标记分布学习范式

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报告内容

- **研究背景**
- **概念定义**
- **学习算法**
- **实验**
- **结论**

机器学习中的多义性（Ambiguity）

非一一映射

标记端多义性

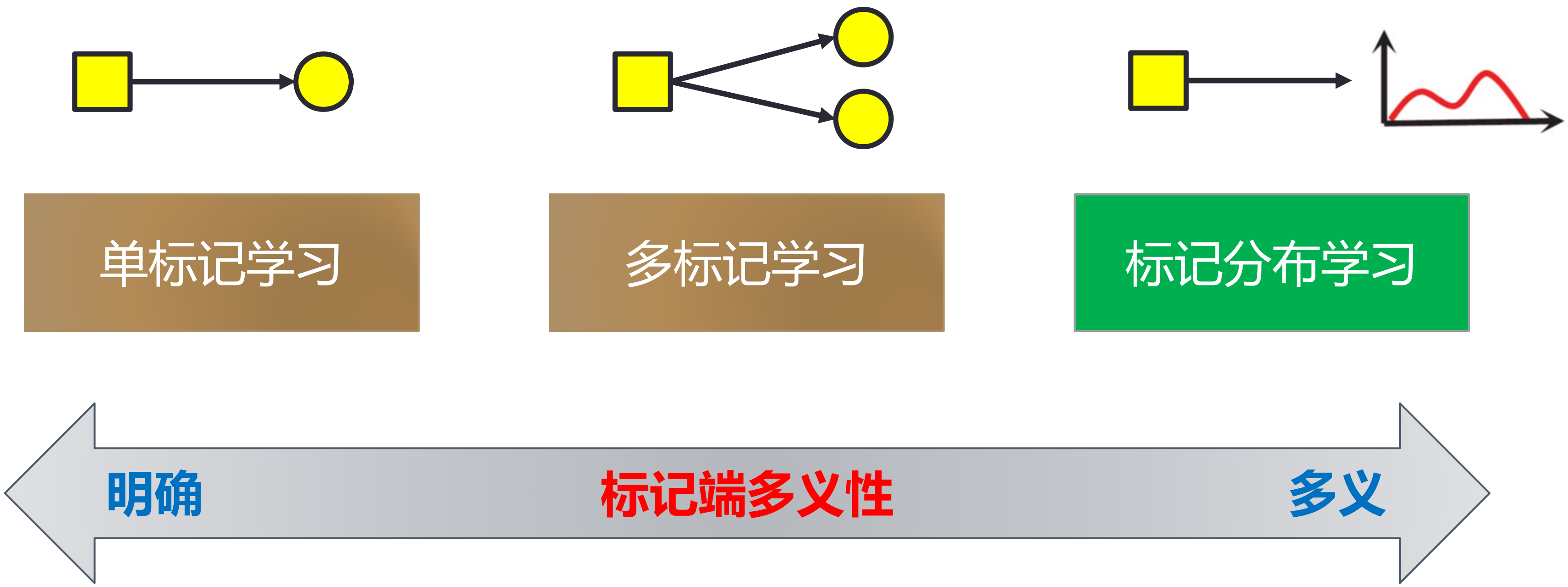
示例 → 机器学习 → 标记

多示例学习范式
（多对一）

多标记学习范式
（一对多）

多示例多标记学习范式
（多对多）

标记端多义性



举例：自然场景图像

- “**哪些**标记可以用于描述该示例?”

云

天空

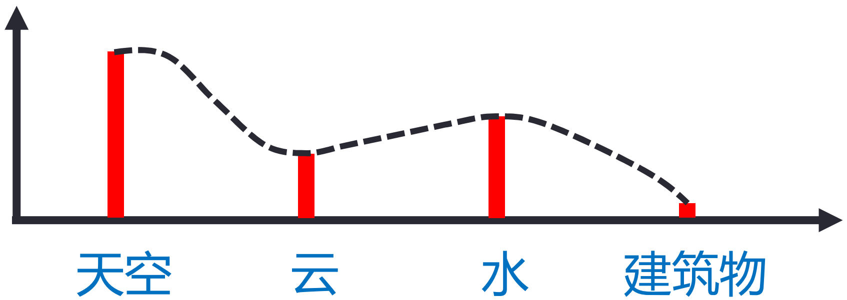
建筑

水

多标记学习

举例：自然场景图像

- “每个标记**如何**描述该示例?”



更多数据…

15个标记分布数据集，可从如下链接下载：
http://cse.seu.edu.cn/PersonalPage/xgeng/LDL

No.	数据集	样例数	特征数	标记数
1	Yeast-alpha	2,465	24	18
2	Yeast-cdc	2,465	24	15
3	Yeast-elu	2,465	24	14
4	Yeast-diau	2,465	24	7
5	Yeast-heat	2,465	24	6
6	Yeast-spo	2,465	24	6
7	Yeast-cold	2,465	24	4
8	Yeast-dtt	2,465	24	4
9	Yeast-spo5	2,465	24	3
10	Yeast-spoem	2,465	24	2
11	Human Gene	30,542	36	68
12	Natural Scene	2,000	294	9
13	SJAFFE	213	243	6
14	SBU_3DFE	2,500	243	6
15	Movie	7,755	1,869	5

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标记分布学习

[Geng, TKDE'16]

对一个示例 $\boldsymbol{x}$ 来说，给每个标记 y 赋予一个实数值 $d_{\boldsymbol{x}}^{y}$，表示 y 描述 $\boldsymbol{x}$ 的程度；

