LIFT: Multi-Label Learning with Label-Specific Features

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Abstract

Multi-label learning deals with the problem where each training example is represented by a *single* instance while associated with *a set of* class labels. For an unseen example, existing approaches choose to determine the membership of each possible class label to it based on *identical* feature set, i.e. the very instance representation of the unseen example is employed in the discrimination processes of all labels. However, this commonly-used strategy might be suboptimal as different class labels usually carry specific characteristics of their own, and it could be beneficial to exploit different feature sets for the discrimination of different labels. Based on the above reflection, we propose a new strategy to multi-label learning by leveraging *label-specific* features, where a simple yet effective algorithm named LIFT is presented. Briefly, LIFT constructs features specific to each label by conducting clustering analysis on its positive and negative instances, and then performs training and testing by querying the clustering results. Extensive experiments across sixteen diversified data sets clearly validate the superiority of LIFT against other well-established multi-label learning algorithms.

1 Introduction

Multi-label learning deals with objects having *multiple* labels simultaneously, which widely exist in real-world applications [Boutell *et al.*, 2004; Elisseeff and Weston, 2002; Schapire and Singer, 2000]. Formally, let $\mathcal{X} = \mathbb{R}^d$ be the d-dimensional input space and $\mathcal{Y} = \{l_1, l_2, \cdots, l_q\}$ be the finite set of q possible labels. Then, the task of multi-label learning (or *multi-label classification*) is to learn a function $h : \mathcal{X} \to 2^{\mathcal{Y}}$ which maps each instance $\boldsymbol{x} \in \mathcal{X}$ into a set of proper labels $h(\boldsymbol{x}) \subseteq \mathcal{Y}$.

During the past decade, considerable number of approaches have been proposed to learn from multi-label data [Tsoumakas *et al.*, 2009]. The common strategy adopted by existing approaches is that *identical* feature representation of the instance, i.e. $\boldsymbol{x}$, is utilized to discriminate all the class labels in $\mathcal{Y}$. This amounts to induce a family of q functions $\{f_1, f_2, \cdots, f_q\}$, where $f_k : \mathcal{X} \to \mathbb{R}$ determines the membership of l_k to each instance such that $h(\boldsymbol{x}) = \{l_k \mid f_k(\boldsymbol{x}) > 0, 1 \leq k \leq q\}$. Here all functions in the family operate on the same feature set $\boldsymbol{x}$. Although this strategy has gained much success in algorithm design, it might be too straightforward and away from being optimal for multi-label learning.

For example, in automatic image annotation, suppose *sky* and *desert* are two possible labels in the label space. Intuitively, *color*-based features would be preferred in discriminating sky and non-sky images, *texture*-based features would be preferred in discriminating desert and non-desert images, while both *color*- and *texture*-based features might be useful in discriminating other labels in the label space. For another example, in text categorization, features related to terms such as *government*, *reform* and *president* might be important in discriminating political and non-political documents, while features related to terms such as *stadium*, *matches* and *champions* might be important in discriminating sport and non-sport documents.

The above observations reflect the fact that, in multi-label learning different class labels in the label space may carry specific characteristics of their own. Therefore, we hypothesize that if *label-specific* features, i.e. the most pertinent and discriminative features for each class label, could be used in the learning process, a more effective solution to the problem of multi-label learning can be expected.

To justify this hypothesis, a new algorithm named LIFT, i.e. *multi-label learning with Label specIfic FeaTures* , is proposed in this paper. LIFT tackles multi-label learning problem with two simple steps. Firstly, for each class label $l_k \in \mathcal{Y}$, clustering analysis is conducted on its positive instances as well as negative instances in the training set, and then features specific to l_k are constructed by querying the clustering results. Secondly, a family of q classifiers are induced where each of them is trained with the generated label-specific features other than the original features under $\mathcal{X}$. To thoroughly evaluate the effectiveness of LIFT, extensive experiments over sixteen regular-scale and large-scale data sets clearly verify that our approach compares favorably against other state-of-the-art multi-label learning algorithms.

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The rest of this paper is organized as follows. Section 2 briefly discusses existing approaches to multi-label learning. Section 3 presents the details of the proposed approach. Section 4 reports the results of comparative studies. Finally, Section 5 concludes and indicates several issues for future work.

2 Related Work

Generally, the task of multi-label learning is rather challenging due to the exponential number of possible *label sets* (i.e. 2^q) to be predicted for an unseen example. To cope with this issue, existing approaches focus on exploiting the correlations between labels to facilitate the learning process, which can be roughly grouped into three categories based on the order of label correlations [Zhang and Zhang, 2010], namely *first-order* approaches, *second-order* approaches and *high-order* approaches.

First-order approaches tackle multi-label learning problem by decomposing it into a number of *independent* binary classification problems. Specifically, a family of q functions $\{f_1, f_2, \cdots, f_q\}$ are learned in a label-by-label style, one for each possible class label [Boutell *et al.*, 2004; Zhang and Zhou, 2007]. First-order approaches are conceptually simple, efficient and easy to implement, while may be less effective due to their ignorance of label correlations.

