]. Another way to tackle multi-label classification problems is so called *Algorithm Adaptation* method [5]. This category of approaches tackles multi-label learning problem by adapting existing popular learning approaches such as AdaBoost, Neural Networks or kNN to deal with the multi-label problems directly [2, 12, 13].

According to the idea of Algorithm Adaptation, Zhang and Zhou [6] proposed Multi-Label  $k$ -Nearest Neighbor (ML- $k$ NN). It is the first lazy learning approach and one of the most influential multi-label classification approaches. The basic idea of this approach is to adapt the classic  $k$ NN algorithm to deal with multi-label classification problems, where maximum a posteriori (MAP) rule is utilized to adaptively adjust decision boundary for each new instance. In this method, the test instances which get the same number of votes among  $k$  nearest neighbors have the same probability to be assigned a label. It may cause improper decision since it ignores the local difference of samples. Actually, in real world data sets, the instances with (or without) label  $l$  from different locations may have different numbers of neighbors with the label  $l$ . Thus, in this paper, we propose a locally adaptive Multi-Label  $k$ -Nearest Neighbor method to address this problem.

## 1.2 Motivation

We begin by conducting a simple experiment to try to show the local difference of samples. The local difference here means the instances with (or without) the  $l$ -th label from different locations may have different numbers of neighbors with the  $l$ -th label.

For a dataset, we first find the  $k$  nearest neighbors of each instance  $x$  and denote as  $\mathcal{N}(x)$ . Then we can count the number of neighbors of  $x$  with label  $l$ . The counting vector can be defined as:

$$\mathbf{C}_x(l) = \sum_{(x^*, Y^*) \in \mathcal{N}(x)} Y^*(l), l \in \mathcal{Y} \quad (1)$$

After calculating above statistics, we can figure out if the distribution of  $\mathbf{C}_x(l)$  is related to the location information. In our experiments, we separate the dataset into five clusters, and use the cluster index to represent location information. For each cluster  $S_j$  and each label  $l$ , we calculate: (1) the average

$C_x(l)$  of the instances with label  $l$  (defined as Eq. (2)); (2) the average  $C_x(l)$  of the instances without label  $l$  (defined as Eq. (3)).

$$\overline{C}(S_j, l) = \frac{1}{|S_j^{l1}|} \sum_{(x,Y) \in S_j^{l1}} C_x(l) \quad (2)$$

$$\overline{C}^*(S_j, l) = \frac{1}{|S_j^{l0}|} \sum_{(x,Y) \in S_j^{l0}} C_x(l) \quad (3)$$

where  $S_j^{l1} = \{(x, Y) | (x, Y) \in S_j, Y(l) = 1\}$  and  $S_j^{l0} = \{(x, Y) | (x, Y) \in S_j, Y(l) = 0\}$ .

We conduct the experiment on an image data set *scene*, which has 2407 instances and 6 labels. The results are shown in Table 1. The first part and the second part respectively show  $\overline{C}(S_j, l)$  and  $\overline{C}^*(S_j, l)$  of each cluster  $S_j$  and each label  $l$ . As is shown in Table 1, for a same label  $l$ , the  $\overline{C}(S_j, l)$  and  $\overline{C}^*(S_j, l)$  of different clusters may vary tremendously.

**Table 1.** Each cell of the table means the average  $C_x(l)$  of the instances with (or without) label  $l$  in each cluster.