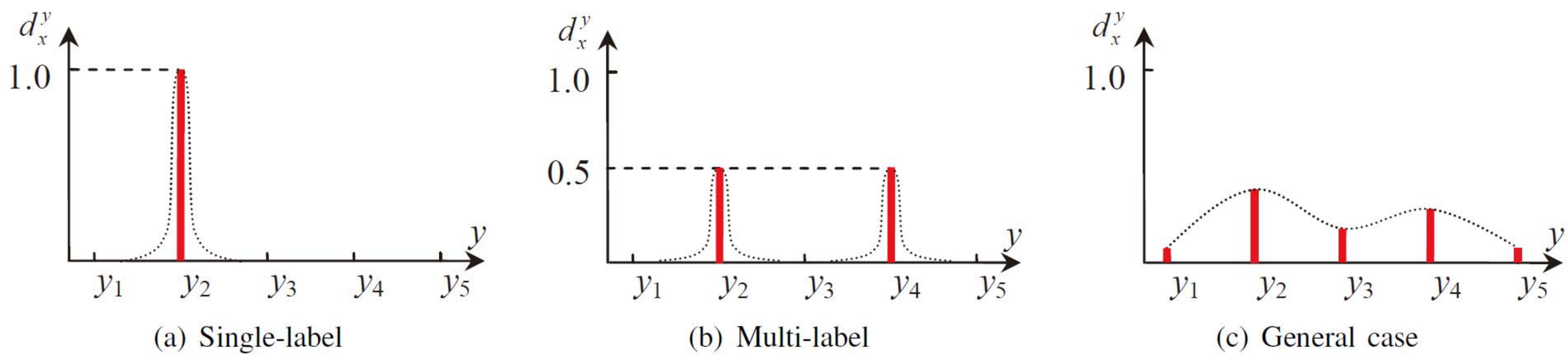
不失一般性，假设 $d_{\boldsymbol{x}}^{y} \in [0,1]$；

进一步假设标记集合是完备集（用所有该集合中的标记一定能够完全描述一个示例），则 $\sum_y d_{\boldsymbol{x}}^{y} = 1$；

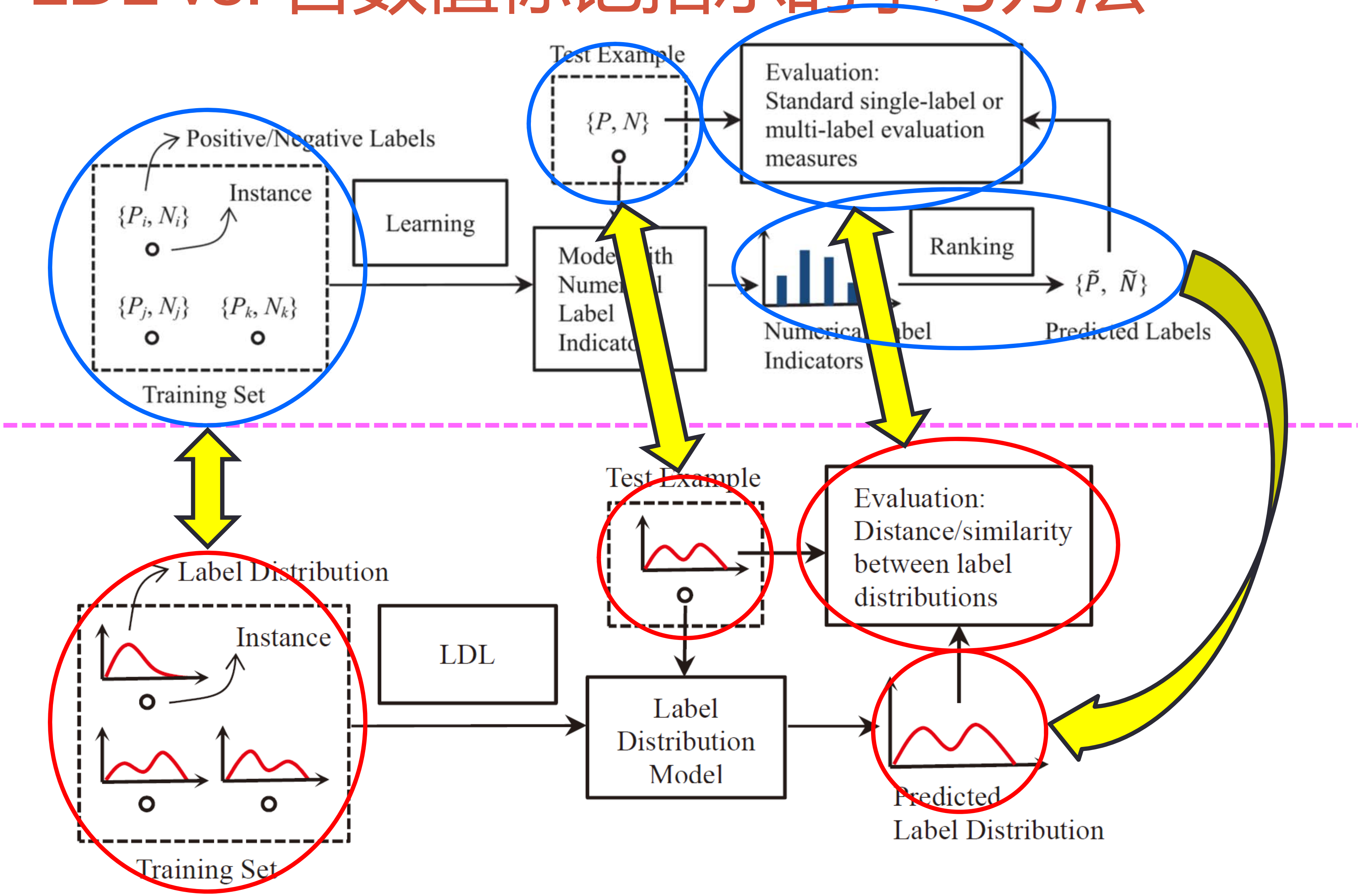
- 满足上述条件的 $d_{\boldsymbol{x}}^{y}$ 称为 y 对 $\boldsymbol{x}$ 的**描述度**
- 对一个示例来讲，所有标记的描述度构成的数据结构称为**标记分布** $D_i = \{d_{\boldsymbol{x}_i}^{y_1}, d_{\boldsymbol{x}_i}^{y_2}, \ldots, d_{\boldsymbol{x}_i}^{y_c}\}$
- 在以标记分布标注的示例上学习的过程称为**标记分布学习（Label Distribution Learning，LDL）**

LDL vs. 传统学习范式

传统单标记学习（SLL）和多标记学习（MLL）
可以看作标记分布学习（LDL）的特例



LDL vs. 含数值标记指示的学习方法



LDL形式化定义

[Geng, TKDE'16]

$$d_{\boldsymbol{x}}^{y} = P(y|\boldsymbol{x})$$

一种可能的形式化定义形式

Let $\mathcal{X} = \mathbb{R}^q$ denote the input space and $\mathcal{Y} = \{y_1, y_2, \ldots, y_c\}$ denote the complete set of labels. Given a training set $S = \{(\boldsymbol{x}_1, D_1), (\boldsymbol{x}_2, D_2), \ldots, (\boldsymbol{x}_n, D_n)\}$, the goal of ldl is to learn a conditional probability mass function $p(y|\boldsymbol{x})$ from S, where $\boldsymbol{x} \in \mathcal{X}$ and $y \in \mathcal{Y}$.

