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A General Formulation for Safely Exploiting Weakly Supervised Data

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What is this paper about

Weakly supervised data is one important machine learning data

It suffers one serious issue

- The usage of weakly supervised data may even degenerate performance, which means, it could be outperformed by its supervised counterpart using only a small number of labeled data

Contribution of this work

In this work, we consider to learn a safe prediction for weakly supervised learning, where safe means it will not be worse than its supervised counterpart. We propose a general formulation and give theoretical analysis. The experiments also show quite promising results

Outline

- **Introduction**
- Proposed Approach
- Experiments
- Conclusion

What is Weakly Supervised Learning

- Weakly supervised learning use the data that does not require a large amount of precise label information
- For Example:
  - Label Noise Learning [Fr´enay and Verleysen 2014]
  - Semi-Supervised Learning [Chapelle et al. 2006)]
  - Domain Adaptation [Pan and Yang 2010]
  - ...

Examples

- Label Noise Learning
  - We have only a small number of high-quality labeled data and a lot of noisy labeled data
- Semi-Supervised Learning
  - We have only limited labeled data and need to leverage a number of unlabeled data
- Domain Adaptation
  - Label information in target domain is not sufficient and we need to exploit further label information from other domains

Weakly supervised learning is not safe

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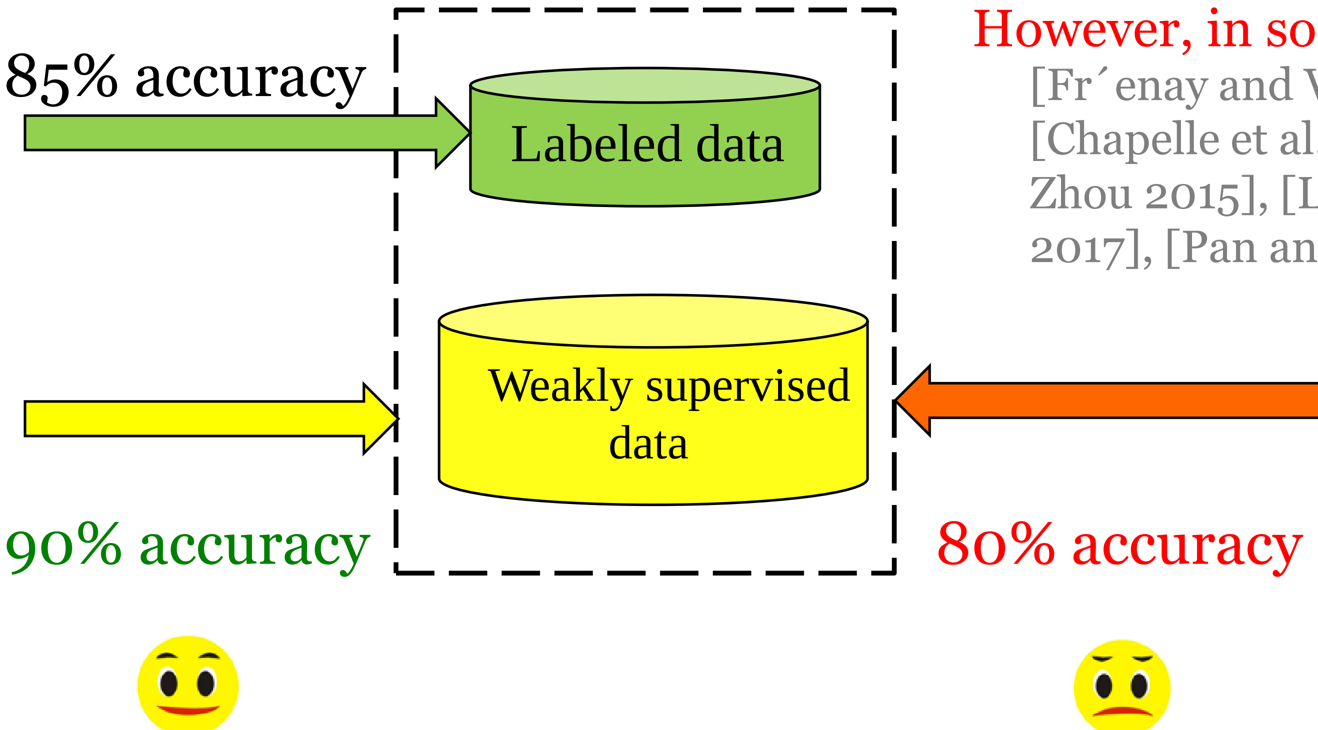
It is often expected that weakly supervised data can help improve performance since more data are used. However, it sometimes fails.