	Label	<i>beach</i>	<i>sunset</i>	<i>fall</i>	<i>field</i>	<i>mountain</i>	<i>urban</i>
$\overline{C}$	Cluster 1	1.432	0.926	1.470	2.000	1.785	5.532
	Cluster 2	1.600	1.500	2.047	6.188	2.256	1.000
	Cluster 3	1.250	5.265	6.055	1.571	0.500	1.090
	Cluster 4	1.044	1.607	1.214	1.936	4.761	2.000
	Cluster 5	4.863	1.333	1.000	2.333	1.444	1.956
$\overline{C}^*$	Cluster 1	0.401	0.029	0.083	0.176	1.073	4.503
	Cluster 2	0.221	0.005	0.219	4.462	1.116	0.167
	Cluster 3	0.098	0.248	1.696	0.201	0.134	0.198
	Cluster 4	0.346	0.067	0.123	0.556	3.759	1.369
	Cluster 5	3.543	0.006	0.195	0.430	0.891	1.084

The above results hint that the distribution of  $C_x(l)$  is significantly related to the location information. In ML- $k$ NN, however, the local difference of samples is ignored, which may cause the improper decision. To take the local difference into account, we propose a locally adaptive Multi-Label  $k$ -Nearest Neighbor method in this paper. In our approach, the test instances which get the same number of votes among  $k$  nearest neighbors may have different probabilities to be assigned a label if they come from different regions. Experimental results on benchmark data sets demonstrate that our approach has superior classification performance with respect to previous ML- $k$ NN algorithm, especially on large scale data sets<sup>1</sup>.

<sup>1</sup> The code available at <https://github.com/DENGBAODAGE/LAMLKNN>.

### 1.3 Paper Organization

The rest of this paper is organized as follows. The related work is discussed in Sect. 2. The details of our approach are proposed in Sect. 3. After that, the experiment results are reported in Sect. 4. Finally, the conclusion is summarized in Sect. 5.

## 2 Related Work

The  $k$ -nearest neighbors ( $k$ NN) rule [7] is one of the oldest and simplest methods for pattern classification. For traditional single-label classification problems, the  $k$ NN rule usually classifies each unlabeled instance by the majority label among its  $k$  nearest neighbors in the training data. The  $k$ NN-based methods often yield competitive results and have been widely used in practical applications mainly due to its implementation simplicity. However, for multi-label classification, the traditional  $k$ NN rule is inappropriate mainly due to the severe class-imbalance issue.

ML- $k$ NN was proposed based on the traditional  $k$ NN algorithm to deal with multi-label classification problems. Rather than classifying new instance by the majority label among its  $k$  nearest neighbors, ML- $k$ NN employs maximum a posteriori (MAP) principle to predict the set of labels of the new instance.

$$\begin{aligned} Y_t(l) &= \arg \max_{b \in \{0,1\}} P(H_b^l | E_{\mathcal{C}_t(l)}^l) \\ &= \arg \max_{b \in \{0,1\}} P(H_b^l) P(E_{\mathcal{C}_t(l)}^l | H_b^l) \end{aligned} \quad (4)$$

where  $Y_t(l)$  is the label vector for the new instance  $t$ .  $\mathcal{C}_t(l)$  is the same as described previously.  $H_l^l$  represents the event that  $t$  has label  $l$ , while  $H_0^l$  represents the event that  $t$  doesn't have label  $l$ .  $E_{\mathcal{C}_t(l)}^l$  denotes the event that, among the  $k$  nearest neighbors of  $t$ , there are exactly  $\mathcal{C}_t(l)$  instances which have label  $l$ . The prior probability  $P(H_b^l)$  and the conditional probability  $P(E_{\mathcal{C}_t(l)}^l | H_b^l)$  in Eq. (4) can all be estimated from the training dataset in advance.

The reported experiment results show that ML- $k$ NN performed well on several real world data sets. However, it ignores the local difference when using utilizing maximum a posteriori rule, and we think the location information of the new instance is helpful especially for large scale data sets.