LDL优化目标

- 参数形式 $p(y|x;\boldsymbol{\theta})$
- 预测分布与真实分布之间的距离度量：K-L散度

$$\begin{aligned}\boldsymbol{\theta}^* &= \operatorname*{argmin}_{\boldsymbol{\theta}} \sum_i \sum_j \left(d_{\boldsymbol{x}_i}^{y_j} \ln \frac{d_{\boldsymbol{x}_i}^{y_j}}{p(y_j|\boldsymbol{x}_i;\boldsymbol{\theta})} \right) \\ &= \operatorname*{argmax}_{\boldsymbol{\theta}} \sum_i \sum_j d_{\boldsymbol{x}_i}^{y_j} \ln p(y_j|\boldsymbol{x}_i;\boldsymbol{\theta}).\end{aligned}$$

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LDL算法

- 三种算法设计策略
  - 问题转化（Problem Transformation）
    将LDL问题转化为传统学习范式
  - 算法改造（Algorithm Adaption）
    将传统学习算法改造为能够处理标记分布
  - 专用算法（Specialized Algorithms）
    为LDL专门设计的算法

专用算法

- 假设 $p(y|x;\boldsymbol{\theta})$ 为最大熵模型（MaxEnt Model）

$$p(y|\boldsymbol{x};\boldsymbol{\theta}) = \frac{1}{Z}\exp\left(\sum_k \theta_{y,k} g_k(\boldsymbol{x})\right) \quad Z = \sum_y \exp\left(\sum_k \theta_{y,k} g_k(\boldsymbol{x})\right)$$

$$\Downarrow$$

$$\begin{aligned}\boldsymbol{\theta}^* &= \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \sum_i \sum_j \left(d_{\boldsymbol{x}_i}^{y_j} \ln \frac{d_{\boldsymbol{x}_i}^{y_j}}{p(y_j|\boldsymbol{x}_i;\boldsymbol{\theta})} \right) \\ &= \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \sum_i \sum_j d_{\boldsymbol{x}_i}^{y_j} \ln p(y_j|\boldsymbol{x}_i;\boldsymbol{\theta}).\end{aligned}$$

$$\Downarrow$$

$$T(\boldsymbol{\theta}) = \sum_{i,j} d_{\boldsymbol{x}_i}^{y_j} \sum_k \theta_{y_j,k} g_k(\boldsymbol{x}_i) - \sum_i \ln \sum_j \exp\left(\sum_k \theta_{y_j,k} g_k(\boldsymbol{x}_i)\right)$$

专用算法

- IIS-LLD [Geng, Yin, and Zhou, TPAMI'13]
  [Geng, Smith-Miles, and Zhou, AAAI'10]

Algorithm 1: IIS-LLD

Input: The training set $S = \{(\boldsymbol{x}_i, D_i)\}_{i=1}^{n}$ and the convergence criterion ε

Output: $p(y|\boldsymbol{x};\boldsymbol{\theta})$

Initialize the model parameter vector $\boldsymbol{\theta}^{(0)}$;

$l \leftarrow 0$;

repeat

  $l \leftarrow l + 1$;

  Solve Eq. (4) for $\delta_{y,k}$;

  $\boldsymbol{\theta}^{(l)} \leftarrow \boldsymbol{\theta}^{(l-1)} + \boldsymbol{\Delta}$;

until $T(\boldsymbol{\theta}^{(l)}) - T(\boldsymbol{\theta}^{(l-1)}) < \varepsilon$;

$p(y|\boldsymbol{x};\boldsymbol{\theta}) \leftarrow \frac{1}{Z}\exp\left(\sum_k \theta_{y,k}^{(l)} g_k(\boldsymbol{x})\right)$;

$$\sum_i p(y_j|\boldsymbol{x}_i;\boldsymbol{\theta}) g_k(\boldsymbol{x}_i) \exp(\delta_{y_j,k} s(g_k(\boldsymbol{x}_i)) g^{\#}(\boldsymbol{x}_i)) - \sum_i d_{\boldsymbol{x}_i}^{y_j} g_k(\boldsymbol{x}_i) = 0, \tag{4}$$

专用算法

- BFGS-LLD
  [Geng, TKDE'16]

$$\frac{\partial T'(\boldsymbol{\theta})}{\partial \theta_{y_j,k}} = \sum_i \frac{\exp\left(\sum_k \theta_{y_j,k} g_k(\boldsymbol{x}_i)\right) g_k(\boldsymbol{x}_i)}{\sum_j \exp\left(\sum_k \theta_{y_j,k} g_k(\boldsymbol{x}_i)\right)} - \sum_i d_{\boldsymbol{x}_i}^{y_j} g_k(\boldsymbol{x}_i). \tag{14}$$

Algorithm 2: BFGS-LLD

Input: The training set $S = \{(\boldsymbol{x}_i, D_i)\}_{i=1}^n$ and the convergence criterion ε
Output: $p(y|\boldsymbol{x};\boldsymbol{\theta})$

