CAIIAM “知识智能及其产业应用论坛”

偏标记学习的研究

(Research on Partial Label Learning)

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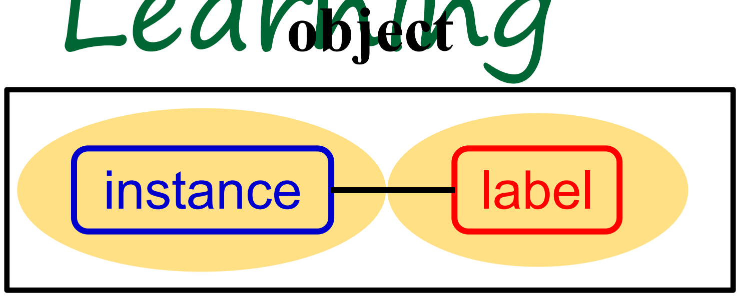
Traditional Supervised Learning

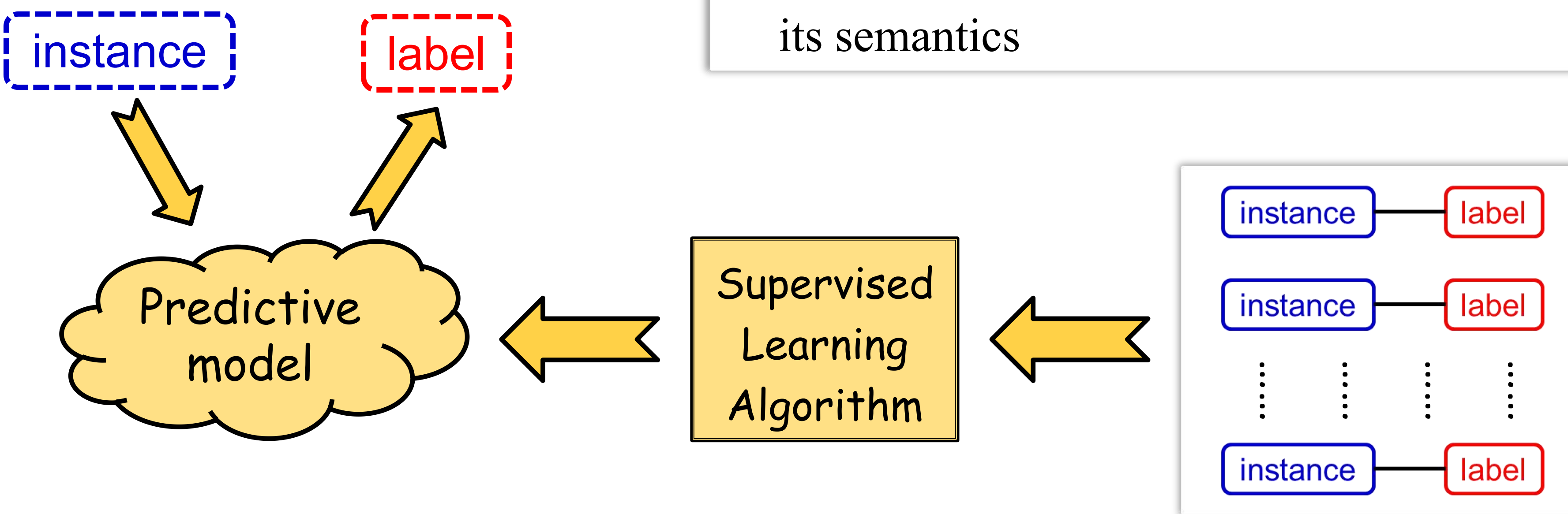


Input Space

represented by a single instance (feature vector) characterizing its properties

Output Space

associated with a single label characterizing its semantics



Basic Assumption: Strong Supervision

label ⟺ supervision information

Key factor for successful learning

(encoding *semantics* and *regularities* for the learning problem)

Strong supervision assumption

- **Sufficient labeling**

  abundant labeled training data are available

- **Explicit labeling**

  object labeling is unique and unambiguous

But, Supervision Is Usually Weak

Difficult to have!

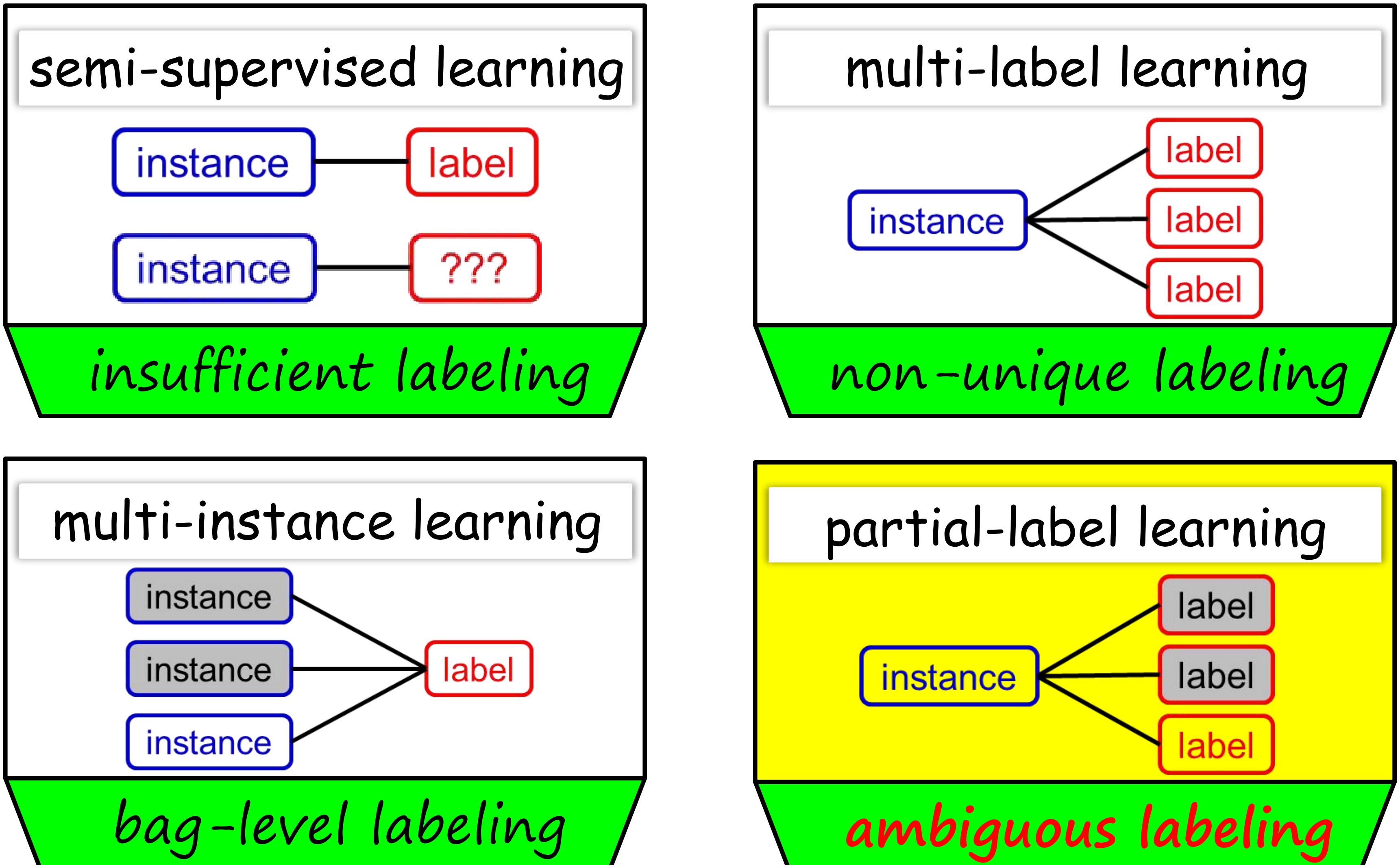
Constrained by:

- Limited resources
- Physical environment
- Problem properties
- ……

Strong supervision (sufficient & explicit) → Strong generalization ability

In practice, we usually have to learn with weak supervision [Zhou, NSR18]

For Example...



semi-supervised learning
instance
label
instance
???
insufficient labeling
multi-label learning
instance
label
label
label
non-unique labeling
multi-instance learning
instance
instance
instance
label
bag-level labeling
partial-label learning
instance
label
label
label
ambiguous labeling

Partial Label Learning

- The Framework

Partial Label

Appreciator A ------→

Appreciator B ------→

Appreciator C ------→

-------→ Picasso style ×

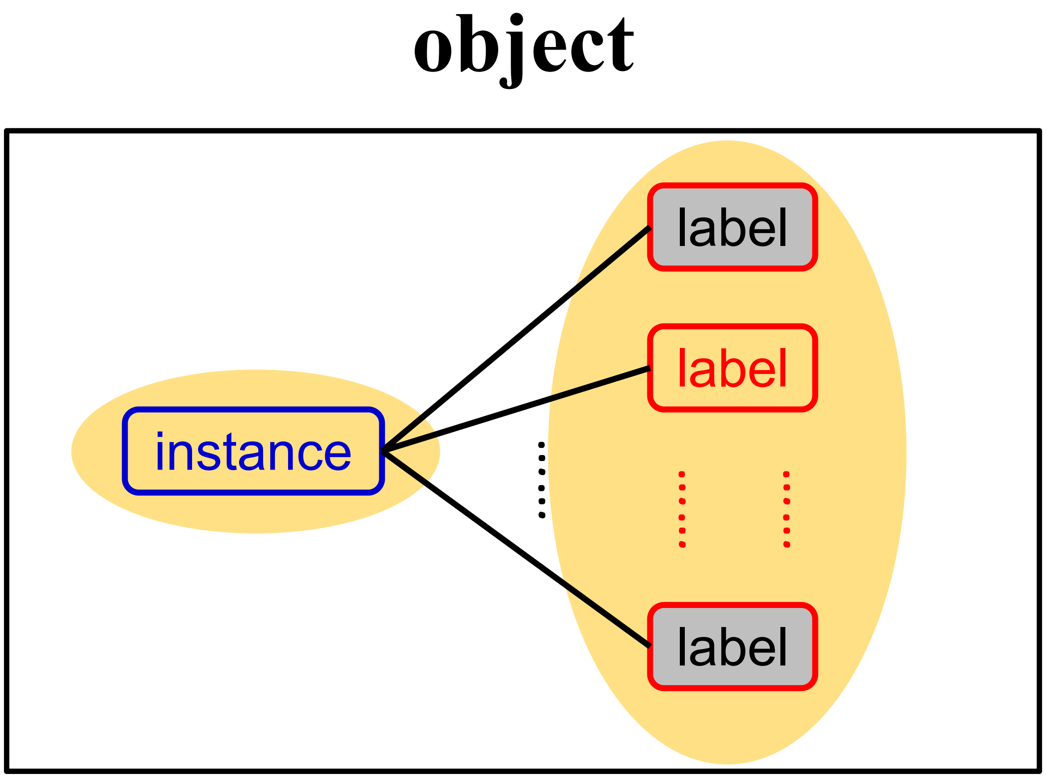
-------→ Monet style ×

-------→ van Gogh style √

Widely exist in real-world applications

- Image classification [Cour et al., JMLR11] [Chen et al., TPAMI18] [Sun et al., AAAI'19]
- Learning from crowds [Raykar et al., JMLR10] [Yu & Zhang, MLJ17]
- Eco-/Bio-informatics [Briggs et al., KDD'12] [Tang & Zhang, AAAI'17] [Yu et al., ICDM'18]
- NLP [Zhou et al., TALLIP18]
- ……