However, in some cases

[Fr´enay and Verleysen 2014], [Chapelle et al. 2006], [Li and Zhou 2015], [Li, Zha and Zhou 2017], [Pan and Yang 2010]

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The Basic Setup

- Suppose we have a set of weakly supervised learning predictions $\{y_i\}_{i=1}^{n}$
- These base predictions can be obtained in various ways, e.g., by different type of algorithms
- Moreover, we can easily train a supervised method with the use of only limited labeled data and let y_0 denote the prediction

The goal: to learn a safe prediction $g((y_1, \cdots y_n), y_0)$, which often outperform, and will not be worse than y_0

A Direct Approach

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Suppose we know the ground-truth $\boldsymbol{y}^*$, we can directly maximize the performance gain

$$\max_{\mathbf{y} \in \mathbb{H}^u} \ell(\mathbf{y}_0, \mathbf{y}^*) - \ell(\mathbf{y}, \mathbf{y}^*)$$

Trained on high-quality labeled data only

Ground Truth

However

Obviously, y^* is unknown

We can construct y^* with $\{y_i\}_{i=1}^{n}$, and consider the worst case for the requirement of safeness.

SafeW

$$\max_{\mathbf{y}\in\mathbb{H}^u} \boxed{\min_{\boldsymbol{\alpha}\in\mathcal{M}}} \ell(\mathbf{y}_0, \sum_{i=1}^{n} \alpha_i \mathbf{y}_i) - \ell(\mathbf{y}, \sum_{i=1}^{n} \alpha_i \mathbf{y}_i)$$

Worst case consideration [Li and Zhou, ICML2011/TPAMI2015; Balsubramani and Freund, COLT2015]

Three Questions about the formulation

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$$\max_{\mathbf{y}\in\mathbb{H}^u}\min_{\boldsymbol{\alpha}\in\mathcal{M}} \ell(\mathbf{y}_0,\sum_{i=1}^{n}\alpha_i\mathbf{y}_i)-\ell(\mathbf{y},\sum_{i=1}^{n}\alpha_i\mathbf{y}_i)$$

- Is this formulation reasonable?
- How to setup the set of weights $\mathcal{M}$?
- How to solve it efficiently?

Is this formulation reasonable?

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$$\max_{\mathbf{y}\in\mathbb{H}^u}\min_{\boldsymbol{\alpha}\in\mathcal{M}} \ell(\mathbf{y}_0, \sum_{i=1}^{n}\alpha_i\mathbf{y}_i) - \ell(\mathbf{y}, \sum_{i=1}^{n}\alpha_i\mathbf{y}_i)$$

Theoretical analysis:

Theorem 1. *Suppose the ground-truth* $\mathbf{y}^*$ *can be constructed by the base learners, i.e.,* $\mathbf{y}^* \in \{\mathbf{y} | \sum_{i=1}^{b}\alpha_i\mathbf{y}_i, \boldsymbol{\alpha} \in \mathcal{M}\}$. *Let* $\hat{\mathbf{y}}$ *and* $\hat{\boldsymbol{\alpha}}$ *be the optimal solution to Eq.(1), we then have* $\ell(\hat{\mathbf{y}}, \mathbf{y}^*) \leq \ell(\mathbf{y}_0, \mathbf{y}^*)$ *and* $\hat{\mathbf{y}}$ *has already achieved the maximal performance gain against* $\mathbf{y}_0$.

If the assumption is not satisfied?

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If $\ell(\cdot,\cdot)$ is η-Lipschitz, i.e., $|\ell(y_1, y_2) - \ell(y_1, y_3| \leq \eta||y_2 - y_3||_1$

Let $\boldsymbol{\beta}^* = \underset{\boldsymbol{\beta} \in \mathcal{M}}{\arg\min}\ \ell(\sum_{i=1}^{n} \beta_i \mathbf{y}_i, \mathbf{y}^*)$ and $\boldsymbol{\epsilon} = \mathbf{y}^* - \sum_{i=1}^{n} \beta_i^* \mathbf{y}_i$