Initialize the model parameter vector $\boldsymbol{\theta}^{(0)}$;
Initialize the inverse Hessian approximation $\boldsymbol{B}^{(0)}$;
Compute $\nabla T'(\boldsymbol{\theta}^{(0)})$ by Eq. (14);
$l \leftarrow 0$;
repeat
  Compute search direction $\boldsymbol{p}^{(l)} \leftarrow -\boldsymbol{B}^{(l)} \nabla T'(\boldsymbol{\theta}^{(l)})$;
  Compute the step length $\alpha^{(l)}$ by a line search procedure to satisfy Eq. (8) and (9);
  $\boldsymbol{\theta}^{(l+1)} \leftarrow \boldsymbol{\theta}^{(l)} + \alpha^{(l)} \boldsymbol{p}^{(l)}$;
  Compute $\nabla T'(\boldsymbol{\theta}^{(l+1)})$ by Eq. (14);
  $\boldsymbol{s}^{(l)} \leftarrow \boldsymbol{\theta}^{(l+1)} - \boldsymbol{\theta}^{(l)}$;
  $\boldsymbol{u}^{(l)} \leftarrow \nabla T'(\boldsymbol{\theta}^{(l+1)}) - \nabla T'(\boldsymbol{\theta}^{(l)})$;
  $\boldsymbol{\rho}^{(l)} \leftarrow \frac{1}{\boldsymbol{s}^{(l)} \boldsymbol{u}^{(l)}}$;
  $\boldsymbol{B}^{(l+1)} \leftarrow (\boldsymbol{I} - \boldsymbol{\rho}^{(l)} \boldsymbol{s}^{(l)} (\boldsymbol{u}^{(l)})^{\mathrm{T}}) \boldsymbol{B}^{(l)} (\boldsymbol{I} - \boldsymbol{\rho}^{(l)} \boldsymbol{u}^{(l)} (\boldsymbol{s}^{(l)})^{\mathrm{T}}) + \boldsymbol{\rho}^{(l)} \boldsymbol{s}^{(l)} (\boldsymbol{s}^{(l)})^{\mathrm{T}}$;
  $l \leftarrow l + 1$;
until $||\nabla T'(\boldsymbol{\theta}^{(l)})|| < \varepsilon$;
$p(y|\boldsymbol{x};\boldsymbol{\theta}) \leftarrow \frac{1}{Z} \exp\left(\sum_k \theta_{y,k}^{(l)} g_k(\boldsymbol{x})\right)$;

专用算法 – 更多...

- 两种算法设计路线
  - **分类**

    用条件质量函数 $p(y|\boldsymbol{x})$ 为示例 $\boldsymbol{x}$ 到标记分布 $\boldsymbol{D}$ 之间的映射建模
    - IIS-LLD [Geng, Smith-Miles and Zhou, AAAI'10]
    - CPNN [Geng, Yin and Zhou, TPAMI'13]
    - BFGS-LLD [Geng, TKDE'16]
    - SCE-LDL [Yang, Geng and Zhou, IJCAI'16]
  - **回归**

    用多元回归为示例 $\boldsymbol{x}$ 到标记分布 $\boldsymbol{D}$ 之间的映射建模
    - LDSVR [Geng and Hou, IJCAI'15]
    - LDLogitBoost [Xing, Geng and Xue, CVPR'16]

算法代码下载地址：
http://cse.seu.edu.cn/PersonalPage/xgeng/LDL

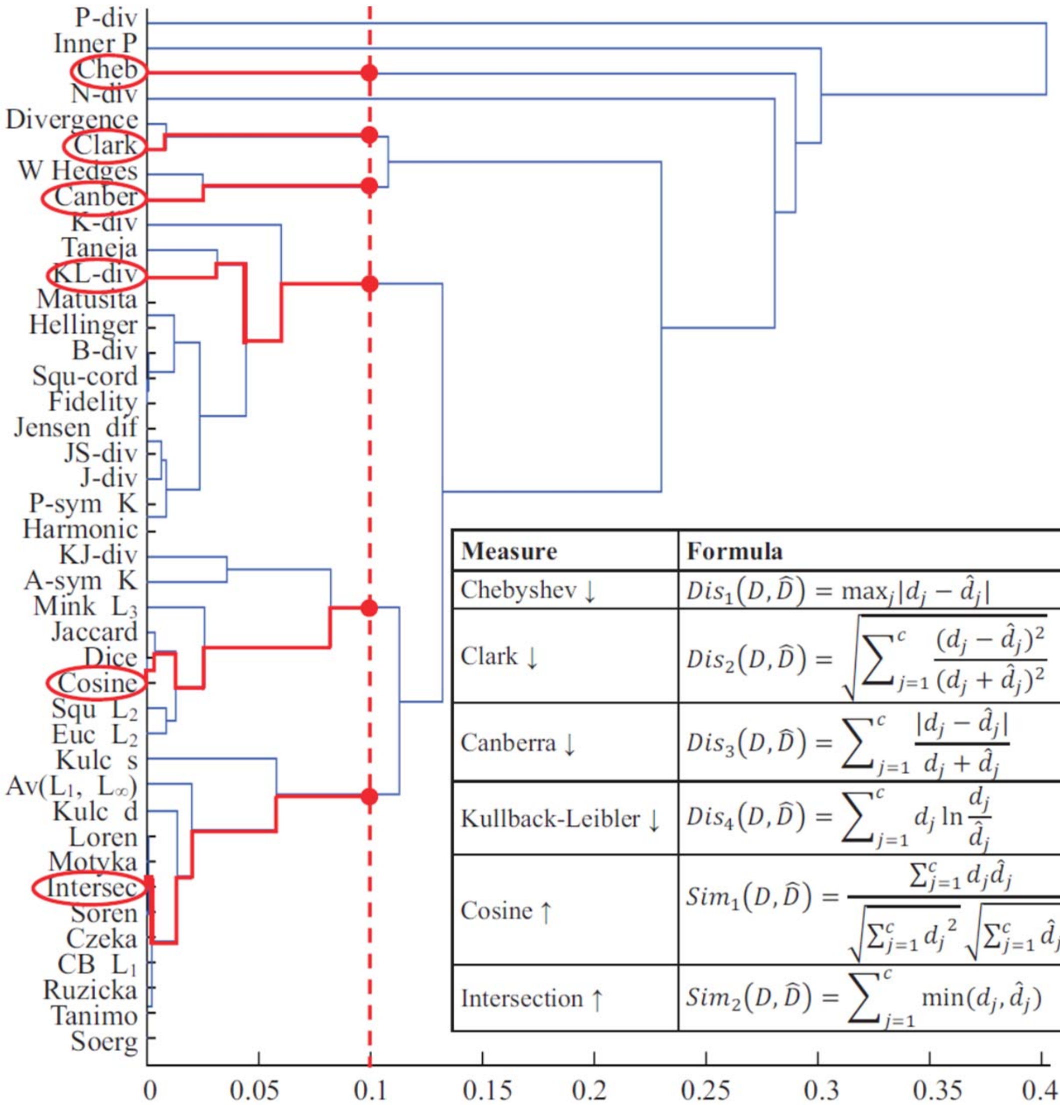
LDL算法评价指标 [Geng, TKDE'16]