Second-order approaches tackle multi-label learning problem by considering *pairwise* relations between labels. Specifically, a family of q functions $\{f_1, f_2, \cdots, f_q\}$ are learned by exploring the interactions between a pair of functions f_k and $f_{k'}$ such as their co-occurrence patterns [Ghamrawi and McCallum, 2005; Zhu *et al.*, 2005] or their ranking constraints [Elisseeff and Weston, 2002; Zhang and Zhou, 2006; Fürnkranz *et al.*, 2008]. Second-order approaches address label correlations to some extent and are relatively effective, while may suffer from the fact that label correlations could go beyond second-order under real-world scenarios.

High-order approaches tackle multi-label learning problem by considering *high-order* relations between labels. Specifically, a family of q functions $\{f_1, f_2, \cdots, f_q\}$ are learned by exploring the influences among a subset of functions $\{f_{k_1}, f_{k_2}, \cdots, f_{k_{q'}}\}$ $(q' \leq q)$ [Tsoumakas and Vlahavas, 2007; Read *et al.*, 2009; Zhang and Zhang, 2010] or among all the functions [Yan *et al.*, 2007; Ji *et al.*, 2008; Cheng and Hüllermeier, 2009]. High-order approaches could address more realistic label correlations, while may exhibit high model complexities.

A commonness of these existing approaches is that they deal with multi-label learning problem mainly from the perspective of output space, i.e. manipulating correlations between labels, and identical features inherited from the original input space are directly used in discriminating all the labels. In the next section, we will present the LIFT approach which works mainly from the perspective of input space, i.e. manipulating label-specific features.

3 The LIFT Approach

Let $\mathcal{D} = \{(\boldsymbol{x}_i, Y_i) \mid 1 \leq i \leq m\}$ be the training set with m multi-label training examples, where $\boldsymbol{x}_i \in \mathcal{X}$ is a d-dimensional feature vector and $Y_i \subseteq \mathcal{Y}$ is the set of labels associated with $\boldsymbol{x}_i$. Then, LIFT learns from $\mathcal{D}$ following two elemental steps, i.e. *label-specific features construction* and *classification models induction*.

Table 1: Pseudo-code of LIFT.

```
$Y$ = LIFT($\mathcal{D}$, $r$, $\mathfrak{L}$, $\boldsymbol{u}$)
Inputs:
$\mathcal{D}$ : the multi-label training set $\{(\boldsymbol{x}_i, Y_i) \mid 1 \leq i \leq m\}$ ($\boldsymbol{x}_i \in \mathcal{X}$,
     $Y_i \subseteq \mathcal{Y}, \mathcal{X} = \mathbb{R}^d, \mathcal{Y} = \{l_1, l_2, \cdots, l_q\}$)
$r$ : the ratio parameter as used in Eq.(2)
$\mathfrak{L}$ : the binary learner for classifier induction
$\boldsymbol{u}$ : the unseen example ($\boldsymbol{u} \in \mathcal{X}$)
Outputs:
$Y$ : the predicted label set for $\boldsymbol{u}$ ($Y \subseteq \mathcal{Y}$)
Process:
1.  for $k = 1$ to $q$ do
2.      Form $\mathcal{P}_k$ and $\mathcal{N}_k$ based on $\mathcal{D}$ according to Eq.(1);
3.      Perform $k$-means clustering on $\mathcal{P}_k$ and $\mathcal{N}_k$, each with $m_k$
        clusters as defined in Eq.(2);
4.      Create the mapping $\phi_k$ for $l_k$ according to Eq.(3);
5.  endfor
6.  for $k = 1$ to $q$ do
7.      Form $\mathcal{D}_k^*$ accroding to Eq.(4);
8.      Induce $f_k^*$ by invoking $\mathfrak{L}$ on $\mathcal{D}_k^*$, i.e. $f_k^* \leftarrow \mathfrak{L}(\mathcal{D}_k^*)$;
9.  endfor
10. $Y = \{l_k \mid f_k^*(\phi_k(\boldsymbol{u})) > 0, 1 \leq k \leq q\}$.
```

In the first step, LIFT aims to generate distinguishing features which capture the specific characteristics of each label to facilitate its discrimination process. To achieve this, LIFT employs *clustering techniques* which have been widely used as stand-alone tools to gain insights into the properties of data [Jain *et al.*, 1999]. Specifically, with respect to each class label $l_k \in \mathcal{Y}$, the set of positive training instances $\mathcal{P}_k$ as well as the set of negative training instances $\mathcal{N}_k$ are denoted as:

$$\begin{aligned} \mathcal{P}_k &= \{\boldsymbol{x}_i \mid (\boldsymbol{x}_i, Y_i) \in \mathcal{D}, l_k \in Y_i\} \\ \mathcal{N}_k &= \{\boldsymbol{x}_i \mid (\boldsymbol{x}_i, Y_i) \in \mathcal{D}, l_k \notin Y_i\} \end{aligned} \qquad (1)$$

In other words, $\mathcal{P}_k$ and $\mathcal{N}_k$ consist of the training instances in $\mathcal{D}$ with and without label l_k respectively.