We have,

Theorem 4. *The performance gain of $\hat{\mathbf{y}}$ against $\mathbf{y}_0$, i.e., $\ell(\mathbf{y}_0, \mathbf{y}^*) - \ell(\hat{\mathbf{y}}, \mathbf{y}^*)$, has a lower-bound $-2\eta||\boldsymbol{\epsilon}||_1$.*

Setup $\mathcal{M}$

For regression $C_{ij} = (y_i - u_i)^\top (y_j - u_j)$, for classification $C_{ij} = y_i^\top y_j$

We prove that $\mathbf{C\alpha}$ indicates the performance of the base learner

And we can think the base learner has a lower-bound performance [Balsubramani and Freund 2015]

Hence, we can setup $\mathcal{M} = \{\boldsymbol{\alpha} | \mathbf{C}\boldsymbol{\alpha} \geq \boldsymbol{\delta}, \mathbf{1}^\top \boldsymbol{\alpha} = 1, \boldsymbol{\alpha} \geq \mathbf{0}\}$

Moreover, if we have prior knowledge, we can setup $\mathcal{M}$ more flexible

Optimization

Original Form:

$$\max_{\mathbf{y}\in\mathbb{H}^u} \min_{\boldsymbol{\alpha}\in\mathcal{M}} \ell(\mathbf{y}_0, \sum_{i=1}^{n} \alpha_i \mathbf{y}_i) - \ell(\mathbf{y}, \sum_{i=1}^{n} \alpha_i \mathbf{y}_i)$$

Usually non-convex and not easy to solve

For regression task, we can get a convex optimization: $\min_{\boldsymbol{\alpha}\in\mathcal{M}} \ell(\mathbf{y}_0, \sum_{i=1}^{n} \alpha_i \mathbf{y}_i)$

For classification task and hinge loss, we can get a linear programming:

$$\min_{\boldsymbol{\alpha}\in\mathcal{M}} \ell(\mathbf{y}_0, \sum_{i=1}^{n} \alpha_i \mathbf{y}_i) + \frac{1}{u} \| \sum_{i=1}^{n} \alpha_i \mathbf{y}_i \|_1 - 1$$

Become much easier to solve

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- **Experiments**
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Label Noise Learning

❑Setup

- 8 frequently-used datasets
- 30% high-quality labeled data and 70% noisy data which their labels are random reversed with a probability p%.

❑Compared Methods

- Baseline
  - Sup-SVM
- 2 state-of-art noisy robust methods
  - Bagging [Fr´enay and Verleysen 2014],
  - rLR [Bootkrajang and Kab´an 2012],
- 3 traditional methods
  - SVM
  - k-NN
  - Logistic Regression(LR)

❑SafeW: adopted SVM, k-NN and LR as base learners.

