

Classification from Positive, Unlabeled and Biased Negative Data

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Motivation

Unlabeled / [Test]

Labeled / [Training]

- Information retrieval, text classification
- Medical diagnosis: healthy population that goes through physical exams is biased

Related Work

- Semi-supervised learning:** N data in general implicitly assumed unbiased ; U data used for regularization
- Dataset shift:** a variant that has been rarely studied
Ex. Covariate shift ; Source component shift
- PU learning:** add bN data
- Pseudo-labeling / Importance-weighting

Problem Setting

Supervised (PN)

Semi-supervised (PNU)

PU

x : feature

y ∈ {+1, -1} : label

s ∈ {+1, -1} : latent variable causing the bias

N data with selection bias

$p(s = +1 | x, y = +1) = 1$

Positive (P) Negative (N)

Positive (P) Negative (N)

Positive (P)

Unlabeled (U)

Unlabeled (U)

Positive (P)

Biased Negative (bN)

Unlabeled (U)

PUbN

Method

Empirical Risk Minimization

Risk Minimization

$$\min_{g \in \mathcal{G}} \mathbb{E}_{(x,y) \sim p(x,y)} [\ell(yg(x))] \quad \xleftarrow{\text{Unbiased Estimator}} \quad \min_{g \in \mathcal{G}} \frac{1}{n} \sum_{i=1}^n \ell(y_i g(x_i)) \quad \begin{array}{l} \#P \text{ data} + \#N \text{ data} \\ \hat{R}(g) \end{array}$$

Q: The N data are biased

$R(g) = \pi R_P^+(g) + \rho R_{bN}^-(g) + \frac{(1 - \pi - \rho) R_{s=-1}^-(g)}{\bar{R}_{s=-1}^-(g)}$

?

Idea: $\sigma(x)$ probability of x being labeled
 $\eta > 0$ determining how much attention paid to U data

$\bar{R}_{s=-1}^-(g) = \mathbb{E}_{x \sim p(x)} [1_{\sigma(x) \leq \eta} \ell(-g(x))(1 - \sigma(x))]$
#U data, Partial risk for samples with low probability of being labeled

$+ \pi \mathbb{E}_{x \sim p_P(x)} \left[1_{\sigma(x) > \eta} \ell(-g(x)) \frac{1 - \sigma(x)}{\sigma(x)} \right] + \rho \mathbb{E}_{x \sim p_{bN}} \left[1_{\sigma(x) > \eta} \ell(-g(x)) \frac{1 - \sigma(x)}{\sigma(x)} \right]$
#P data #bN data

Partial risk for samples with high probability of being labeled

$R_P^+(g) := \mathbb{E}_{x \sim p_P(x)} [\ell(g(x))] \quad \pi := p(y = +1) \quad \ell : \text{loss function}$
 $R_{bN}^-(g) := \mathbb{E}_{x \sim p_{bN}(x)} [\ell(-g(x))] \quad \rho := p(y = -1, s = +1)$
 $R_{s=-1}^-(g) := \mathbb{E}_{x \sim p(x|s=-1)} [\ell(-g(x))] \quad \sigma(x) := p(s = +1 | x)$

Algorithm Outline

Step 1

estimate $\sigma = p(s=+1|.)$: s as label

nnPU classifier (Kiryo+ NeurIPS 2017)

Step 2

final classifier: y as label

ERM: pseudo labeling + weight adjustment

Regarded as N

y = +1 y = -1

bN

Unlabeled (U)

PU risk estimator

Q: Severe overfitting

A: Avoid regarding all U as N

$R(g) = \mathbb{E}_{x \sim p(x)} \ell(-g(x)) + \pi \mathbb{E}_{x \sim p_P(x)} [\ell(g(x)) - \ell(-g(x))] \quad \begin{array}{l} \#U \text{ data} \\ \#P \text{ data} \end{array}$

Non-negative correction

N partial risk ≥ 0

$\tilde{R}_{pu}(g) = \frac{\pi}{n_P} \sum_{x \in \mathcal{X}_P} [\ell(g(x))] + \max \left\{ 0, \frac{1}{n_U} \sum_{x \in \mathcal{X}_U} \ell(-g(x)) - \frac{\pi}{n_P} \sum_{x \in \mathcal{X}_P} [\ell(-g(x))] \right\} \quad \begin{array}{l} \#P \text{ data} \\ \#U \text{ data} \\ \#P \text{ data} \end{array}$