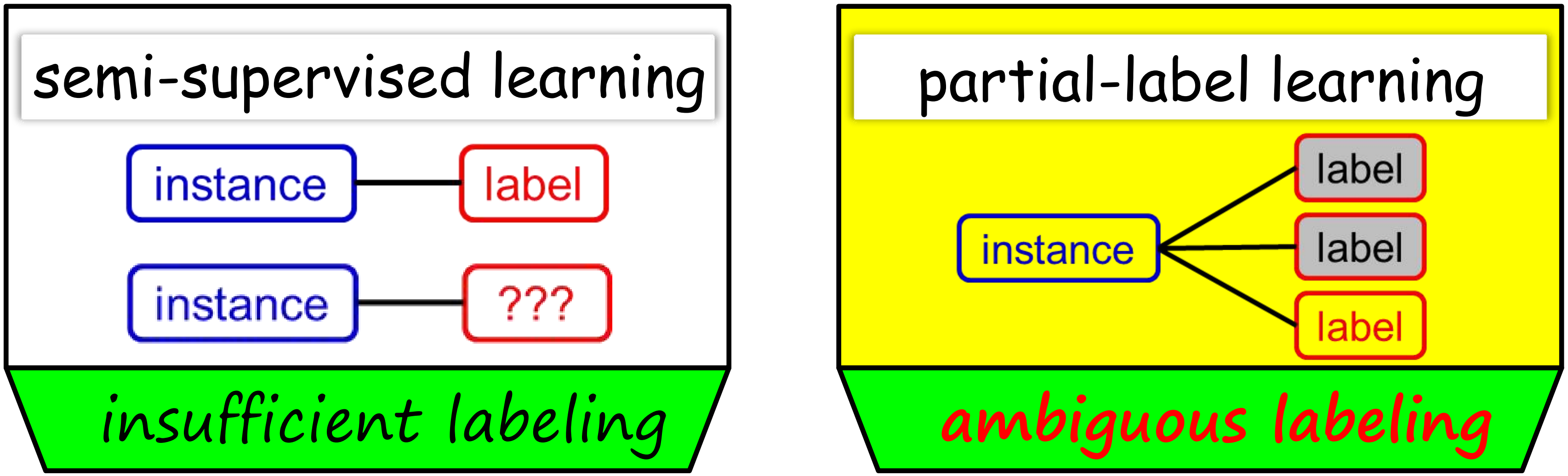
Partial-Label Learning (PLL)



- Each object is associated with multiple candidate labels
- Only one of the candidate label is the unknown ground-truth label

Partial-Label Learning (PLL)