- 预测标记分布与真实标记分布之间的平均距离/相似度

从41种度量中，通过一个单连接聚合层次聚类过程选择出6种度量

选择准则：

1. 任意两个度量之间距离大于0.1；
2. 每个度量来自不同语法族；
3. 一般不易受到不稳定情况（如分母为0）影响；
4. 常见度量



Measure	Formula
Chebyshev ↓	$Dis_1(D,\hat{D}) = \max_j \lvert d_j - \hat{d}_j \rvert$
Clark ↓	$Dis_2(D,\hat{D}) = \sqrt{\sum_{j=1}^{c} \frac{(d_j - \hat{d}_j)^2}{(d_j + \hat{d}_j)^2}}$
Canberra ↓	$Dis_3(D,\hat{D}) = \sum_{j=1}^{c} \frac{\lvert d_j - \hat{d}_j \rvert}{d_j + \hat{d}_j}$
Kullback-Leibler ↓	$Dis_4(D,\hat{D}) = \sum_{j=1}^{c} d_j \ln \frac{d_j}{\hat{d}_j}$
Cosine ↑	$Sim_1(D,\hat{D}) = \frac{\sum_{j=1}^{c} d_j \hat{d}_j}{\sqrt{\sum_{j=1}^{c} d_j^2}\sqrt{\sum_{j=1}^{c} \hat{d}_j^2}}$
Intersection ↑	$Sim_2(D,\hat{D}) = \sum_{j=1}^{c} \min(d_j, \hat{d}_j)$

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真实世界数据

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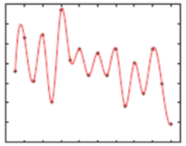
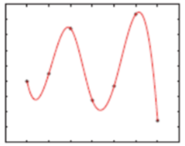
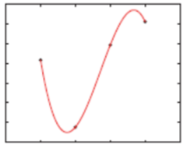
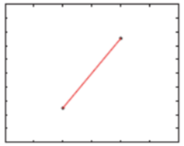
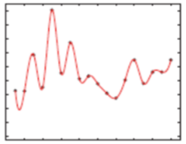
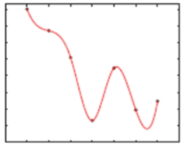
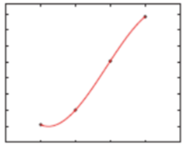
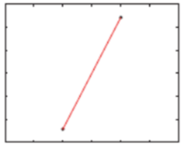
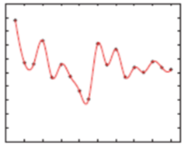
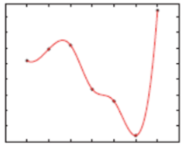
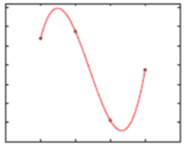
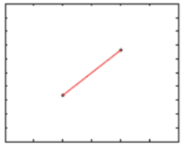
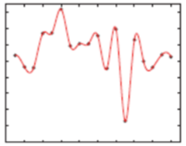
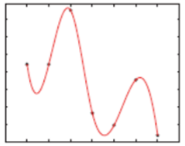
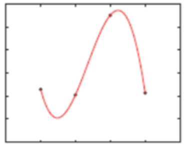
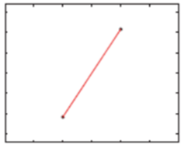
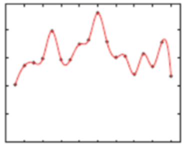
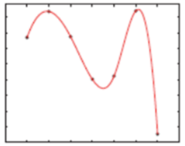
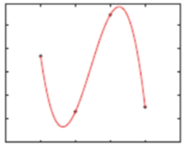
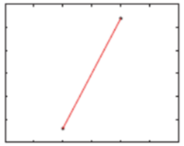
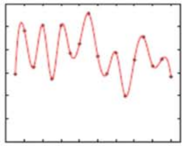
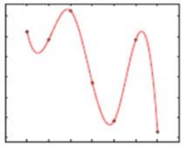
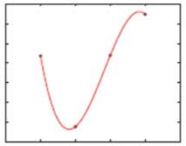
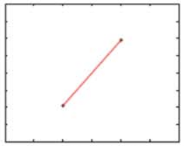
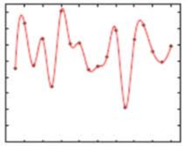
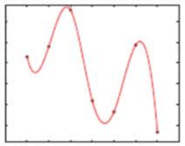
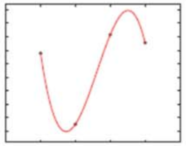
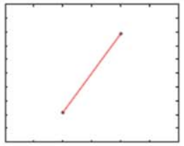
典型预测结果举例