There are also some other  $k$ NN based approaches to handle multi-label classification problems. Note that ML- $k$ NN is a first-order approach which reasons the relevance of each label separately. Considering that this method is ignorant of exploiting label correlations, a dependent multi-label classification method derived from ML- $k$ NN is proposed in [14], which takes into account the dependencies between labels. In order to exploit the non-parametric property of classical  $k$ NN method, Wang et al. [15] further developed classical KNN method, and proposed a Class Balanced K-Nearest Neighbor (BKNN) approach for multi-label classification. This method picks up the most representative training data

points from every class with equal number, such that the label of a test data point is determined via the information from all the classes in a balanced manner. In [18], a  $k$ NN based ranking approach is proposed to solve the multi-label classification problem. This approach exploits a ranking model to learn which neighbor’s labels are more trustable candidates for a weighted KNN-based strategy, and then assigns higher weights to those candidates when making weighted-voting decisions.

### 3 Methodology

As described in previous sections, we try to take the local difference into account by modifying the posterior probability expression used in ML- $k$ NN algorithm. How to exploit the location information when using MAP principle to assign labels to a new instance? In this section, we introduce a Locally Adaptive Multi-Label  $k$ -Nearest Neighbor algorithm to address this problem.

Inspired by the results presented in Sect. 1.2, we firstly separate the training data into  $m$  groups  $S_1, S_2, \dots, S_m$  via clustering, where the average  $\mathbf{C}_x(l)$  of instances in the different clusters may vary tremendously. For each test instance  $t$ , we can identify which group should it be assigned to by measuring the distance between the test instance and each cluster center.

$$w_t = \arg \min_{1 \leq j \leq m} \|x_t - c_j\|^2 \tag{5}$$

where  $w_t$  is the index of cluster to which should the test instance  $t$  assign.  $c_j$  stands for the center point of cluster  $S_j$ .

Therefore we can get two important information of the test instance  $t$ :  $\mathbf{C}_t$  (records the numbers of  $x$ ’s neighbors with each label) and  $w_t$  (stands for the index of cluster to which should the test instance  $t$  assign). Then based on the membership counting vector  $\mathbf{C}_t$  and the location information  $w_t$ , the category vector  $Y_t$  can be determined using the following maximum a posteriori principle:

$$Y_t(l) = \arg \max_{b \in \{0,1\}} P(H_b^l | E_{\mathbf{C}_t(l)}^l, W_{w_t}) \tag{6}$$

where  $H_b^l$  and  $E_{\mathbf{C}_t(l)}^l$  is the same as described in Sect. 2.  $W_{w_t}$  denotes the event that the test instance  $t$  can be assigned to the cluster  $S_{w_t}$ . Based on Bayes theorem, we have:

$$Y_t(l) = \arg \max_{b \in \{0,1\}} P(H_b^l) P(E_{\mathbf{C}_t(l)}^l, W_{w_t} | H_b^l) \tag{7}$$

The prior probability  $P(H_b^l)$  and the likelihood  $P(E_{\mathbf{C}_t(l)}^l, W_{w_t} | H_b^l)$  can be estimated from the training data.

Equation (6) can also be rewritten by another way (based on Bayes theorem):

$$\begin{aligned}
Y_t(l) &= \arg \max_{b \in \{0,1\}} P(H_b^l, E_{\mathbf{C}_t(l)}^l, W_{w_t}) \\
&= \arg \max_{b \in \{0,1\}} P(H_b^l, W_{w_t}) P(E_{\mathbf{C}_t(l)}^l | H_b^l, W_{w_t}) \\
&= \arg \max_{b \in \{0,1\}} P(W_{w_t}) P(H_b^l | W_{w_t}) P(E_{\mathbf{C}_t(l)}^l | H_b^l, W_{w_t})
\end{aligned} \tag{8}$$

where  $P(W_{w_t})$  represents the prior probability that  $W_{w_t}$  holds.  $P(H_b^l | W_{w_t})$  represents the conditional probability that  $H_b^l$  holds when  $W_{w_t}$  holds. Furthermore, the conditional probability  $P(E_{\mathbf{C}_t(l)}^l | H_b^l, W_{w_t})$  represents the likelihood that the instance  $x$  has  $\mathbf{C}_t(l)$  neighbors with label  $l$  when  $H_b^l$  and  $W_{w_t}$  both hold.