The popular k-means algorithm [Jain *et al.*, 1999] is adopted to partition $\mathcal{P}_k$ into m_k^+ disjoint clusters whose centers are denoted as $\{\boldsymbol{p}_1^k, \boldsymbol{p}_2^k, \cdots, \boldsymbol{p}_{m_k^+}^k\}$. Similarly, $\mathcal{N}_k$ is also partitioned into m_k^- disjoint clusters whose centers are denoted as $\{\boldsymbol{n}_1^k, \boldsymbol{n}_2^k, \cdots, \boldsymbol{n}_{m_k^-}^k\}$. Here, we choose to set equivalent number of clusters for $\mathcal{P}_k$ and $\mathcal{N}_k$, i.e. $m_k^+ = m_k^- = m_k$. In this way, clustering information gained from positive instances as well as negative instances are treated with equal importance. Specifically, the number of clusters retained for both positive and negative instances is set to be:

$$m_k = r \cdot \min\left(|\mathcal{P}_k|, |\mathcal{N}_k|\right) \qquad (2)$$

Here, $|\cdot|$ represents the set cardinality and $r \in [0, 1]$ is the ratio parameter controlling the number of clusters thus retained.

Intuitively, the retained cluster centers characterize the underlying structure of input space, and can be used as the bases for label-specific features construction with regard to l_k. In

Table 2: Characteristics of the experimental data sets.

Data set	$\|\mathcal{S}\|$	$dim(\mathcal{S})$	$L(\mathcal{S})$	$F(\mathcal{S})$	$LCard(\mathcal{S})$	$LDen(\mathcal{S})$	$DL(\mathcal{S})$	$PDL(\mathcal{S})$	Domain	URL[*]
emotions	593	72	6	numeric	1.869	0.311	27	0.046	music	URL 1
genbase	662	1185	27	nominal	1.252	0.046	32	0.048	biology	URL 1
medical	978	1449	45	nominal	1.245	0.028	94	0.096	text	URL 2
enron	1702	1001	53	nominal	3.378	0.064	753	0.442	text	URL 2
image	2000	294	5	numeric	1.236	0.247	20	0.010	images	URL 3
scene	2407	294	6	numeric	1.074	0.179	15	0.006	images	URL 1
yeast	2417	103	14	numeric	4.237	0.303	198	0.082	biology	URL 3
slashdot	3782	1079	22	nominal	1.181	0.054	156	0.041	text	URL 2
corel5k	5000	499	374	nominal	3.522	0.009	3175	0.635	images	URL 1
rcv1 (subset 1)	6000	944	101	numeric	2.880	0.029	1028	0.171	text	URL 1
rcv1 (subset 5)	6000	944	101	numeric	2.642	0.026	946	0.158	text	URL 1
bibtex	7395	1836	159	nominal	2.402	0.015	2856	0.386	text	URL 1
corel16k (sample 1)	13766	500	153	nominal	2.859	0.019	4803	0.349	images	URL 1
corel16k (sample 2)	13761	500	164	nominal	2.882	0.018	4868	0.354	images	URL 1
corel16k (sample 3)	13760	500	154	nominal	2.829	0.018	4812	0.350	images	URL 1
ohsumed	13929	1002	23	nominal	1.663	0.072	1147	0.082	text	URL 2

[*] URL 1: `http://mulan.sourceforge.net/datasets.html`
URL 2: `http://meka.sourceforge.net/#datasets`
URL 3: `http://cse.seu.edu.cn/people/zhangml/Resources.htm#data`

detail, LIFT creates a mapping $\phi_k : \mathcal{X} \to \mathcal{Z}_k$ from the original d-dimensional space $\mathcal{X}$ to the $2m_k$-dimensional label-specific feature space $\mathcal{Z}_k$ as follows:[1]

$$\phi_k(\boldsymbol{x}) = \big[\mathbf{d}(\boldsymbol{x},\boldsymbol{p}_1^k),\cdots,\mathbf{d}(\boldsymbol{x},\boldsymbol{p}_{m_k}^k),\mathbf{d}(\boldsymbol{x},\boldsymbol{n}_1^k),\cdots,\mathbf{d}(\boldsymbol{x},\boldsymbol{n}_{m_k}^k)\big] \quad (3)$$

Here, $\mathbf{d}(\cdot,\cdot)$ returns the distance between two instances and is set to the Euclidean metric in this paper.