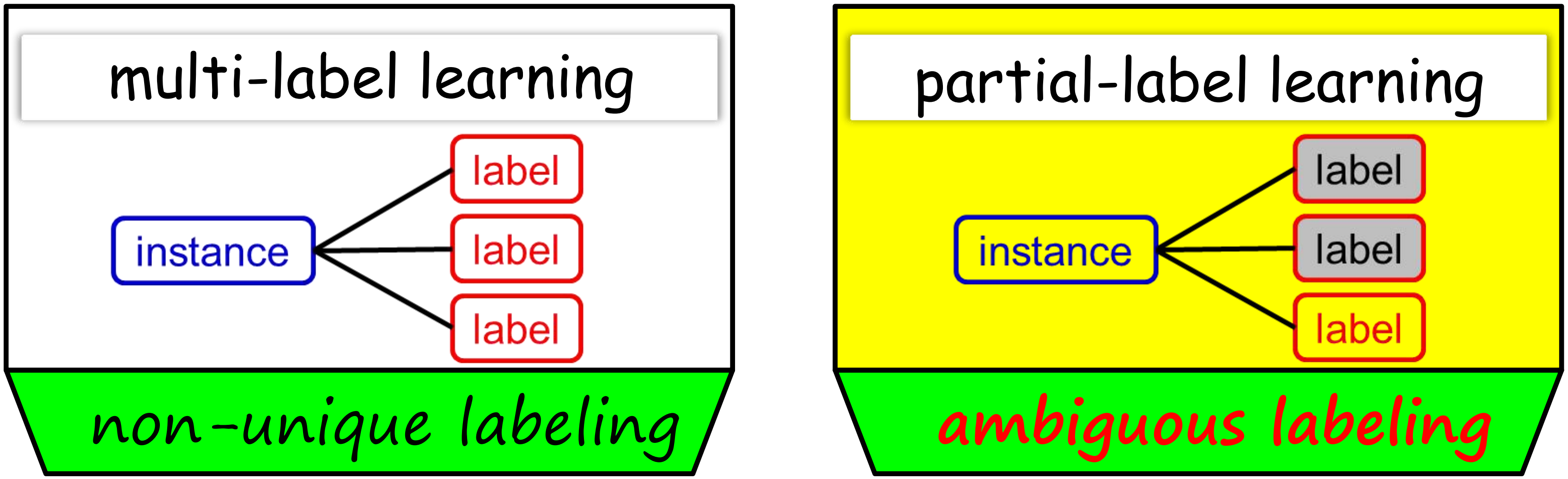
PLL vs. SSL



Unlabel: ground-truth label assumes the whole label space

Partial label: ground-truth label is confined within the candidate label set

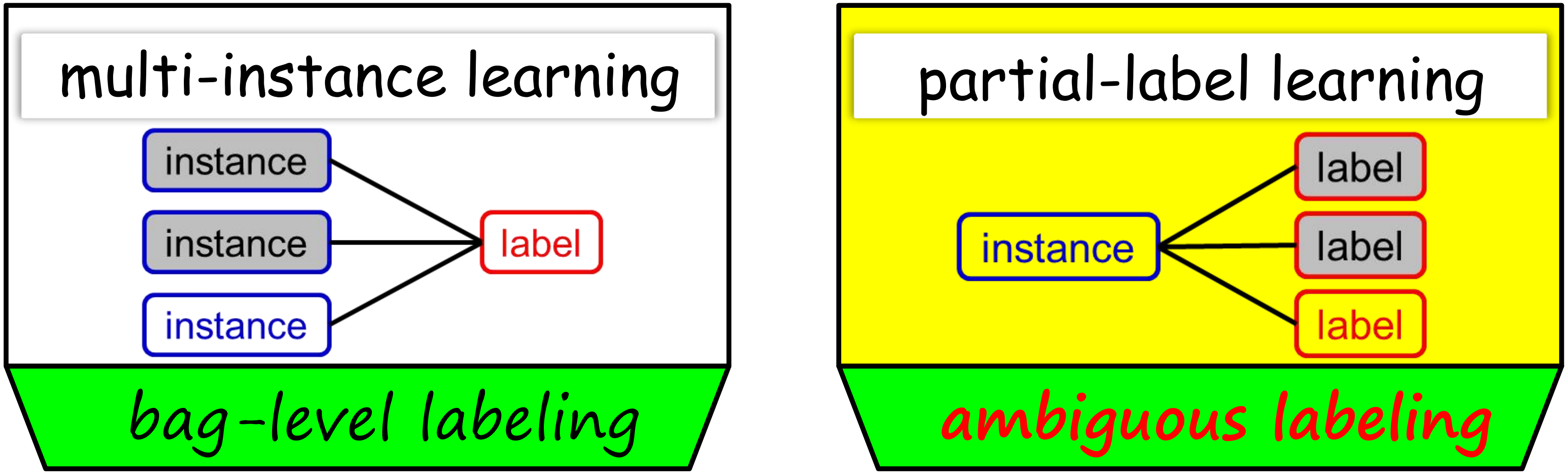
PLL vs. MLL



Multi-label: all the associated labels are valid ones

Partial label: only one of the associated label is valid

PLL vs. MIL



Multi-instance: one label assigned to a bag of instances, with ambiguity in the input space

Partial label: multiple labels assigned to a single instance, with ambiguity in the output space

Partial Label Learning

- Existing Approaches

Formal Definition of PLL

Settings

$\mathcal{X}$: d-dimensional feature space $\mathbb{R}^d$

$\mathcal{Y}$: label space with q labels $\{y_1, y_2, \cdots, y_q\}$

Inputs

$\mathcal{D}$: training set with m examples $\{(\boldsymbol{x}_i, S_i) \mid 1 \leq i \leq m\}$

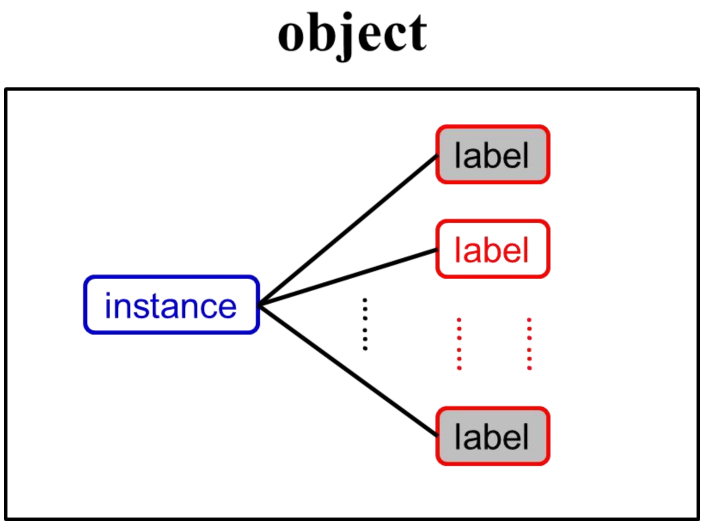
$\boldsymbol{x}_i \in \mathcal{X}$ is a d-dimensional feature vector $(\boldsymbol{x}_{i1}, \boldsymbol{x}_{i2}, \cdots, \boldsymbol{x}_{id})^{\mathrm{T}}$

$S_i \subseteq \mathcal{Y}$ is the candidate label set for $\boldsymbol{x}_i$, with its (unknown) ground-truth label $y_i \in S_i$

Outputs

h : multi-class predictor $\mathcal{X} \rightarrow \mathcal{Y}$

Key Challenge



Ambiguous labeling

ground-truth label not accessible by the learning algorithm

Common strategy: Disambiguation

- Disambiguation by ground-truth label identification
- Disambiguation by candidate label averaging

Disambiguation by Identification

Basic strategy

treating the ground-truth label as latent variable → identified via iterative refining procedure such as EM

$$\boxed{\hat{y}_i} = \arg\max_{y \in S_i} \boxed{F(\boldsymbol{x}_i, y; \boldsymbol{\theta})}$$

Latent ground-truth label

Parametric classification model

[Nguyen & Caruana, KDD'08] [Liu & Dietterich, NIPS'12] [Chen et al., CVPR'13] [Zhang et al., KDD'16] [Yu & Zhang, MLJ17] [Chen et al., TPAMI18]

Disambiguation by Identification (Cont.)

Maximum-likelihood formulation:

$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} \sum\nolimits_{i=1}^{m} \log\left(\sum\nolimits_{y \in S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta})\right)$$

Maximum margin formulation:

$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} \sum\nolimits_{i=1}^{m} \log\left(\max_{y \in S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta}) - \max_{y \notin S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta}))\right)$$

……

Potential weakness:

the identified label may turn out to be the false positive label

Disambiguation by Averaging

Basic strategy

treating all the candidate labels in an equal manner → make final prediction by averaging their modeling outputs

$$\boxed{\frac{1}{|S_i|}\sum_{y\in S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta})} \bigoplus \boxed{F(\boldsymbol{x}_i, y; \boldsymbol{\theta}) \ (y \notin S_i)}$$

Average output over candidate labels

Output over non-candidate labels

[Hullermeier & Beringer, IDA06] [Cour et al., CVPR'09] [Cour et al., JMLR11] [Zhang & Yu, IJCAI'15] [Gong et al., TCYB18]

Disambiguation by Averaging (Cont.)