By comparing Eqs. (8) and (4) (in Sect. 2), it is intuitive to understand how we exploit the location information by involving  $W_{w_t}$  in posterior probability expression. In our method, the category vector  $Y_t$  of the new instance  $t$  depends on the membership counting vector  $\mathbf{C}_t$  as well as the location information  $w_t$ . Unlike ML- $k$ NN, our approach can derive different probabilities of assigning a label to new instances which get the same number of votes among  $k$  nearest neighbors but come from different regions. Actually, ML- $k$ NN can be regarded as a special case of our approach with  $m = 1$ . Note that Eqs. (7) and (8) we described above are actually equivalent. We choose the latter version in our implementation.

All the three terms in Eq. (8) can be estimated from the training data. Firstly, the prior probability  $P(W_{w_t})$  is estimated by calculating the proportion of the cluster  $S_{w_t}$  in training data:

$$P(W_{w_t}) = \frac{|S_{w_t}|}{|S_{train}|} \tag{9}$$

where  $|S_{w_t}|$  and  $|S_{train}|$  is the size of cluster  $w_t$  and training dataset.

Then the conditional probability  $P(H_b^l | W_{w_t})$  are estimated by counting the number of training examples associated with each label in each cluster:

$$\begin{aligned}
P(H_1^l | W_{w_t}) &= \frac{s + \sum_{(x,Y) \in S_{w_t}} Y(l)}{2 \times s + |S_{w_t}|} \quad (l \in \mathcal{Y}) \\
P(H_0^l | W_{w_t}) &= 1 - P(H_1^l | W_{w_t}) \quad (l \in \mathcal{Y})
\end{aligned} \tag{10}$$

where  $s$  is the smoothing parameter controlling the effect of uniform prior on the estimation [6].

Finally, the estimation process for likelihoods  $P(E_{\mathbf{C}_t(l)}^l | H_b^l, W_{w_t})$  is involved. For each label  $l$ , we calculate:

$$\begin{aligned}
\mathcal{K}_i(r) &= \sum_{(x,Y) \in S_{w_t}} Y(l) \cdot \mathbb{I}[\mathbf{C}_x(l) = r] \quad (l \in \mathcal{Y}, 0 \leq r \leq k) \\
\mathcal{K}'_i(r) &= \sum_{(x,Y) \in S_{w_t}} (1 - Y(l)) \cdot \mathbb{I}[\mathbf{C}_x(l) = r] \quad (l \in \mathcal{Y}, 0 \leq r \leq k)
\end{aligned} \tag{11}$$

$\mathcal{K}_l(C)$  counts the number of training examples which have label  $l$  and have exactly  $C$  neighbors with label  $l$ , while  $\mathcal{K}'_l(C)$  counts the number of training examples which don't have label  $l$  and have exactly  $C$  neighbors with label  $l$ . For any  $\cdot$ ,  $\llbracket \cdot \rrbracket$  equals 1 if  $\cdot$  holds and 0 otherwise. After calculate  $\mathcal{K}_l(C)$  and  $\mathcal{K}'_l(C)$ , we can estimate the likelihood in Eq. (8):

$$\begin{aligned} P(E_{\mathcal{C}_t(l)}^l | H_1^l, W_{w_t}) &= \frac{s + \mathcal{K}_l(\mathcal{C}_t(l))}{s \times (k + 1) + \sum_{r=0}^k \mathcal{K}_l(r)} \\ P(E_{\mathcal{C}_t(l)}^l | H_0^l, W_{w_t}) &= \frac{s + \mathcal{K}'_l(\mathcal{C}_t(l))}{s \times (k + 1) + \sum_{r=0}^k \mathcal{K}'_l(r)} \end{aligned} \quad (12)$$

The following pseudo-code illustrates the complete description of our method. In training phase, we estimate the prior probability  $P(W_j)$ , the conditional probabilities  $P(H_1^l | W_j)$ ,  $P(H_0^l | W_j)$ , the statistics  $\mathcal{K}_l(r)$ , and  $\mathcal{K}'_l(r)$  (steps from 5 to 13). In classifying phase, the predicted label set of test instance  $t$  can be determined using the maximum a posteriori principle (by substituting Eqs. (9), (10) and (12) into (8)).