Real	 18 Labels	 7 Labels	 4 Labels	 2 Labels
PT-Bayes	 {0.048, 0.552, 1.885, 0.036} {0.960 0.891}	 {0.042, 0.230, 0.492, 0.016} {0.984, 0.929}	 {0.170, 0.516, 0.911, 0.128} {0.907, 0.786}	 {0.192, 0.310, 0.421, 0.086} {0.939, 0.808}
PT-SVM	 {0.006, 0.105, 0.368, 0.0012} {0.9988, 0.980}	 {0.040, 0.190, 0.359, 0.011} {0.990, 0.949}	 {0.041, 0.108, 0.188, 0.006} {0.995 0.954}	 {0.018, 0.025, 0.036, 0.001} {0.999, 0.982}
AA-kNN	 {0.005, 0.091, 0.282, 0.0009} {0.9991, 0.9844}	 {0.028, 0.151, 0.381, 0.007} {0.993, 0.945}	 {0.030, 0.080, 0.124, 0.003} {0.997, 0.970}	 {0.058, 0.085, 0.118, 0.007} {0.994, 0.942}
AA-BP	 {0.008, 0.156, 0.583, 0.003} {0.997, 0.968}	 {0.014, 0.076, 0.172, 0.002} {0.998, 0.975}	 {0.036, 0.085, 0.145 0.004} {0.996, 0.964}	 {0.069, 0.102, 0.143, 0.010} {0.991, 0.931}
SA-IIS	 {**0.004**, **0.083**, 0.283, **0.00077**} {**0.99923**, 0.9843}	 {0.013, 0.072, 0.160, 0.002} {0.998, 0.977}	 {0.016, 0.042 0.067 0.0008} {0.9992, 0.984}	 {0.012, 0.018, 0.025, 0.0003} {0.9997, 0.988}
SA-BFGS	 {0.006, 0.086, **0.260**, 0.00081} {0.99919, **0.986**}	 {**0.012**, **0.056**, **0.120**, **0.001**} {**0.999**, **0.983**}	 {**0.014**, **0.034**, **0.055**, **0.0006**} {**0.9994**, **0.987**}	 {**0.007**, **0.010**, **0.014**, **0.0001**} {**0.9999**, **0.993**}

真实世界数据（定量分析）

Experimental Results (mean $\pm$ std(rank)) on the Real-World Datasets Measured by Kullback-Leibler Divergence $\downarrow$

Dataset	PT-Bayes	PT-SVM	AA-kNN	AA-BP	SA-IIS	SA-BFGS
Yeast-alpha	0.719 $\pm$ 0.080(6)	0.009 $\pm$ 0.002(4)	0.0066 $\pm$ 0.001(2)	0.081 $\pm$ 0.011(5)	0.0067 $\pm$ 0.001(3)	**0.006 $\pm$ 0.001(1)**
Yeast-cdc	0.603 $\pm$ 0.073(6)	0.010 $\pm$ 0.002(4)	0.0083 $\pm$ 0.001(3)	0.060 $\pm$ 0.007(5)	0.0082 $\pm$ 0.001(2)	**0.007 $\pm$ 0.001(1)**
Yeast-elu	0.556 $\pm$ 0.071(6)	0.008 $\pm$ 0.001(4)	0.0074 $\pm$ 0.0004(3)	0.051 $\pm$ 0.009(5)	0.0073 $\pm$ 0.0005(2)	**0.006 $\pm$ 0.0004(1)**
Yeast-diau	0.306 $\pm$ 0.036(6)	0.019 $\pm$ 0.002(4)	0.015 $\pm$ 0.001(3)	0.024 $\pm$ 0.004(5)	0.014 $\pm$ 0.001(2)	**0.013 $\pm$ 0.001(1)**
Yeast-heat	0.255 $\pm$ 0.040(6)	0.0148 $\pm$ 0.001(4)	0.0145 $\pm$ 0.001(3)	0.021 $\pm$ 0.004(5)	0.0133 $\pm$ 0.0004(2)	**0.0126 $\pm$ 0.0005(1)**
Yeast-spo	0.281 $\pm$ 0.031(6)	0.0304 $\pm$ 0.005(4)	0.0302 $\pm$ 0.002(3)	0.034 $\pm$ 0.006(5)	0.0254 $\pm$ 0.003(2)	**0.0246 $\pm$ 0.003(1)**
Yeast-cold	0.208 $\pm$ 0.031(6)	0.0147 $\pm$ 0.001(4)	0.014 $\pm$ 0.001(3)	0.0149 $\pm$ 0.002(5)	0.013 $\pm$ 0.001(2)	**0.012 $\pm$ 0.001(1)**
Yeast-dtt	0.206 $\pm$ 0.029(6)	0.0073 $\pm$ 0.001(4)	0.0072 $\pm$ 0.001(3)	0.009 $\pm$ 0.001(5)	0.0070 $\pm$ 0.001(2)	**0.006 $\pm$ 0.001(1)**
Yeast-spo5	0.214 $\pm$ 0.025(6)	0.03010 $\pm$ 0.003(3)	0.033 $\pm$ 0.003(5)	0.031 $\pm$ 0.003(4)	0.03007 $\pm$ 0.003(2)	**0.029 $\pm$ 0.003(1)**
Yeast-spoem	0.190 $\pm$ 0.038(6)	0.0280 $\pm$ 0.004(4)	0.0285 $\pm$ 0.003(5)	0.026 $\pm$ 0.003(3)	0.025 $\pm$ 0.003(2)	**0.024 $\pm$ 0.003(1)**
Human Gene	1.887 $\pm$ 0.766(6)	0.240 $\pm$ 0.019(3)	0.301 $\pm$ 0.026(4)	0.500 $\pm$ 0.068(5)	0.238 $\pm$ 0.019(2)	**0.236 $\pm$ 0.019(1)**
Natural Scene	3.065 $\pm$ 0.487(6)	1.447 $\pm$ 0.243(4)	2.767 $\pm$ 0.137(5)	0.875 $\pm$ 0.029(3)	0.870 $\pm$ 0.026(2)	**0.854 $\pm$ 0.062(1)**
s-JAFFE	0.074 $\pm$ 0.014(4)	0.086 $\pm$ 0.016(5)	0.071 $\pm$ 0.023(3)	0.113 $\pm$ 0.030(6)	0.070 $\pm$ 0.012(2)	**0.064 $\pm$ 0.016(1)**
s-BU_3DFE	0.079 $\pm$ 0.004(4)	0.089 $\pm$ 0.007(6)	0.065 $\pm$ 0.002(2)	0.085 $\pm$ 0.009(5)	0.068 $\pm$ 0.004(3)	**0.049 $\pm$ 0.002(1)**
Movie	0.953 $\pm$ 0.352(6)	0.268 $\pm$ 0.079(5)	0.201 $\pm$ 0.011(4)	0.179 $\pm$ 0.03(3)	**0.137 $\pm$ 0.013(1)**	0.140 $\pm$ 0.020(2)
Avg. Rank	5.73	4.13	3.40	4.60	2.07	1.07