Note that we do not claim that the above process is the best possible practice for label-specific features construction. Actually, the mapping ϕ_k can be implemented in alternative ways, such as setting different number of clusters for positive and negative instances (i.e. $m_k^+ \neq m_k^-$), utilizing more sophisticated distance for $\mathbf{d}(\cdot,\cdot)$ other than the Euclidean metric, or even employing *k*NN rule [Wang *et al.*, 2010] to identify the bases for feature mapping other than invoking the k-means procedure, etc. Nevertheless, LIFT's simple construction process of label-specific features suffices to yield competitive performance as shown in Section 4.

In the second step, LIFT aims to induce a family of q classification models $\{f_1^*, f_2^*, \cdots, f_q^*\}$ with the generated label-specific features. Specifically, for each class label $l_k \in \mathcal{Y}$, a binary training set $\mathcal{D}_k^*$ with m examples is created from $\mathcal{D}$ and ϕ_k as follows:

$$\mathcal{D}_k^* = \{(\phi_k(\boldsymbol{x}_i), Y_i(k)) \mid (\boldsymbol{x}_i, Y_i) \in \mathcal{D}\} \text{ where}$$
$$Y_i(k) = +1 \text{ if } l_k \in Y_i;\ \text{Otherwise},\ Y_i(k) = -1 \quad (4)$$

Based on $\mathcal{D}_k^*$, any binary learner can be applied to induce a classification model $f_k^* : \mathcal{Z}_k \to \mathbb{R}$ for l_k. Given an unseen example $\boldsymbol{u} \in \mathcal{X}$, its associated label set is predicted as $Y = \{l_k \mid f_k^*(\phi_k(\boldsymbol{u})) > 0, 1 \leq k \leq q\}$. In principle, the classifiers induction process of LIFT is similar to those of the *first-order* approaches discussed in Section 2. The major difference lies that LIFT induces the classifier on each label with label-specific features instead of the original ones.

In summary, Table 1 presents the complete description of LIFT. Based on the multi-label training examples, LIFT firstly constructs label-specific features for each possible class label (steps 1 to 5); After that, a family of q binary classification models are induced based on the constructed features in a round-robin style (steps 6 to 9); Finally, the unseen example is fed to the learned system for prediction (step 10).

Note that the idea of exploiting label-specific features should be regarded a *meta-strategy* to multi-label learning, and LIFT serves as one possible instantiation of this strategy. There are learning algorithms such as decision trees which can implicitly do feature selection during their learning process. However, this is only a by-product of these algorithms and should not be regarded a stand-alone tool for feature construction. Employing algorithms such as decision trees in first-order approaches could yield similar methods to LIFT. However, the major difference lies in that the former one wraps around the construction of label-specific features and the induction of learning models, while LIFT constructs label-specific features independent of the model induction.

4 Experiments

4.1 Configuration

To thoroughly evaluate the performance of our approach, a total of sixteen real-world multi-label data sets are studied in this paper. For each data set $\mathcal{S} = \{(\boldsymbol{x}_i, Y_i) \mid 1 \leq i \leq p\}$, we use $|\mathcal{S}|$, $dim(\mathcal{S})$, $L(\mathcal{S})$ and $F(\mathcal{S})$ to denote the properties of *number of examples*, *number of features*, *number of possible class labels*, and *feature type* respectively. In addition, several other multi-label properties [Read *et al.*, 2009; Tsoumakas *et al.*, 2009] are denoted as:

[1]Note that in multi-label learning, the distribution of positive instances and negative instances for each label is usually *imbalanced* with $|\mathcal{P}_k| \ll |\mathcal{N}_k|$. Thus, the dimensionality of $\mathcal{Z}_k$, i.e. $2\cdot r\cdot \min(|\mathcal{P}_k|, |\mathcal{N}_k|)$, would be of reasonable size in most cases. As an intance, for the *ohsumed* data set with 13929 examples and 1002 features (Table 2), the dimensionality of the label-specific feature space is only around 100 ± 93 across all labels with $r = 0.1$.

Table 3: Experimental results of each comparing algorithm (mean±std. deviation) on the eight regular-scale data sets.