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**Train**( $S_{train}, k, m$ )

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1  Divide training data into  $m$  clusters  $\{S_1, S_2, \dots, S_m\}$  with  $k$ -means
2  for  $i = 1$  to  $|S_{train}|$  do:
3    Identify  $k$  nearest neighbors  $\mathcal{N}(x_i)$  for  $x_i$ 
4  end
5  for  $j = 1$  to  $m$  do:
6     $P(W_j) = \frac{|S_j|}{|S_{train}|}$ 
7    for  $l = 1$  to  $L$  do:
8       $P(H_1^l | W_j) = \frac{s + \sum_{(x,Y) \in S_j} Y(l)}{2 \times s + |S_j|}$ 
9       $P(H_0^l | W_j) = 1 - P(H_1^l | W_j)$ 
10      $\mathcal{K}_l(r) = \sum_{(x,Y) \in S_j} Y(l) \cdot \llbracket \mathcal{C}_x(l) = r \rrbracket$       ( $0 \leq r \leq k$ )
11      $\mathcal{K}'_l(r) = \sum_{(x,Y) \in S_j} (1 - Y(l)) \cdot \llbracket \mathcal{C}_x(l) = r \rrbracket$       ( $0 \leq r \leq k$ )
12   end
13 end

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**Classify**( $t, k$ )

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- 1 Identify  $S_{w_t}$  (the cluster should  $t$  be assigned to) using Equation (5)
  - 2 Identify  $k$  nearest neighbors  $\mathcal{N}(t)$  for  $t$
  - 3 **for**  $l = 1$  to  $L$  **do**:
  - 4   Calculate  $C_t(l)$  according to Equation (1)
  - 5   Estimate  $P(E_{C_t(l)}^l|H_1^l, W_{w_t})$  and  $P(E_{C_t(l)}^l|H_0^l, W_{w_t})$  according to (12)
  - 6    $Y_t(l) = \arg \max_{b \in \{0,1\}} P(H_b^l|E_{C_t(l)}^l, W_{w_t})$   
        $= \arg \max_{b \in \{0,1\}} P(W_{w_t})P(H_b^l|W_{w_t})P(E_{C_t(l)}^l|H_b^l, W_{w_t})$
  - 7 **end**
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## 4 Experiment

We compare the our proposed method with other multi-label lazy learning algorithms on several data sets. In the following sections, we first describe the experiment setup including the data sets, the evaluation metrics, and the compared algorithms; Then we discuss the experiment results.

### 4.1 Experiment Setup

**Data Sets:** We evaluated the algorithm presented in the previous section on twelve data sets<sup>2</sup> of varying size and difficulty. The statistics of the data sets are shown in Table 2. Six regular-scale data sets (first part) as well as six large-scale data sets (second part) are included (the data sets are roughly ordered by the number of instances). There are two additional properties [10] to measure the density of labels:

- The cardinality of a dataset  $\mathcal{S}$  is the mean of the number of labels of the instances that belong to  $\mathcal{S}$ , defined as:

$$cardinality(\mathcal{S}) = \frac{1}{n} \sum_{i=1}^n |Y_i| \quad (13)$$

- The density of  $\mathcal{S}$  is the mean of the number of labels of the instances that belong to  $\mathcal{S}$  divided by  $L$ , defined as:

$$density(\mathcal{S}) = \frac{1}{n} \sum_{i=1}^n \frac{|Y_i|}{L} \quad (14)$$

**Metrics:** In multi-label learning, the evaluation is more complicated than that in single-label learning. Various evaluation metrics have been proposed to measure

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<sup>2</sup> Data sets were downloaded from <http://mulan.sourceforge.net/datasets.html> and <http://meka.sourceforge.net/#datasets>.