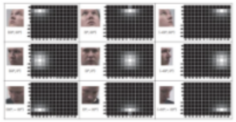
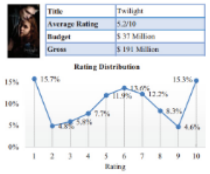
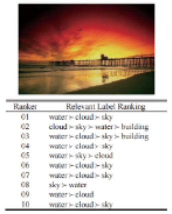
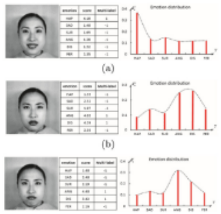
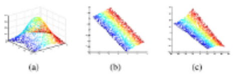
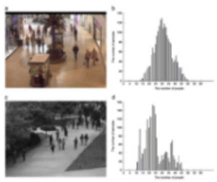
真实世界数据（定量分析）

- 算法比较（6个指标上平均排序一致）

  SA-BFGS > SA-IIS > AA-*k*NN > PT-SVM > AA-BP > PT-Bayes

  - 专用算法（SA-BFGS和SA-IIS）比传统算法转化（PT）或改造（AA）来的算法更好；
  - SA-BFGS比SA-IIS更好一些；
  - PT-Bayes的Gaussian假设可能不适用真实世界数据；
  - AA-BP较容易过配；
  - AA-*k*NN保留了标记分布的整体性，而PT-SVM破坏了这种整体性

实际应用

	Facial Age Estimation • X. Geng, Q. Wang, and Y. Xia. Facial Age Estimation by A … on (*ICPR'14*), Stockholm, Sweden, 2014, pp. 4465 - 4470. • X. Geng, C. Yin, and Z.-H. Zhou. Facial Age Estimation by … *MI*), 2013, 35(10): 2401-2412. • X. Geng, K. Smith-Miles, Z.-H. Zhou. Facial Age Estimatio … *AAI'10*), Atlanta, GA, 2010, pp. 451-456. **人脸年龄估计**
	Head Pose Estimation • X. Geng and Y. Xia. Head Pose Estimation Based on Mult … *ecognition* (*CVPR'14*),Columbus, OH, 2014, pp. 1837-1842. **头部姿态估计**
	Pre-release Prediction of Movies • X.Geng and P.Hou. Pre-release Prediction of Crowd Opinion on Movies by Label Distribution Learning. In: *Proceedings of the International Joint Conference on Artificial Intelligence* (***IJCAI'15***), Buenos Aires, Argentina, 2015, 3511-3517. **电影评价预测**
	Multi-label Ranking • X. Geng and L.-L Luo. Multilabel Ranking with Inconsistent Rankers. In: *Proceedings of IEEE International Conference on Computer Vision and Pattern Recognition* (***CVPR'14***), Columbus, OH, 2014, pp. 3742-3747. **自然场景图像多标记排序**
	Emotion Distribution Recognition • X.Geng and P.Hou. Y. Zhou, H. Xue and X. Geng, Emotion Distribution Recognition from Facial Expressions. In: *Proceedings of the 23rd ACM International Conference on Multimedia* (***ACM MM'15***), Brisbane, Australia, 2015, 1247-1250. **情感分布识别**
	Multi-label Learning • P. Hou, X. Geng and M.-L. Zhang. Multi-Label Manifold Learning. In: *Proceedings of the 30th AAAI Conference on Artificial Intelligence* (***AAAI'16***), Phoenix, AZ, 2016, in press. • Y.-K. Li, M.-L. Zhang and X. Geng. Leveraging implicit relative labeling-importance information for effective multi-label learning. In: *Proceedings of the 15th IEEE International Conference on Data Mining* (***ICDM'15***), Atlantic City, NJ, 2015, 251-260.
	Crowd Counting • Z. Zhang, M. Wang, X. Geng. Crowd Counting in Public Video Surveillance by Label Distribution Learning. *Neurocomputing*, 2015, vol. 166: 151-163. **人群计数**

报告内容

- **研究背景**
- **概念定义**
- **学习算法**
- **实验**
- **结论**

总结

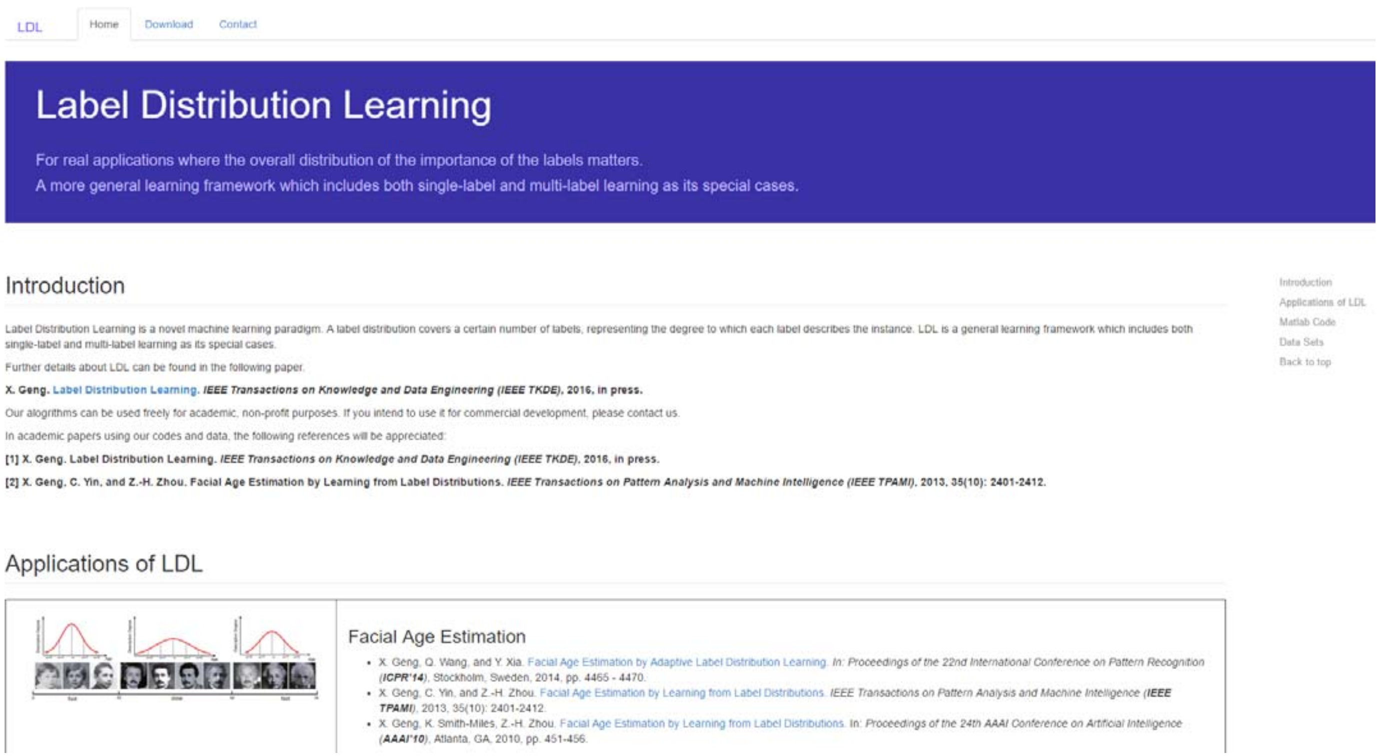
- **标记分布学习**
  - 是一种比传统单标记和多标记学习更为泛化的学习范式
  - 能够处理标记的不同重要程度（描述度）
  - 对某些实际问题匹配的更好
  - 需要专门的算法设计