Convex formulation:

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \sum_{i=1}^{m} \Psi\left(\frac{1}{|S_i|}\sum_{y\in S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta})\right) + \sum_{y\notin S_i} \Psi\left(-F(\boldsymbol{x}_i, y; \boldsymbol{\theta})\right)$$

Instance-based formulation:

$$f(\boldsymbol{x}^*) = \arg\max_{y\in\mathcal{Y}} \sum\nolimits_{j\in\mathcal{N}(\boldsymbol{x}^*)} [\![y \in S_j]\!]$$

……

Potential weakness: ground-truth output overwhelmed by false positive outputs

Partial Label Learning

- Recent Work I

Feature-Aware Disambiguation

Common strategy: Disambiguation

- Disambiguation by identification

$$\hat{y}_i = \arg\max_{y \in S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta})$$

- Disambiguation by averaging

$$\frac{1}{|S_i|} \sum_{y \in S_i} F(\boldsymbol{x}_i, y; \boldsymbol{\theta}) \quad \bigoplus \quad F(\boldsymbol{x}_i, y; \boldsymbol{\theta}) \ (y \notin S_i)$$

Distinguishing the modeling outputs of a single instance over all labels

An intuitive assumption

Information from feature (instance) space may help the disambiguation process

The PL-LEAF Approach [KDD'16; KDD'19]

The usefulness of feature space information

$(\boldsymbol{x}, \{\boxed{y_2}, \boxed{y_3}\})$

$(\boldsymbol{x}', \{y_1, \boxed{y_2}\})$

$(\boldsymbol{x}'', \{\boxed{y_3}, y_4\})$

feature space $\Rightarrow$ label space

$d(\boldsymbol{x}, \boldsymbol{x}') < d(\boldsymbol{x}, \boldsymbol{x}'')$

$\mathbb{P}(y_2 \mid \boldsymbol{x}) > \mathbb{P}(y_3 \mid \boldsymbol{x})$

Feature-aware disambiguation

- Structural relationships among training examples in the feature space would be retained in the label space
- Induce predictive model by exploiting the disambiguated labeling information

Graph-based Feature-Aware Disambiguation

kNN weighted graph $\mathcal{G} = (V, E, \mathbf{W})$

$$V = \{\boldsymbol{x}_i \mid 1 \le i \le m\} \qquad E = \{(\boldsymbol{x}_i, \boldsymbol{x}_j) \mid \boldsymbol{x}_i \in \text{kNN}(\boldsymbol{x}_j),\ i \ne j\}$$

$$\mathbf{W} = [W_{ij}]_{m \times m} \qquad \begin{aligned} &\min_{\mathbf{W}_{\cdot j}} \left\| \boldsymbol{x}_j - \textstyle\sum_{(\boldsymbol{x}_i, \boldsymbol{x}_j) \in E} W_{ij} \cdot \boldsymbol{x}_i \right\|^2 \\ &\text{s.t.}: \ \textstyle\sum_{(\boldsymbol{x}_i, \boldsymbol{x}_j) \in E} W_{ij} = 1 \\ &\qquad W_{ij} \ge 0 \ \ (\forall (\boldsymbol{x}_i, \boldsymbol{x}_j) \in E) \end{aligned}$$

Labeling confidences $\boldsymbol{\Lambda} = [\boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2, \ldots, \boldsymbol{\lambda}_m]$

labeling confidences over candidate labels are generated by referring to the structural relationships

$$\begin{aligned} &\min_{\boldsymbol{\Lambda}} \ \textstyle\sum_{j=1}^{m} \left\| \boldsymbol{\lambda}_j - \textstyle\sum_{(\boldsymbol{x}_i, \boldsymbol{x}_j) \in E} W_{ij} \cdot \boldsymbol{\lambda}_i \right\|^2 \\ &\text{s.t.}: \ \lambda_{jk} = 0 \ \ (\forall 1 \le j \le m,\ y_k \notin S_j) \\ &\qquad \lambda_{jk} \ge 0 \ \ (\forall 1 \le j \le m,\ y_k \in S_j) \\ &\qquad \textstyle\sum_{y_k \in S_j} \lambda_{jk} = 1 \ \ (\forall 1 \le j \le m) \end{aligned}$$

Predictive Model Induction

Transform $\mathcal{D}$ into its disambiguated counterpart $\mathcal{D}_{\text{dis}}$

$(\boldsymbol{x}_i, S_i) \Rightarrow (\boldsymbol{x}_i, \boldsymbol{\lambda}_i)$

candidate label set $\Rightarrow$ (real-valued) labeling confidence

Induce predictive model via *multi-regression SVR (MSVR)*

$$\{\boldsymbol{\Theta}, \boldsymbol{b}\} = \{(\boldsymbol{\theta}_k, b_k) \mid 1 \leq k \leq q\}$$

$$L(\boldsymbol{\Theta}, \boldsymbol{b}) = \frac{1}{2}\sum_{k=1}^{q} ||\boldsymbol{\theta}_k||^2 + C_1 \sum_{i=1}^{m} \underbrace{L_1(u_i)}_{\varepsilon\text{-insensitive loss}} + C_2 \sum_{i=1}^{m} \underbrace{v_i}_{\text{PL empirical loss}}$$

iterative gradient-based optimization with closed-form solution in each iteration

Experimental Setup

Comparing Algorithms

PL-LEAF : k=10 for kNN graph construction; kernelized MSVR

averaging-based disambiguatio

CLPL: Base learner: SVM with squared hinge loss

PL-kNN: # nearest neighbors = 10

identification-based disambiguation

PL-SVM: Regularization parameter pool $\{10^{-3},\ldots,10^{3}\}$

LSB-CMM: # mixture components = q

Experimental Protocol

Ten-times random train/test split + Pairwise t-test

Controlled UCI Data Sets

Controlled UCI Data Sets			
Data set	# Examples	# Features	# Class Labels
vehicle	846	18	4
segment	2,310	18	7
abalone	4,177	7	29
satimage	6,345	36	7
usps	9,298	256	10
pendigits	10,992	16	10

Generating an **artificial** PL data set from an UCI data set with three controlling parameters p, r, ϵ