**Table 2.** Multi-label data sets used in experiments.

<i>name</i>	<i>domain</i>	<i>instances</i>	<i>dimension</i>	<i>labels</i>	<i>cardinality</i>	<i>density</i>
Emotions	Music	593	72	6	1.869	0.311
Birds	Audio	645	260	19	1.014	0.053
Enron	Text	1702	1001	53	3.378	0.064
Scene	Image	2407	294	6	1.074	0.179
Yeast	Biology	2417	103	14	4.237	0.3003
Slashdot	Text	3782	1079	22	1.181	0.054
bibtex	Text	7395	1836	159	2.402	0.015
corel5k	Image	5000	499	374	3.522	0.009
corel16k (1)	Image	13766	500	153	2.859	0.019
corel16k (2)	Image	13761	500	164	2.882	0.018
corel16k (3)	Image	13760	500	154	2.829	0.018
Ohsumed	Text	13929	1002	23	1.663	0.072

the performance of multi-label classifier. We use five commonly used metrics: *hamming loss*, *ranking loss*, *coverage*, *one error* and *average precision* [17]. These above five metrics evaluate the performance of a multi-label classifier from different horizon. Note that for average precision, the larger the values the better the performance, while for other four metrics, the smaller the values the better the performance.

**Compared Algorithms:** We compare the performance of our proposed method with that of three other  $k$ NN-based multi-label approaches: BR $k$ NN, ML- $k$ NN and DML- $k$ NN. BR $k$ NN [16] is an adaptation of the  $k$ NN algorithm that is conceptually equivalent to using BR method in conjunction with the traditional  $k$ NN algorithm. As we discussed in Sect. 2, DML- $k$ NN is an extension approach based on ML- $k$ NN, which takes into account the dependencies between labels.

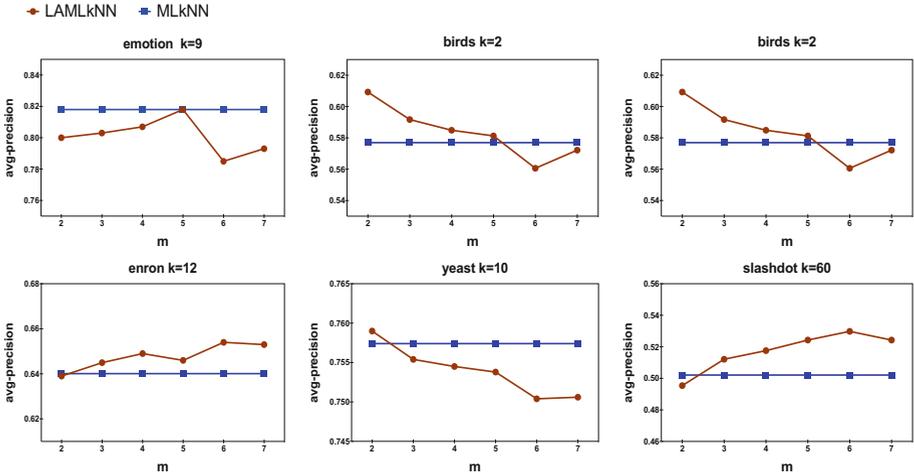
## 4.2 Results

Following the experiment setup described above, we conduct the comparison experiments. The experimental results of each algorithm on each data set are respectively reported in Tables 3 and 4. For each algorithm, the  $k$  value is determined by cross-validation. We can see that our proposed method LAML- $k$ NN outperform the compared methods in most cases. Furthermore, the advantages of our approach are more obvious on the large-scale data sets (in Table 4) than that on the regular-scale data sets (in Table 3).