Estimation Error Bound

With probability at least $1 - \delta$

$$R(\hat{g}) - R(g^*) \leq \frac{4\pi L_\ell \mathfrak{R}_{n_P, p_P}(\mathcal{G}) + 2\pi C_\ell \sqrt{\frac{\ln(6/\delta)}{2n_P}}}{\eta} + \frac{4\rho L_\ell \mathfrak{R}_{n_{bN}, p_{bN}}(\mathcal{G}) + 2\rho C_\ell \sqrt{\frac{\ln(6/\delta)}{2n_{bN}}}}{\eta} \quad \begin{array}{l} \#P \text{ data} \\ \#bN \text{ data} \end{array}$$

$$+ 4L_\ell \mathfrak{R}_{n_U, p}(\mathcal{G}) + 2C_\ell \sqrt{\frac{\ln(6/\delta)}{2n_U}} + 2C_\ell \sqrt{\zeta\epsilon} + \frac{2C_\ell}{\eta} \sqrt{(1 - \zeta)\epsilon} \quad \begin{array}{l} \#U \text{ data} \\ \text{Bias due to inexact approximation of } \sigma \end{array}$$

$\mathfrak{R}_{n,q}(\mathcal{G})$: Rademacher Complexity

$\hat{\sigma}$: estimate of σ $\zeta := p(\hat{\sigma}(x) \leq \eta)$ $\epsilon := \mathbb{E}_{x \sim p(x)} [|\hat{\sigma}(x) - \sigma(x)|^2]$

Assumption ℓ is L_ℓ -Lipschitz $\sup_{g \in \mathcal{G}} \|g\|_\infty \leq C_g$ $\sup_{|z| \leq C_g} \ell(z) \leq C_\ell$

- If RC terms vanish asymptotically, it holds a.s.
- Classical convergence rate + bias
- To control ϵ : approximation error + estimation error

Experiments

Setting

- Models: ConvNet / ResNet / FCN + Training: Amsgrad
- VALIDATION!** equally composed of P+U+bN
- 1/10 #U ~ #P = #bN ; Same model for the two steps

Baselines

- nnPNU (Sakai+ 2017 ICML): linear combination of PU and PN risk
- PU → PN: one classifier for s and one to separate P from bN

Results

Dataset	P	π	bN	p	nnPU/nnPNU	PUbN(N)	PU → PN	
MNIST	2, 4, 6, 8, 10	0.49	1, 3, 5	0.3	5.76 ± 1.04	4.64 ± 0.62	NA	
			9 > 5 > others	0.2	5.33 ± 0.97	4.05 ± 0.27	4.00 ± 0.30	
				0.2	4.60 ± 0.65	3.91 ± 0.66	3.77 ± 0.31	
CIFAR-10					12.02 ± 0.65	10.70 ± 0.57	NA	
			Airplane, automobile, ship, truck	0.4	10.25 ± 0.38	9.71 ± 0.51	10.37 ± 0.65	
				Horse > deer = frog > others	0.25	9.98 ± 0.53	9.92 ± 0.42	10.17 ± 0.35
CIFAR-10				Cat, dog, horse	0.3			
				Bird, frog	0.2			
				Car, truck	0.2			
					23.78 ± 1.04	21.13 ± 0.90	NA	
					22.00 ± 0.53	18.83 ± 0.71	19.88 ± 0.62	
					22.00 ± 0.74	20.19 ± 1.06	21.83 ± 1.36	
20 Newsgroups	alt., comp., misc., rec.	0.56		Not given	14.67 ± 0.87	13.30 ± 0.53	NA	
			sci. talk.	0.21	14.69 ± 0.46	13.10 ± 0.90	13.58 ± 0.97	
			soc. > talk. > sci.	0.17	14.38 ± 0.74	12.61 ± 0.75	13.76 ± 0.66	
				0.1	14.41 ± 0.76	12.18 ± 0.59	12.92 ± 0.51	

MNIST PCA

nnPNU

Other N

PubN

P

bN

bN data helps