Evaluation criterion	Algorithm	emotions	genbase	medical	enron	image	scene	yeast	slashdot
	LIFT	**0.188±0.021**	0.003±0.001	0.012±0.001	**0.046±0.003**	**0.156±0.017**	**0.077±0.009**	**0.193±0.010**	**0.038±0.002**
	BSVM	0.199±0.022	**0.001±0.001**	**0.010±0.001**	0.060±0.003	0.176±0.007	0.104±0.006	0.199±0.010	0.047±0.002
Hamming loss ↓	ML-KNN	0.194±0.013	0.005±0.002	0.016±0.002	0.052±0.002	0.170±0.008	0.084±0.008	0.195±0.011	0.052±0.001
	BP-MLL	0.219±0.021	0.004±0.002	0.019±0.002	0.052±0.003	0.253±0.024	0.282±0.014	0.205±0.009	0.047±0.002
	ECC	0.192±0.027	**0.001±0.001**	**0.010±0.001**	0.055±0.004	0.180±0.015	0.096±0.010	0.208±0.010	0.046±0.003
	LIFT	0.243±0.074	**0.000±0.000**	0.157±0.044	0.244±0.041	**0.266±0.037**	**0.196±0.026**	0.221±0.020	0.392±0.023
	BSVM	0.253±0.070	0.002±0.005	0.151±0.054	0.308±0.050	0.314±0.021	0.250±0.027	0.230±0.023	0.479±0.024
One-error ↓	ML-KNN	0.263±0.067	0.009±0.011	0.252±0.045	0.313±0.035	0.320±0.026	0.219±0.029	0.228±0.029	0.639±0.017
	BP-MLL	0.318±0.057	**0.000±0.000**	0.327±0.057	0.237±0.038	0.600±0.079	0.821±0.031	0.235±0.031	0.381±0.026
	ECC	**0.216±0.085**	**0.000±0.000**	**0.099±0.034**	**0.212±0.026**	0.289±0.026	0.226±0.034	**0.176±0.022**	**0.377±0.034**
	LIFT	**0.281±0.022**	0.018±0.011	**0.039±0.022**	0.220±0.017	**0.168±0.019**	**0.065±0.007**	0.452±0.015	0.106±0.006
	BSVM	0.295±0.027	**0.011±0.005**	0.047±0.011	0.425±0.037	0.189±0.021	0.089±0.009	0.514±0.018	0.203±0.010
Coverage ↓	ML-KNN	0.300±0.019	0.021±0.013	0.060±0.025	0.247±0.014	0.194±0.020	0.078±0.010	**0.447±0.014**	0.187±0.008
	BP-MLL	0.300±0.022	0.025±0.012	0.047±0.024	**0.204±0.012**	0.343±0.029	0.374±0.024	0.456±0.019	**0.102±0.007**
	ECC	0.322±0.022	0.013±0.007	0.071±0.023	0.387±0.032	0.199±0.020	0.091±0.008	0.516±0.015	0.156±0.015
	LIFT	**0.144±0.024**	0.004±0.006	**0.026±0.020**	0.074±0.008	**0.143±0.018**	**0.062±0.008**	**0.163±0.011**	0.091±0.006
	BSVM	0.156±0.034	**0.001±0.002**	0.032±0.012	0.180±0.022	0.169±0.019	0.089±0.011	0.200±0.013	0.180±0.008
Ranking loss ↓	ML-KNN	0.163±0.022	0.006±0.006	0.042±0.021	0.093±0.007	0.175±0.019	0.076±0.012	0.166±0.015	0.173±0.010
	BP-MLL	0.173±0.020	0.008±0.006	0.032±0.018	**0.068±0.006**	0.366±0.037	0.434±0.026	0.171±0.015	**0.087±0.007**
	ECC	0.233±0.040	0.008±0.008	0.098±0.032	0.241±0.025	0.245±0.024	0.135±0.013	0.285±0.022	0.255±0.020
	LIFT	**0.821±0.033**	0.995±0.006	**0.877±0.035**	0.703±0.027	**0.825±0.023**	**0.886±0.014**	**0.770±0.017**	0.699±0.017
	BSVM	0.807±0.037	**0.998±0.004**	0.871±0.047	0.591±0.035	0.796±0.015	0.849±0.016	0.749±0.019	0.589±0.020
Average precision ↑	ML-KNN	0.799±0.031	0.989±0.010	0.806±0.036	0.626±0.022	0.792±0.017	0.869±0.017	0.765±0.021	0.500±0.016
	BP-MLL	0.779±0.027	0.988±0.010	0.782±0.042	**0.705±0.025**	0.601±0.040	0.445±0.018	0.754±0.020	**0.713±0.017**
	ECC	0.796±0.042	0.994±0.006	0.872±0.033	0.640±0.025	0.794±0.016	0.852±0.016	0.728±0.019	0.682±0.025
	LIFT	**0.848±0.021**	0.988±0.014	0.931±0.038	0.739±0.021	**0.860±0.018**	**0.948±0.010**	**0.685±0.023**	0.863±0.014
	BSVM	0.833±0.017	**0.989±0.014**	**0.942±0.026**	0.711±0.035	0.831±0.022	0.916±0.008	0.642±0.017	0.841±0.018
AUC ↑	ML-KNN	0.840±0.020	0.981±0.017	0.852±0.036	0.639±0.024	0.833±0.020	0.934±0.013	0.681±0.012	0.610±0.019
	BP-MLL	0.829±0.015	0.984±0.013	0.910±0.037	**0.756±0.031**	0.666±0.024	0.703±0.032	0.674±0.019	**0.865±0.025**
	ECC	0.824±0.025	0.982±0.016	0.857±0.040	0.661±0.019	0.820±0.021	0.914±0.010	0.604±0.007	0.767±0.016