The experimental results on benchmark data sets and diverse evaluation metrics validate the superior effectiveness of our approach to existing  $k$ NN-based multi-label approaches. Meanwhile, the experimental results demonstrate the number of clusters does not significantly affect the classifier’s performance on

**Table 3.** Experimental results of each algorithm on regular-scale data sets.

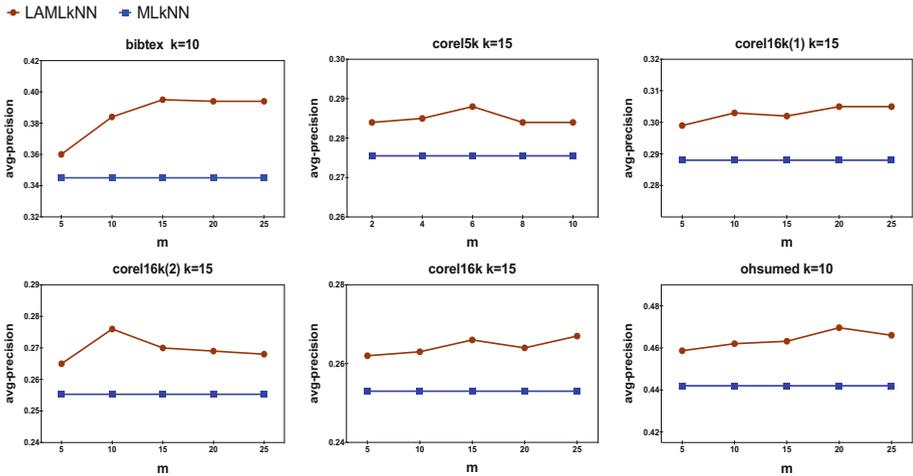
Metrics	Algorithms	Emotions	Birds	Enron	Scene	Yeast	Slashdot
Hamming loss	LAML <i>k</i> NN	0.197	0.045	<b>0.050</b>	0.097	<b>0.198</b>	<b>0.050</b>
	ML <i>k</i> NN	0.191	<b>0.044</b>	0.051	<b>0.096</b>	0.198	0.053
	BR <i>k</i> NN	0.193	0.045	0.058	0.105	0.203	0.090
	DML <i>k</i> NN	<b>0.187</b>	0.045	0.051	0.097	0.198	0.051
Ranking loss	LAML <i>k</i> NN	0.151	<b>0.093</b>	<b>0.088</b>	0.090	<b>0.170</b>	<b>0.157</b>
	ML <i>k</i> NN	<b>0.145</b>	0.102	0.093	0.096	0.171	0.168
	BR <i>k</i> NN	0.151	0.119	0.152	0.106	0.183	0.242
	DML <i>k</i> NN	0.147	0.101	0.092	<b>0.083</b>	0.170	0.161
OneError	LAML <i>k</i> NN	<b>0.243</b>	<b>0.709</b>	<b>0.252</b>	<b>0.230</b>	<b>0.236</b>	<b>0.610</b>
	ML <i>k</i> NN	0.253	0.728	0.280	0.233	0.242	0.645
	BR <i>k</i> NN	0.267	0.726	0.459	0.291	0.242	0.891
	DML <i>k</i> NN	0.253	0.721	0.282	0.238	0.237	0.612
Coverage	LAML <i>k</i> NN	0.307	<b>0.138</b>	<b>0.240</b>	0.093	<b>0.454</b>	<b>0.172</b>
	ML <i>k</i> NN	<b>0.298</b>	0.147	0.249	0.096	0.455	0.184
	BR <i>k</i> NN	0.303	0.172	0.382	0.105	0.472	0.253
	DML <i>k</i> NN	0.300	0.145	0.246	<b>0.086</b>	0.455	0.176
Avg-Precision	LAML <i>k</i> NN	<b>0.818</b>	<b>0.609</b>	<b>0.654</b>	0.856	<b>0.759</b>	<b>0.530</b>
	ML <i>k</i> NN	0.818	0.578	0.640	0.852	0.757	0.502
	BR <i>k</i> NN	0.810	0.570	0.564	0.824	0.754	0.334
	DML <i>k</i> NN	0.816	0.580	0.643	<b>0.857</b>	0.758	0.526