Label Noise Learning

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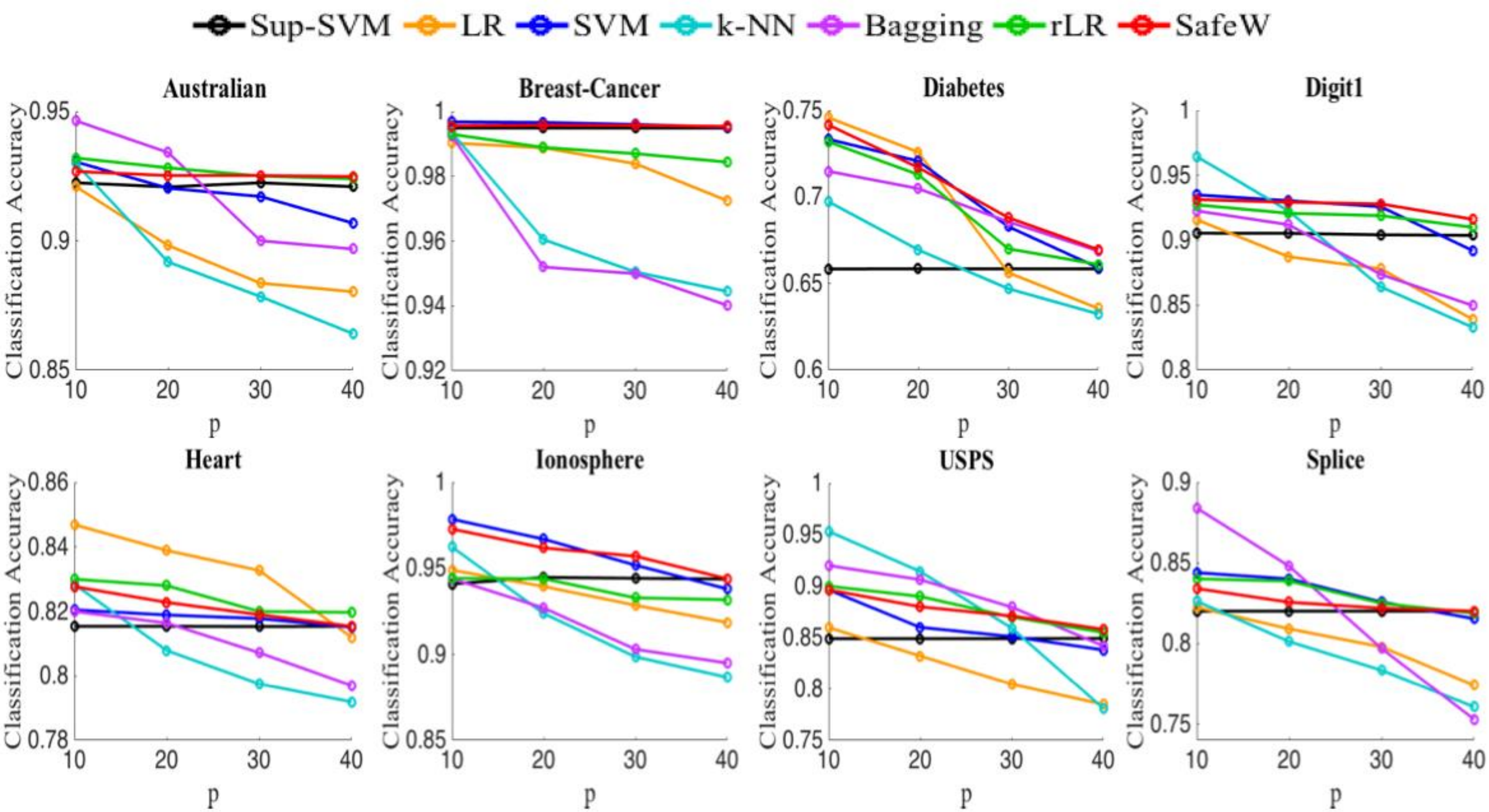
Classification accuracy on 8 datasets with p range from 10% to 40%



Domain Adaptation

- Setup
  - 2 benchmark datasets: 20newgroup, landmine
- Compared Methods
  - Baseline
    - Logistic Regression
  - 4 transfer learning methods
    - Original
    - MIDA [Yan, Kou, and Zhang 2016]
    - TCA [Pan et al. 2011]
    - TrAdaBoost [Dai et al. 2007]
- SafeW: adopted Original, MIDA and TCA as base learners.

Domain Adaptation

20newsgroup: 19,997 news and 20 groups

Dataset	Logistic Regression	Original	MIDA	TCA	TrAdaBoost	SafeW
Comp vs Rec	$.7028 \pm .0091$	$\mathbf{.7492 \pm .0135}$	$\mathbf{.7961 \pm .0197}$	$\mathbf{.7940 \pm .0162}$	$\mathbf{.8077 \pm .0155}$	$\mathbf{.7956 \pm .0170}$
Comp vs Sci	$.8225 \pm .0662$	$\boxed{.7985 \pm .0194}$	$\mathbf{.8946 \pm .0188}$	$.8255 \pm .0172$	$\mathbf{.8583 \pm .0201}$	$\mathbf{.8925 \pm .0212}$
Comp vs Talk	$.8423 \pm .0685$	$\boxed{.8022 \pm .0182}$	$\boxed{.8231 \pm .0164}$	$.8434 \pm .0110$	$\boxed{.8247 \pm .0143}$	$.8451 \pm .0158$
Sci vs Talk	$.7294 \pm .1045$	$.7100 \pm .0121$	$\mathbf{.7456 \pm .0164}$	$\boxed{.7022 \pm .0092}$	$.7166 \pm .0213$	$\mathbf{.7468 \pm .0153}$
Rec vs Sci	$.8006 \pm .0758$	$\boxed{.7754 \pm .0161}$	$.8033 \pm .0151$	$\mathbf{.8440 \pm .0118}$	$.8016 \pm .0151$	$\mathbf{.8435 \pm .0157}$
Rec vs Talk	$.8278 \pm .0446$	$.8276 \pm .0115$	$\mathbf{.8566 \pm .0105}$	$\mathbf{.8580 \pm .0128}$	$\mathbf{.8415 \pm .0113}$	$\mathbf{.8579 \pm .0105}$
Average	.7876	.7805	.8199	.8112	.8084	.8302
Win/Tie/Loss against LR		1/2/3	4/1/1	3/2/1	3/2/1	**5/1/0**

Directly using weakly supervised data often degenerate performance while SafeW does not suffer this problem.