• $LCard(\mathcal{S}) = \frac{1}{p}\sum_{i=1}^{p}|Y_i|$: *label cardinality* which measures the average number of labels per example;

• $LDen(\mathcal{S}) = \frac{LCard(\mathcal{S})}{L(\mathcal{S})}$: *label density* which normalizes $LCard(\mathcal{S})$ by the number of possible labels;

• $DL(\mathcal{S}) = |\{Y|(\boldsymbol{x}, Y) \in \mathcal{S}\}|$: *distinct label sets* which counts the number of distinct label combinations in $\mathcal{S}$;

• $PDL(\mathcal{S}) = \frac{DL(\mathcal{S})}{|\mathcal{S}|}$: *proportion of distinct label sets* which normalizes $DL(\mathcal{S})$ by the number of examples.

Table 2 summarizes the detailed characteristics of those multi-label data sets used in our experiments. Roughly ordered by $|\mathcal{S}|$, eight regular-scale data sets (first part, $|\mathcal{S}| < 5000$) as well as eight large-scale data sets (second part, $|\mathcal{S}| \geq 5000$) are included. As shown in Table 2, the sixteen data sets cover a broad range of cases whose characteristics are diversified with respect to different multi-label properties.

In this paper, LIFT is compared with four well-established multi-label learning algorithms, including BSVM [Boutell *et al.*, 2004], ML-KNN [Zhang and Zhou, 2007], BP-MLL [Zhang and Zhou, 2006] and ECC [Read *et al.*, 2009]. As discussed in Section 2, BSVM and ML-KNN are *first-order* approaches which work in a similar way as LIFT by generating classifiers in a label-wise style, though under the original feature space $\mathcal{X}$. In addition, BP-MLL is a *second-order* approach and ECC is a *high-order* approach both of which consider exploiting label correlations in their learning processes. For fair comparison, LIBSVM (with linear kernel) [Chang and Lin, 2001] is employed as the binary learner for classifier induction to instantiate LIFT, BSVM and ECC.

As shown in Table 1, in addition to set $\mathfrak{L}$ as linear kernel LIBSVM, the other factor needed to be specified for LIFT is r, i.e. the ratio parameter as used in Eq.(2). In this paper, r is set to be 0.1 for all data sets.[2] Furthermore, parameter configurations suggested in respective literatures are used for the other comparing algorithms. For BSVM, models are learned via the cross-training strategy [Boutell *et al.*, 2004]; For ML-KNN, the number of nearest neighbors considered is set to be 10 [Zhang and Zhou, 2007]; For BP-MLL, the number of hidden neurons is set to be 20% of the input dimensionality and the maximum number of training epochs is set to be 100 [Zhang and Zhou, 2006]; For ECC, the ensemble size is set to be 10 and the sampling ratio is set to be 67% [Read *et al.*, 2009].

4.2 Results

Performance evaluation in multi-label learning is more complicated than traditional single-label learning, as each example could be associated with multiple labels simultaneously. Firstly, five evaluation criteria popularly used in multi-label learning are employed, i.e. *hamming loss*, *one-error*, *coverage*, *ranking loss* and *average precision* [Schapire and Singer, 2000; Tsoumakas *et al.*, 2009].[3] Briefly, these criteria evaluate the quality of the predicted label set for each test example and then return the averaged value across all the test examples. In addition, we also employ the AUC criterion (area

[2]In preliminary experiments, a number of values have been tested for r by increasing it from 0.02 to 0.2 (stepsize 0.02). Results show that the performance of LIFT becomes stable as r approaches 0.1.

[3]Due to page limit, formal definitions on these criteria can be found in the references therein. In this paper, the *coverage* criterion is further normalized by $|\mathcal{Y}|$ so that all reported performance measures vary between [0,1].

Table 4: Experimental results of each comparing algorithm (mean±std. deviation) on the eight large-scale data sets.

