Multi Class Classification without Multi Class Label

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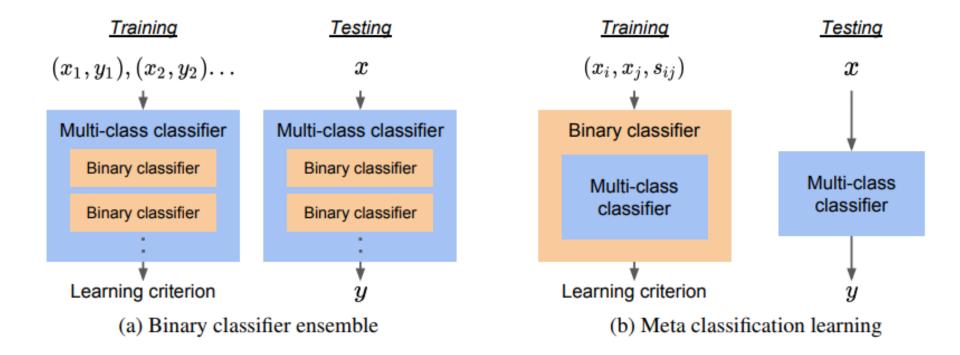
Motivation

- Per class label are expensive to collect
- Labeling require prior knowledge
- Different methods for different types of labeling:
 - Supervised learning
 - Cross-task unsupervised learning
 - Semi-supervised learning

Motivation

- Similarity label instead of class label
 - Reduce problem to binary classification
 - one-vs-one
 - one-vs-all
- Contributions:
 - New Loss function to encapsulate multi-class classifier in binary classifier
 - Experiments on supervised, unsupervised and semi-supervised settings

General Idea



MCL

$$\mathcal{L}(\theta; \mathbf{X}, \mathbf{Y}, \mathbf{S}) = P(\mathbf{X}, \mathbf{Y}, \mathbf{S}; \theta) = P(\mathbf{S}|\mathbf{Y})P(\mathbf{Y}|\mathbf{X}; \theta)P(\mathbf{X})$$

$$P(S_{ij} = 1 | Y_i, Y_j) = 1$$
 $Y_i = Y_j$
 $P(S_{ij} = 0 | Y_i, Y_j) = 1$ $Y_i \neq Y_j$

$$P(S|Y) = \prod_{i,j} P(S_{ij}|Y_i, Y_j)$$

MCL

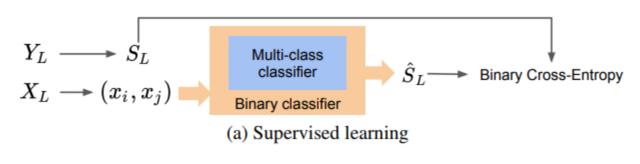
$$\begin{split} \mathcal{L}(\theta; \mathbf{X}, \mathbf{S}) &\approx \sum_{\mathbf{Y}} \mathsf{P}(\mathbf{S}|\mathbf{Y}) \mathsf{P}(\mathbf{Y}|\mathbf{X}; \theta) \\ &\approx \prod_{i,j} \Big(\sum_{Y_i = Y_j} \mathbb{1}[s_{ij} = 1] \mathsf{P}(Y_i|x_i; \theta) \mathsf{P}(Y_j|x_j; \theta) + \\ &\sum_{Y_i \neq Y_j} \mathbb{1}[s_{ij} = 0] \mathsf{P}(Y_i|x_i; \theta) \mathsf{P}(Y_j|x_j; \theta) \Big). \\ L_{meta}(\theta) &= -\sum_{i,j} \log \Big(\sum_{Y_i = Y_j} \mathbb{1}[s_{ij} = 1] \mathsf{P}(Y_i|x_i; \theta) \mathsf{P}(Y_j|x_j; \theta) + \\ &\sum_{Y_i \neq Y_j} \mathbb{1}[s_{ij} = 0] \mathsf{P}(Y_i|x_i; \theta) \mathsf{P}(Y_j|x_j; \theta) \Big) \\ &= -\sum_{i,j} s_{ij} \log(f(x_i; \theta)^T f(x_j; \theta)) + (1 - s_{ij}) \log(1 - f(x_i; \theta)^T f(x_j; \theta)). \end{split}$$

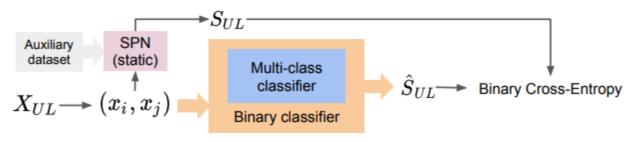
MCL

$$g(x_i, x_j, f(\cdot, \theta)) = f(x_i; \theta)^T f(x_j; \theta) = \hat{s}_{ij}$$