- **标记分布学习适用于**
  - **数据本身具有某种天然的描述度度量**
  - **标记之间有较强相关性**
  - **同一示例由多个标注源标注并产生不一致性**
  - **同一示例与多个标记相关，且标记重要程度不同**
  - **……**

对LDL感兴趣？

所有LDL论文、算法代码和数据集可从如下地址下载：

http://cse.seu.edu.cn/PersonalPage/xgeng/LDL



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Label Distribution Learning

For real applications where the overall distribution of the importance of the labels matters.
A more general learning framework which includes both single-label and multi-label learning as its special cases.

Introduction

Introduction
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Label Distribution Learning is a novel machine learning paradigm. A label distribution covers a certain number of labels, representing the degree to which each label describes the instance. LDL is a general learning framework which includes both single-label and multi-label learning as its special cases.

Further details about LDL can be found in the following paper.

X. Geng. Label Distribution Learning. *IEEE Transactions on Knowledge and Data Engineering (IEEE TKDE)*, 2016, in press.

Our alogrithms can be used freely for academic, non-profit purposes. If you intend to use it for commercial development, please contact us.

In academic papers using our codes and data, the following references will be appreciated:

[1] X. Geng. Label Distribution Learning. *IEEE Transactions on Knowledge and Data Engineering (IEEE TKDE)*, 2016, in press.

[2] X. Geng, C. Yin, and Z.-H. Zhou. Facial Age Estimation by Learning from Label Distributions. *IEEE Transactions on Pattern Analysis and Machine Intelligence (IEEE TPAMI)*, 2013, 35(10): 2401-2412.

Applications of LDL

Facial Age Estimation

- X. Geng, Q. Wang, and Y. Xia. Facial Age Estimation by Adaptive Label Distribution Learning. *In: Proceedings of the 22nd International Conference on Pattern Recognition (**ICPR'14**)*, Stockholm, Sweden, 2014, pp. 4465 - 4470.
- X. Geng, C. Yin, and Z.-H. Zhou. Facial Age Estimation by Learning from Label Distributions. *IEEE Transactions on Pattern Analysis and Machine Intelligence (**IEEE TPAMI**)*, 2013, 35(10): 2401-2412.
- X. Geng, K. Smith-Miles, Z.-H. Zhou. Facial Age Estimation by Learning from Label Distributions. In: *Proceedings of the 24th AAAI Conference on Artificial Intelligence (**AAAI'10**)*, Atlanta, GA, 2010, pp. 451-456.

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5. Xin Geng and Peng Hou. Pre-release Prediction of Crowd Opinion on Movies by Label Distribution Learning. In: *Proceedings of the International Joint Conference on Artificial Intelligence (**IJCAI'15**)*, Buenos Aires, Argentina, 2015, 3511-3517.
6. Ying Zhou, Hui Xue, Xin Geng, Emotion Distribution Recognition from Facial Expressions. In: *Proceedings of the 23rd ACM International Conference on Multimedia (**ACM MM'15**)*, Brisbane, Australia, 2015, 1247-1250.
7. Yu-Kun Li, Min-Ling Zhang, Xin Geng. Leveraging implicit relative labeling-importance information for effective multi-label learning. In: *Proceedings of the 15th IEEE International Conference on Data Mining (**ICDM'15**)*, Atlantic City, NJ, in press.
8. Xin Geng and Yu Xia. Head Pose Estimation Based on Multivariate Label Distribution. In: *Proceedings of IEEE International Conference on Computer Vision and Pattern Recognition* (***CVPR'14***), Columbus, OH, 2014, pp. 1837-1842.
9. Xin Geng and Longrun Luo. Multilabel Ranking with Inconsistent Rankers. In: *Proceedings of IEEE International Conference on Computer Vision and Pattern Recognition* (***CVPR'14***), Columbus, OH, 2014, pp. 3742-3747.
10. Xin Geng, Chao Yin, and Zhi-Hua Zhou. Facial Age Estimation by Learning from Label Distributions. *IEEE Transactions on Pattern Analysis and Machine Intelligence (**IEEE TPAMI**)*, 2013, 35(10): 2401-2412.
11. Xin Geng and Rongzi Ji. Label Distribution Learning. In Proceedings of the 2013 International Conference on Data Mining Workshops (***ICDMW'13***), Dallas, TA, 2013, pp. 377-383.
12. Xin Geng, Kate Smith-Miles, Zhi-Hua Zhou. Facial Age Estimation by Learning from Label Distributions. In: *Proceedings of the 24th AAAI Conference on Artificial Intelligence* (***AAAI'10***), Atlanta, GA, 2010, pp. 451-456.

致谢

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谢谢！

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