Evaluation criterion	Algorithm	corel5k	rcv1 (subset 1)	rcv1 (subset 5)	bibtex	corel16k (sample 1)	corel16k (sample 2)	corel16k (sample 3)	ohsumed
Hamming loss ↓	LIFT	**0.009±0.001**	**0.026±0.001**	**0.022±0.001**	**0.012±0.001**	**0.019±0.001**	**0.017±0.001**	**0.018±0.001**	**0.056±0.001**
	BSVM	0.011±0.001	**0.026±0.001**	0.023±0.001	0.016±0.001	**0.019±0.001**	0.018±0.001	0.019±0.001	0.064±0.001
	ML-KNN	**0.009±0.001**	0.027±0.001	0.024±0.001	0.014±0.001	**0.019±0.001**	0.018±0.001	**0.018±0.001**	0.071±0.001
	BP-MLL	0.010±0.001	0.033±0.001	0.029±0.001	0.016±0.001	**0.019±0.001**	0.018±0.001	**0.018±0.001**	0.081±0.001
	ECC	0.014±0.001	0.033±0.003	0.028±0.002	0.016±0.001	0.030±0.001	0.028±0.001	0.029±0.001	0.067±0.001
One-error ↓	LIFT	0.674±0.028	0.414±0.018	**0.405±0.030**	0.375±0.025	0.674±0.012	0.666±0.010	0.666±0.012	0.352±0.012
	BSVM	0.822±0.034	**0.396±0.013**	0.432±0.090	0.444±0.011	0.868±0.008	0.863±0.015	0.848±0.011	0.386±0.009
	ML-KNN	0.737±0.016	0.548±0.018	0.499±0.029	0.589±0.019	0.732±0.011	0.732±0.013	0.740±0.012	0.646±0.011
	BP-MLL	0.732±0.022	0.714±0.017	0.718±0.019	0.431±0.024	0.710±0.015	0.732±0.009	0.712±0.013	0.384±0.010
	ECC	**0.655±0.016**	0.441±0.028	0.408±0.044	**0.341±0.022**	**0.657±0.020**	**0.663±0.019**	**0.660±0.013**	**0.347±0.011**
Coverage ↓	LIFT	0.288±0.017	**0.122±0.007**	**0.118±0.008**	0.137±0.006	0.308±0.006	0.299±0.009	0.301±0.009	0.171±0.006
	BSVM	0.519±0.019	0.219±0.008	0.200±0.011	0.226±0.010	0.328±0.006	0.318±0.006	0.320±0.005	0.185±0.005
	ML-KNN	0.306±0.017	0.219±0.010	0.198±0.009	0.340±0.008	0.335±0.005	0.326±0.010	0.332±0.006	0.308±0.007
	BP-MLL	**0.261±0.013**	0.222±0.010	0.229±0.008	**0.096±0.005**	**0.287±0.005**	**0.292±0.007**	**0.286±0.005**	**0.161±0.005**
	ECC	0.734±0.016	0.353±0.017	0.342±0.013	0.347±0.011	0.566±0.009	0.567±0.010	0.557±0.013	0.241±0.005
Ranking loss ↓	LIFT	0.122±0.008	**0.048±0.003**	**0.047±0.004**	0.073±0.005	0.155±0.002	**0.149±0.004**	0.150±0.005	0.105±0.003
	BSVM	0.258±0.012	0.097±0.004	0.091±0.008	0.127±0.006	0.182±0.003	0.174±0.003	0.176±0.003	0.117±0.004
	ML-KNN	0.134±0.008	0.105±0.005	0.095±0.005	0.209±0.006	0.173±0.002	0.166±0.005	0.168±0.003	0.228±0.006
	BP-MLL	**0.116±0.006**	0.115±0.006	0.118±0.004	**0.051±0.003**	**0.147±0.001**	0.156±0.004	**0.149±0.004**	**0.099±0.004**
	ECC	0.586±0.014	0.382±0.025	0.369±0.025	0.411±0.013	0.628±0.018	0.640±0.013	0.640±0.013	0.287±0.009
Average precision ↑	LIFT	**0.293±0.015**	**0.594±0.009**	**0.626±0.021**	**0.568±0.013**	**0.323±0.007**	**0.320±0.006**	**0.323±0.005**	**0.696±0.007**
	BSVM	0.154±0.026	0.588±0.008	0.600±0.047	0.516±0.010	0.189±0.004	0.186±0.006	0.194±0.005	0.663±0.006
	ML-KNN	0.244±0.010	0.478±0.011	0.530±0.019	0.350±0.011	0.287±0.004	0.282±0.006	0.279±0.006	0.444±0.009
	BP-MLL	0.239±0.009	0.388±0.012	0.391±0.005	0.557±0.013	0.313±0.004	0.281±0.005	0.288±0.005	0.682±0.006
	ECC	0.234±0.011	0.475±0.020	0.507±0.028	0.512±0.013	0.257±0.010	0.247±0.010	0.250±0.009	0.644±0.007
AUC ↑	LIFT	0.719±0.016	**0.925±0.011**	**0.925±0.015**	0.911±0.005	0.689±0.008	0.707±0.008	0.703±0.012	0.860±0.007
	BSVM	0.661±0.018	0.900±0.011	0.908±0.010	0.875±0.006	0.687±0.008	0.697±0.007	0.695±0.011	0.835±0.007
	ML-KNN	0.541±0.004	0.667±0.018	0.685±0.016	0.676±0.007	0.571±0.004	0.587±0.006	0.573±0.008	0.599±0.006
	BP-MLL	**0.734±0.008**	0.862±0.012	0.853±0.011	**0.933±0.005**	**0.752±0.006**	**0.761±0.004**	**0.752±0.008**	**0.865±0.004**
	ECC	0.567±0.009	0.613±0.004	0.612±0.006	0.733±0.011	0.577±0.006	0.581±0.006	0.578±0.004	0.777±0.008

under the ROC curve) to evaluate the quality of the predictions for each class label and then return the averaged value across all the class labels.