Domain Adaptation

Landmine: 29 domain, 9 features

Dataset	Logistic Regression	Original	MIDA	TCA	TrAdaBoost	SafeW
Domain 20	.9215 ± .0173	.9237 ± .0034	**.9265 ± .0039**	.9255 ± .0045	.9183 ± .0029	**.9271 ± .0035**
Domain 21	.9360 ± .0095	.9310 ± .0047	.9384 ± .0045	.9304 ± .0051	.9261 ± .0033	.9396 ± .0038
Domain 22	.9594 ± .0051	.9555 ± .0038	.9506 ± .0065	**.9650 ± .0017**	.9095 ± .0026	**.9648 ± .0016**
Domain 23	.9361 ± .0095	.9310 ± .0041	**.9424 ± .0045**	.9314 ± .0051	**.9627 ± .0043**	**.9426 ± .0038**
Domain 24	.9535 ± .0052	.9524 ± .0029	.9447 ± .0025	.9432 ± .0029	.9535 ± .0034	.9550 ± .0024
Average	.9413	.9387	.9405	.9391	.9340	.9458
Win/Tie/Loss against LR		0/3/2	2/1/2	1/1/3	1/2/2	**3/2/0**

We have similar observations.

Semi-Supervised Learning

❑Setup

- 8 commonly used regression datasets
- 10 labeled data are chosen for each dataset

❑Compared Methods

- Baseline
  - 1NN
- Semi-Supervised Regressor
  - Self-kNN [Yarowsky 1995]
  - Self-LS [Hastie, Tibshirani, and Friedman 2001]
- Ensemble methods
  - Average
  - Safer [Li, Zha and Zhou 2017]

❑For Average, Safer and SafeW: adopted Self-kNN(Euclidean), Self-kNN(Cosine) and Self-LS as base learners.

Semi-Supervised Learning

Mean Square Error on 8 datasets

Dataset	1NN	Self-*k*NN(Euclidean)	Self-*k*NN(Cosine)	Self-LS	Average	Safer	SAFEW
abalone	.020 ± .010	**.014 ± .005**	**.014 ± .003**	**.013 ± .004**	**.012 ± .003**	**.013 ± .005**	**.013 ± .005**
bodyfat	.019 ± .005	.018 ± .006	.019 ± .005	.041 ± .013	.023 ± .009	.018 ± .007	.017 ± .005
cadata	.083 ± .029	**.063 ± .012**	**.058 ± .009**	**.056 ± .007**	**.057 ± .009**	**.060 ± .013**	**.057 ± .005**
cpusmall	.024 ± .012	.027 ± .011	.028 ± .009	.025 ± .010	.024 ± .005	.025 ± .011	.024 ± .009
housing	.039 ± .010	.036 ± .009	.033 ± .006	.036 ± .009	**.034 ± .008**	**.034 ± .009**	**.033 ± .005**
mg	.051 ± .009	**.039 ± .006**	**.038 ± .006**	**.035 ± .015**	**.038 ± .014**	**.038 ± .006**	**.038 ± .006**
mpg	.022 ± .007	.020 ± .006	.018 ± .006	.021 ± .008	.020 ± .006	**.019 ± .004**	**.018 ± .004**
pyrim	.023 ± .006	**.021 ± .005**	.022 ± .005	.052 ± .014	**.020 ± .007**	**.020 ± .006**	**.020 ± .006**
Ave. Mse.	.035	.030	.029	.035	.029	.030	.028
Win/Tie/Loss against 1NN		4/3/1	3/4/1	3/3/2	5/2/1	**6/2/0**	**6/2/0**

SafeW also obtain safe predictions

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Conclusion

- We propose a general formulation for safely exploiting weakly supervised data

- It has three advantages

  - Has safeness guarantee for commonly used loss functions in both regression and classification tasks

  - Can setup the weight of base learner flexibly

  - Can be solved globally in an efficient manner

Thanks!