Controlled UCI Data Sets

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Generating an **artificial** PL data set from an UCI data set with three controlling parameters p, r, ϵ

p : Proportion of examples which are partially labeled $(|S_i| \neq 1)$

r : # false positive labels in candidate label set $(|S_i| = r + 1)$

ϵ : Co-occurring probability for one extra candidate label

Fix r (=1, 2, 3), varying $p \in \{0.1, \ldots, 0.7\}$

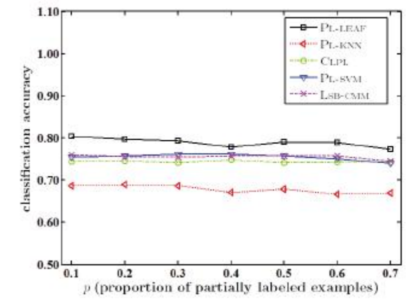
Fix r (=1), p (=1), varying $\epsilon \in \{0.1, \ldots, 0.7\}$

28 configurations per UCI data set

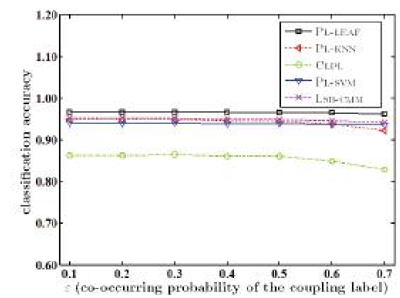
Controlled UCI Data Sets (Cont.)

Table 3: Win/tie/loss counts (pairwise t-test at 0.05 significance level) on the classification performance of PL-LEAF against each comparing algorithm.

	PL-LEAF against			
	PL-KNN	CLPL	PL-SVM	LSB-CMM
[Figure 1]	26/7/9	31/11/0	27/13/2	20/16/6
[Figure 2]	28/7/7	42/0/0	35/7/0	23/16/3
[Figure 3]	28/7/7	40/2/0	33/9/0	23/12/7
[Figure 4]	29/6/7	39/3/0	32/10/0	26/12/4
In Total	**111/27/30**	**152/16/0**	**127/39/2**	**92/56/20**



(a) vehicle



(e) usps

Out of 168 statistical tests (28 configurations x 6 UCI data sets)

- PL-LEAF outperforms PL-KNN and CLPL in 66.0% and 90.4% cases
- PL-LEAF outperforms PL-SVM and LSB-CMM in 75.5% and 54.7% cases

Real-World Data Sets

Real-World Data Sets					
Data set	# Examples	# Features	# Class Labels	Avg. # CLs	Task Domain
FG-NET	1,002	262	78	7.48	*facial age estimation* [20]
Lost	1,122	108	16	2.23	*automatic face naming* [8]
MSRCv2	1,758	48	23	3.16	*object classification* [16]
BirdSong	4,998	38	13	2.18	*bird song classification* [3]
Soccer Player	17,472	279	171	2.09	*automatic face naming* [25]
Yahoo! News	22,991	163	219	1.91	*automatic face naming* [12]

automatic face naming

instance: face cropped from image/video

candidate labels: names extracted from associated captions/subtitles

object classification

instance: image segmentation

candidate labels: objects appearing within the same image

bird song classification

instance: singing syllable of the bird

candidate labels: bird species jointly singing within 10-seconds period

URL: http://palm.seu.edu.cn/zhangml/Resources.htm#partial data

Real-World Data Sets (Cont.)

Table 4: Classification accuracy (mean±std) of each comparing algorithm on the real-world partial label data sets. In addition, •/○ indicates whether the performance of PL-LEAF is statistically superior/inferior to the comparing algorithm on each data set (pairwise t-test at 0.05 significance level).

	PL-LEAF	PL-KNN	CLPL	PL-SVM	LSB-CMM
FG-NET	0.072±0.010	0.037±0.008•	0.047±0.017•	0.058±0.010•	0.056±0.008•
FG-NET (MAE3)	0.411±0.012	0.284±0.035•	0.240±0.045•	0.343±0.022•	0.344±0.026•
FG-NET (MAE5)	0.550±0.018	0.438±0.033•	0.343±0.055•	0.473±0.016•	0.478±0.025•
Lost	0.664±0.020	0.332±0.030•	0.670±0.024	0.639±0.056	0.591±0.019•
MSRCv2	0.459±0.013	0.417±0.012•	0.375±0.020•	0.417±0.027•	0.431±0.008•
BirdSong	0.706±0.012	0.637±0.009•	0.624±0.009•	0.671±0.018•	0.692±0.015•
Soccer Player	0.515±0.004	0.494±0.004•	0.347±0.004•	0.430±0.004•	0.506±0.006•
Yahoo! News	0.597±0.004	0.403±0.004•	0.457±0.005•	0.615±0.002○	0.594±0.007

- On ***FG-NET***, ***MSRCv2, BirdSong*** and ***Soccer Player***, PL-LEAF is superior to all the comparing algorithms
- On ***Lost***, PL-LEAF is superior or at least comparable to all the comparing algorithms
- On ***Yahoo! News***, PL-LEAF is only inferior to PL-SVM

Partial Label Learning

- Recent Work II

Disambiguation-free PLL

Goal of PLL Induce a multi-class predictor $h : \mathcal{X} \rightarrow \mathcal{Y}$

Popular Binary Decomposition

- One-vs-Rest (#classifiers: q)
- One-vs-One (#classifiers: $q(q-1)/2$)

Not applicable due to the unknown ground-truth label

PL-ECOC (Partial-label Learning with Error-Correcting Output Codes)

Two major advantages

- Naturally enable binary decomposition
- Disambiguation-free

The PL-ECOC Approach [TKDE17]

Illustrative procedure of ECOC

	h_1	h_2	h_3	h_4	h_5	h_6	h_7
y_1	+1	-1	+1	+1	+1	-1	-1
y_2	+1	+1	-1	-1	+1	-1	+1
y_3	-1	+1	-1	+1	+1	+1	-1
y_4	+1	-1	-1	+1	-1	-1	+1
y_5	-1	-1	+1	-1	-1	+1	+1
$\boldsymbol{x}^*$	+1	-1	-1	+1	-1	+1	-1

For each multi-class example $(\boldsymbol{x}_i, y_i)$

- $h_1(\boldsymbol{x}_i) = +1$ if $y_i \in \{y_1, y_2, y_4\}$
- $h_1(\boldsymbol{x}_i) = -1$ if $y_i \in \{y_3, y_5\}$

Identify the class with closest codeword to test instance $\boldsymbol{x}^*$

The PL-ECOC Approach (Cont.)