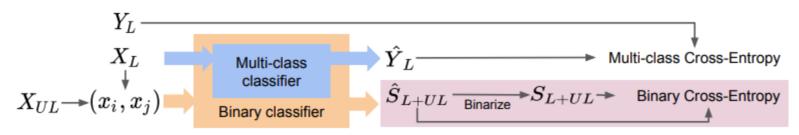
$$L_{meta} = -\sum_{i,j} s_{ij} \log \hat{s}_{ij} + (1 - s_{ij}) \log(1 - \hat{s}_{ij})$$

Learning Settings





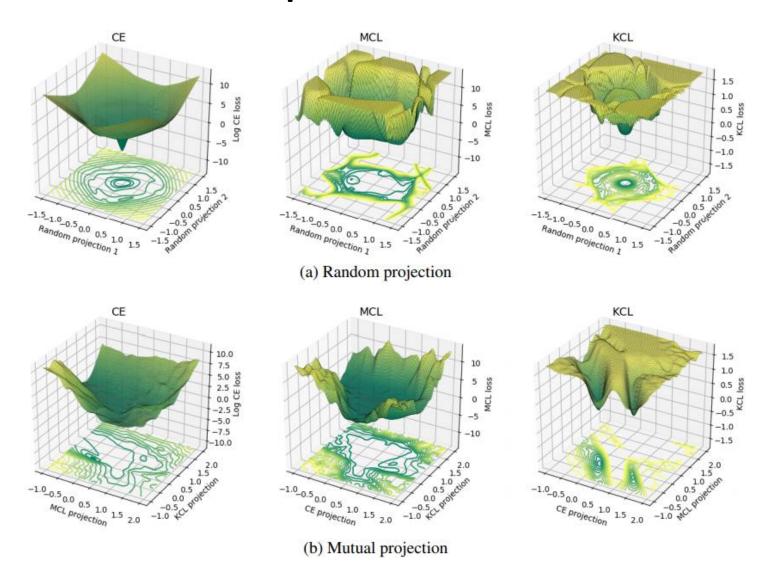
(b) Unsupervised transfer learning



(c) Pseudo-MCL for semi-supervised learning

- Supervised Classification
 - Image classification

Dataset #class		Network	(Class label) CE	(Pairwise label) KCL MCL		
MNIST	10	LeNet	0.6%	0.5%	0.6%	
CIFAR10	10	LeNet	14.9%	16.4%	15.1%	
		VGG8	10.2%	10.2%	10.2%	
		VGG11	8.9%	72.2(10.4)%	9.4%	
		VGG16	7.6%	*81.1(10.3)%	8.3%	
		ResNet18	6.7%	73.8%	6.6%	
		ResNet34	6.6%	79.3%	6.3%	
		ResNet50	6.6%	79.6%	5.9%	
		ResNet101	6.5%	79.9%	5.6 %	
CIFAR100	100	VGG8	35.4%	*45.3(40.2)%	36.1%	



- Unsupervised Transfer Learning:
 - Omniglot:
 - 20 images per 1623 handwritten characters
 - Train on 964 character and test on the others
 - ImageNet:
 - Images in 1000 class
 - Train on 882 class and test on the others
- Compare with clustering algorithms
- Two settings:
 - Known number of clusters
 - Unknown number of clusters

Method	ACC	ACC(K=100)	NMI	NMI(K=100)
K-means	71.9%	34.5%	0.713	0.671
LSC	73.3%	33.5%	0.733	0.655
LPNMF	43.0%	21.8%	0.526	0.500
KCL	73.8%	65.2%	0.750	0.715
MCL	74.4%	71.5%	0.762	0.765

Method	ACC	ACC (K=100)	NMI	NMI (K=100)
K-means (MacQueen et al., 1967)	21.7%	18.9%	0.353	0.464
LPNMF (Cai et al., 2009)	22.2%	16.3%	0.372	0.498
LSC (Chen & Cai, 2011)	23.6%	18.0%	0.376	0.500
ITML (Davis et al., 2007)	56.7%	47.2%	0.674	0.727
SKKm (Anand et al., 2014)	62.4%	46.9%	0.770	0.781
SKLR (Amid et al., 2016)	66.9%	46.8%	0.791	0.760
CSP (Wang et al., 2014)	62.5%	65.4%	0.812	0.812
MPCK-means (Bilenko et al., 2004)	81.9%	53.9%	0.871	0.816
KCL (Hsu et al., 2018)	82.4%	78.1%	0.889	0.874
MCL (ours)	83.3%	80.2%	0.897	0.893

- Semi-Supervised Setting:
 - CIFAR 10
 - 4k labeled
 - 46k unlabeled

Method	CIFAR10 4k labels		
Supervised	$25.4\pm1.0\%$		
Pseudo-Label	$19.8 \pm 0.7\%$		
Π -model	$19.6 \pm 0.4\%$		
VAT	$18.2\pm0.4\%$		
SPN-MCL	$22.8 \pm 0.5\%$		
Pseudo-MCL	$18.0 \pm 0.4\%$		

Question?