**Fig. 1.** Comparison results on six regular-scale data sets.

**Table 4.** Experimental results of each algorithm on large-scale data sets.

Metrics	Algorithms	bibtex	corel5k	corel16k(1)	corel16k(2)	corel16k(3)	Ohsumed
Hamming loss	LAML $k$ NN	<b>0.014</b>	<b>0.009</b>	<b>0.019</b>	<b>0.016</b>	<b>0.017</b>	<b>0.070</b>
	ML $k$ NN	0.014	0.009	0.019	0.016	0.017	0.071
	BR $k$ NN	0.015	0.010	0.019	0.016	0.017	0.072
	DML $k$ NN	0.014	0.009	0.019	0.016	0.017	0.071
Ranking loss	LAML $k$ NN	<b>0.145</b>	<b>0.118</b>	<b>0.160</b>	0.180	0.184	<b>0.214</b>
	ML $k$ NN	0.217	0.127	0.175	0.181	0.183	0.231
	BR $k$ NN	0.297	0.292	0.268	0.279	0.259	0.277
	DML $k$ NN	0.208	0.127	0.174	<b>0.179</b>	<b>0.179</b>	0.231
OneError	LAML $k$ NN	<b>0.542</b>	<b>0.670</b>	<b>0.698</b>	<b>0.731</b>	<b>0.732</b>	<b>0.613</b>
	ML $k$ NN	0.578	0.706	0.736	0.782	0.769	0.639
	BR $k$ NN	0.680	0.742	0.771	0.917	0.769	0.706
	DML $k$ NN	0.576	0.722	0.729	0.767	0.764	0.640
Coverage	LAML $k$ NN	<b>0.222</b>	<b>0.272</b>	<b>0.312</b>	<b>0.316</b>	<b>0.331</b>	<b>0.292</b>
	ML $k$ NN	0.354	0.298	0.342	0.326	0.336	0.311
	BR $k$ NN	0.431	0.591	0.493	0.475	0.476	0.361
	DML $k$ NN	0.332	0.299	0.339	0.327	0.332	0.311
Avg-Precision	LAML $k$ NN	<b>0.395</b>	<b>0.288</b>	<b>0.305</b>	<b>0.276</b>	<b>0.267</b>	<b>0.470</b>
	ML $k$ NN	0.349	0.275	0.288	0.255	0.253	0.442
	BR $k$ NN	0.268	0.210	0.200	0.170	0.222	0.394
	DML $k$ NN	0.350	0.265	0.291	0.266	0.258	0.441

**Fig. 2.** Comparison results on six large-scale data sets.

large-scale data sets. We fix the  $k$  value as well as change  $m$  (the number of clusters) for our proposed approach, then compare the *average precision* of each case with that of ML- $k$ NN. From Fig. 2 we can see, on these six large-scale data sets, across all the  $m$  value, our approach superior to ML- $k$ NN. But the performance of our approach is sensitive to the cluster number  $m$  on small-scale data sets (see in Fig. 1). The proposed approach may inferior to ML- $k$ NN if we select improper  $m$  for small-scale data sets (e.g. *emotions* and *yeast*). We think one possible reason may be due to lack of prior acknowledge when the size of each cluster is too small.

## 5 Conclusion

To achieve more effective multi-label classification using lazy learning method, in this paper, we introduced an original  $k$ NN-based multi-label classification algorithm. We show how to take into account the local difference of samples by modifying the posterior probability expression previously used in ML- $k$ NN algorithm. The experimental results on benchmark data sets demonstrate effective classification of our approach, especially on large scale data sets.

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