Illustrative procedure of PL-ECOC

	h_1	h_2	h_3	h_4	h_5	h_6	h_7
y_1	+1	-1	+1	+1	+1	-1	-1
y_2	+1	+1	-1	-1	+1	-1	+1
y_3	-1	+1	-1	+1	+1	+1	-1
y_4	+1	-1	-1	+1	-1	-1	+1
y_5	-1	-1	+1	-1	-1	+1	+1
$\boldsymbol{x}^*$	-1	+1	-1	+1	+1	-1	-1

For each partial-label example $(\boldsymbol{x}_i, S_i)$

- $h_1(\boldsymbol{x}_i) = +1$ if $S_i \subseteq \{y_1, y_2, y_4\}$
- $h_1(\boldsymbol{x}_i) = -1$ if $S_i \subseteq \{y_3, y_5\}$
- ignored w.r.t. h_1 otherwise

make prediction in the same way as ECOC

The PL-ECOC Approach

Complete Pipeline of PL-ECOC

- Coding matrix generation

randomly generate a q-bits column vector $\boldsymbol{v}$ → derive the binary training set $B_{\boldsymbol{v}}$ from the PL training set $\xrightarrow{|B_v| \geq \tau}$ set $\boldsymbol{v}$ as a column coding of the coding matrix

Repeat until reaching the ECOC coding length *L*

- Binary classifier induction

induce a total of L binary classifiers, one for each column coding

- Make prediction for unseen instance

identify the class whose codeword is closest to the classifiers' outputs on unseen instance

Experimental Setup

Comparing Algorithms

PL-ECOC : Coding length $=\lceil 10 \cdot \log_2(q) \rceil$; Base learner: Libsvm

averaging-based disambiguation

CLPL: Base learner: SVM with squared hinge loss

PL-kNN: # nearest neighbors = 5

identification-based disambiguation

PL-SVM: Regularization parameter pool $\{10^{-3},\ldots,10^{3}\}$

LSB-CMM: # mixture components = q

Experimental Protocol

Ten-fold cross-validation + Pairwise t-test

Controlled UCI Data Sets

TABLE 3
Win/tie/loss counts (pairwise t-test at 0.05 significance level) on the classification performance of PL-ECOC against each comparing algorithm on the controlled UCI data sets.

PL-ECOC against		Data Sets (names in abbreivation)										
		Eco.	Der.	Veh.	Seg.	Aba.	Sat.	Usp.	Pen.	Let.	**Subtotal**	**In Total**
PL-KNN	[Figure 1]	0/7/0	1/6/0	7/0/0	3/4/0	7/0/0	0/7/0	7/0/0	5/2/0	7/0/0	**37/26/0**	**156/96/0**
	[Figure 2]	0/7/0	3/4/0	7/0/0	2/5/0	7/0/0	0/7/0	7/0/0	7/0/0	5/2/0	**38/25/0**	
	[Figure 3]	0/7/0	2/5/0	7/0/0	4/3/0	7/0/0	1/6/0	7/0/0	7/0/0	5/2/0	**40/23/0**	
	[Figure 4]	2/5/0	3/4/0	7/0/0	2/5/0	7/0/0	3/4/0	7/0/0	6/1/0	4/3/0	**41/22/0**	
CLPL	[Figure 1]	0/7/0	0/7/0	6/1/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**48/15/0**	**181/71/0**
	[Figure 2]	0/7/0	0/7/0	3/4/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**45/18/0**	
	[Figure 3]	0/7/0	0/7/0	3/4/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**45/18/0**	
	[Figure 4]	0/7/0	1/6/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**43/20/0**	
PL-SVM	[Figure 1]	0/7/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**49/14/0**	**195/57/0**
	[Figure 2]	0/7/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**49/14/0**	
	[Figure 3]	0/7/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**49/14/0**	
	[Figure 4]	0/7/0	0/7/0	6/1/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	7/0/0	**48/15/0**	
LSB-CMM	[Figure 1]	7/0/0	0/7/0	1/6/0	7/0/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	**43/20/0**	**179/73/0**
	[Figure 2]	7/0/0	0/7/0	1/6/0	7/0/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	**43/20/0**	
	[Figure 3]	7/0/0	0/7/0	4/3/0	7/0/0	0/7/0	7/0/0	7/0/0	7/0/0	7/0/0	**46/17/0**	
	[Figure 4]	7/0/0	2/5/0	1/6/0	7/0/0	2/5/0	7/0/0	7/0/0	7/0/0	7/0/0	**47/16/0**	

Out of 252 statistical tests (28 configurations x 9 UCI data sets)

- None of the comparing algorithms significantly outperformed PL-ECOC
- PL-ECOC outperforms PL-KNN and CLPL in 61.9% and 71.8% cases respectively
- PL-ECOC outperforms PL-SVM and LSB-CMM in 77.3% and 71.0% cases respectively

Real-World Data Sets (Cont.)

TABLE 4
Predictive accuracy (mean±std) of each comparing algorithm on the real-world PL data sets. In addition, •/∘ indicates whether the performance of PL-ECOC is statistically superior/inferior to the comparing algorithm on each data set (pairwise t-test at 0.05 significate level).