On each data set, *ten-fold cross validation* is conducted and the mean value and standard deviation of each evaluation criterion is recorded. For AUC and average precision, the *larger* the values the better the performance; While for the other four criteria, the *smaller* the values the better the performance. All the above criteria serve as good indicators for comprehensive comparative studies as they evaluate the performance of an algorithm from various aspects.

Tables 3 and 4 report the detailed experimental results on the regular-scale and large-scale data sets respectively. For each evaluation criterion, "↓" indicates "the smaller the better" while "↑" indicates "the larger the better". Furthermore, the best performance among the five comparing algorithms is highlighted in boldface.

Across all the 96 configurations (i.e. 16 data sets × 6 criteria as shown in the two tables), LIFT ranks in *1st* place among the five comparing algorithms at 47.9% cases, in *2nd* place at 45.8% cases, in *3rd* place at only 6.3% cases, and never ranks in *4th* and *5th* places. To perform comparative analysis in more well-founded ways, *Friedman test* is further examined which is a favorable statistical test for comparisons of more than two algorithms over multiple data sets [Demšar, 2006].

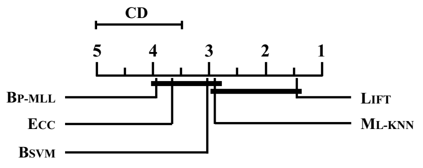
For each evaluation criterion, Friedman test at 0.05 significance level (five algorithms, sixteen data sets) rejects the null hypothesis of "equal" performance, which leads to the use of post-hoc tests to find out which algorithms actually differ. Specifically, *Nemenyi test* is utilized where the performance of two algorithms is significantly different if their average ranks over all data sets differ by at least one *critical difference* (CD). Figure 1 gives the CD diagrams [Demšar, 2006] for each evaluation criterion, where the average rank of each comparing algorithm is marked along the axis (lower ranks to the right). Groups of algorithms that are not significantly different according to Nemenyi test are connected with a thick line. The critical difference (CD=1.525 at 0.05 significance level) is also shown above the axis in each subfigure.

To summarize, out of all the 24 comparisons (4 algorithms to compare × 6 criteria), LIFT achieves statistically comparable performance in only 33% cases, i.e. the 8 comparisons against ML-KNN on *hamming loss* (Fig.1 a), against ECC on *one-error* (Fig.1 b), against BSVM and BP-MLL on *coverage* (Fig.1 c), on *ranking loss* (Fig.1 d), and on *AUC* (Fig.1 f). Rather impressively, LIFT achieves statistically superior performance in all the other 67% cases and no algorithms have once outperformed LIFT. These results clearly validate the superior effectiveness of our approach to the other well-established multi-label learning algorithms.

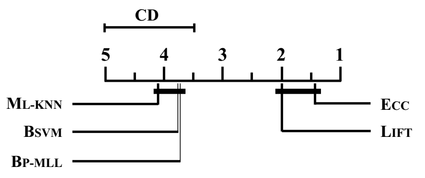
5 Conclusion

The major contributions of our work are two-fold: 1) A new strategy to multi-label learning via label-specific features is proposed, which suggests a new direction for learning from multi-label data; 2) A simple algorithm named LIFT is designed to justify the proposed strategy, whose effectiveness is thoroughly validated based on extensive comparative studies.

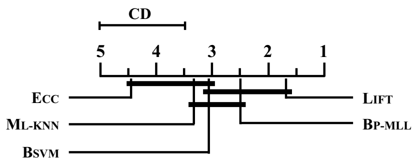
In the future, it is interesting to see whether LIFT can be further improved by incorporating label correlations into its



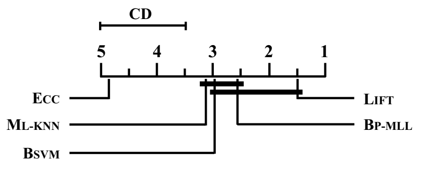
(a) Hamming loss



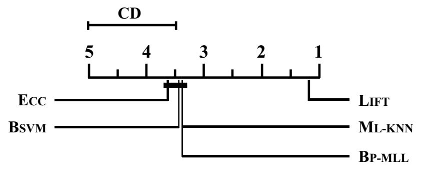
(b) One-error



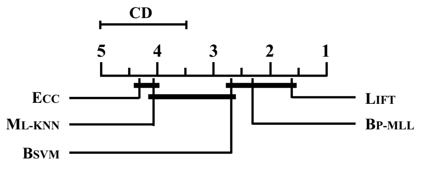
(c) Coverage



(d) Ranking loss



(e) Average precision



(f) AUC

Figure 1: CD diagrams [Demšar, 2006] of the comparing algorithms under each evaluation criterion.

label-specific features construction step as well as classification models induction step. Furthermore, designing other ways to fulfill the strategy of label-specific features is a direction very worth studying.

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