	PL-ECOC	PL-KNN	CLPL	PL-SVM	LSB-CMM
Lost	0.703±0.052	0.424±0.041•	0.742±0.038∘	0.729±0.040	0.707±0.055
MSRCv2	0.505±0.027	0.448±0.037•	0.413±0.039•	0.482±0.043	0.456±0.031•
BirdSong	0.740±0.016	0.614±0.024•	0.632±0.017•	0.663±0.032•	0.717±0.024•
Soccer Player	0.537±0.020	0.497±0.014•	0.368±0.010•	0.443±0.014•	0.525±0.015
LYN 10	0.694±0.010	0.460±0.012•	0.605±0.013•	0.692±0.009	0.703±0.010∘
LYN 20	0.697±.0.012	0.469±0.015•	0.585±0.010•	0.686±0.011•	0.702±0.011
LYN 50	0.694±0.008	0.472±0.014•	0.540±0.012•	0.666±0.002•	0.679±0.007•
LYN 100	0.680±0.012	0.459±0.010•	0.507±0.011•	0.655±0.010•	0.673±0.010
LYN 200	0.662±0.010	0.457±0.014•	0.462±0.009•	0.636±0.010•	0.648±0.007•

- On ***BirdSong***, ***LYN 50*** and ***LYN 200***, PL-ECOC is superior to all the comparing algorithms
- On ***Soccer Player***, ***LYN 20***, ***LYN 100*** and ***MSRCv2***, PL-ECOC is superior or at least comparable to all the comparing algorithms
- On ***Lost*** and ***LYN 10***, PL-ECOC is inferior to the comparing algorithms in only two cases (CLPL on *Lost*; LSB-CMM on *LYN 10*)

Sensitivity Analysis for Coding Length

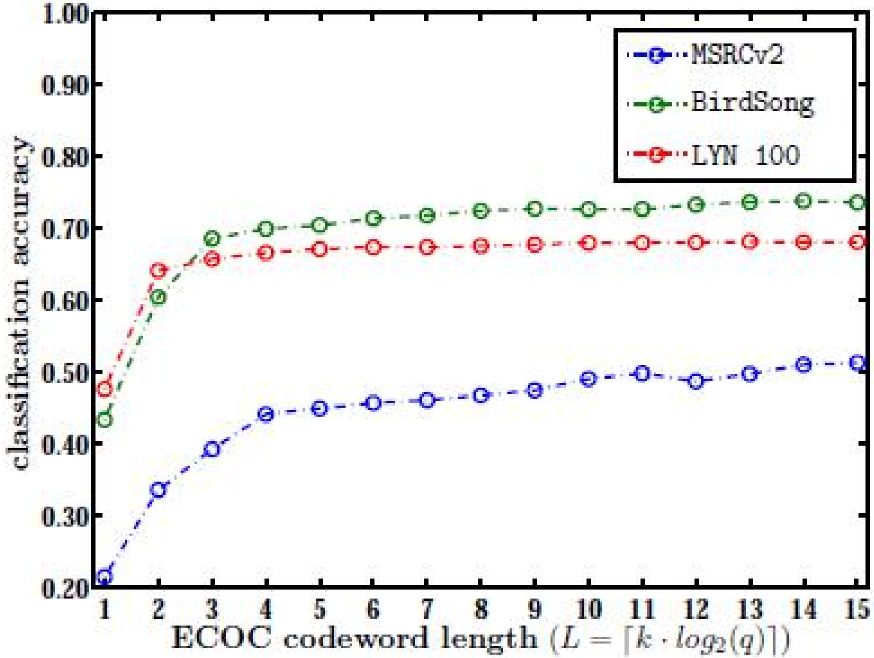


Fig. 5. Classification accuracy of PL-ECOC changes as the codeword length L increases from $\lceil log_2(q) \rceil$ to $\lceil 15 \cdot log_2(q) \rceil$ with step-size $\lceil log_2(q) \rceil$.

- Accuracy improves as the coding length increases
- Becomes stable as coding length approaches $\lceil 10 \cdot \log_2(q) \rceil$

Partial Label Learning

- Related Resources

Introductory Papers

- Cour T, Sapp B, Taskar B. Learning from partial labels. **Journal of Machine Learning Research**, 2011, 12(May): 1501-1536.
- Zhang M-L, Yu F, Tang C-Z. Disambiguation-free partial label learning. **IEEE Transactions on Knowledge and Data Engineering**, 2017, 29(10): 2155-2167.
- Zhang M-L, Zhou Z-H. A review on multi-label learning algorithms. **IEEE Transactions on Knowledge and Data Engineering**, 2014, 26(8): 1819-1837.
- Amores J. Multiple instance classification: Review, taxonomy, and comparative study. **Artificial Intelligence**, 201, 81-105.
- Zhou Z-H, Zhang M-L, Huang S-J, Li Y-F. Multi-instance multi-label learning. **Artificial Intelligence**, 2012, 176(1): 2291-2320.
- Geng X. Label Distribution Learning. **IEEE Transactions on Knowledge and Data Engineering**, 2016, 28(7): 1734-1748.
- ……

Data Sets

- Partial label learning (PLL)
  - http://palm.seu.edu.cn/zhangml/Resources.htm#partial_data
  - http://www.timotheecour.com/tv_data/tv_data.html
  - http://web.engr.oregonstate.edu/~briggsf/
  - http://research.microsoft.com/en-us/projects/objectclassrecognition/
- Multi-label learning (MLL)
  - http://mulan.sourceforge.net/datasets.html
  - http://meka.sourceforge.net/#datasets
  - http://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/multilabel.html
- Multi-instance multi-label learning (MIML)
  - http://lamda.nju.edu.cn/data_MIMLimage.ashx
  - http://lamda.nju.edu.cn/data_MItext.ashx
  - http://lamda.nju.edu.cn/data_MIMLprotein.ashx

Codes

- Partial label learning (PLL)
  - http://www.timotheecour.com/tv_data/partial_label_learning_toolbox.html
  - http://web.engr.oregonstate.edu/~liuli/files/LSB-CMM_1.0.tar.gz
  - http://cse.seu.edu.cn/PersonalPage/zhangml/Resources.htm#codes
- Multi-label learning (MLL)
  - http://mulan.sourceforge.net/index.html
  - http://meka.sourceforge.net/
  - http://palm.seu.edu.cn/zhangml/Resources.htm#codes_mll
- Multi-instance multi-label learning (MIML)
  - http://lamda.nju.edu.cn/code_MIML.ashx
- Label distribution learning (LDL)
  - http://cse.seu.edu.cn/PersonalPage/xgeng/LDL

Thanks!