What Makes Partial-Label Learning Algorithms Effective?

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NEURAL INFORMATION PROCESSING SYSTEMS

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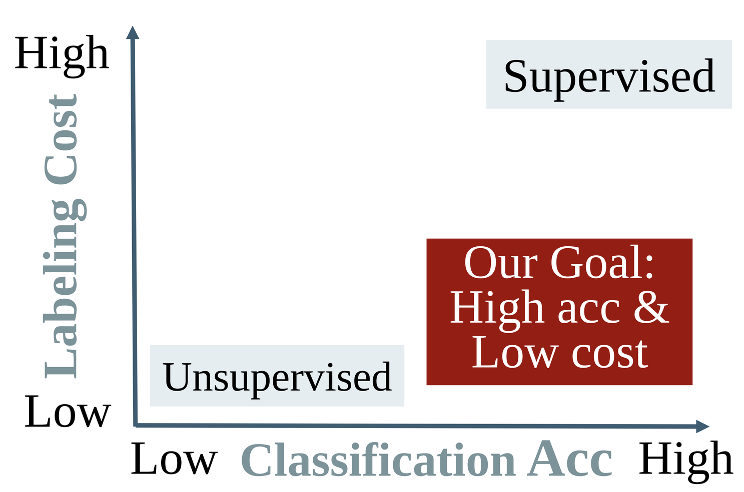
Background



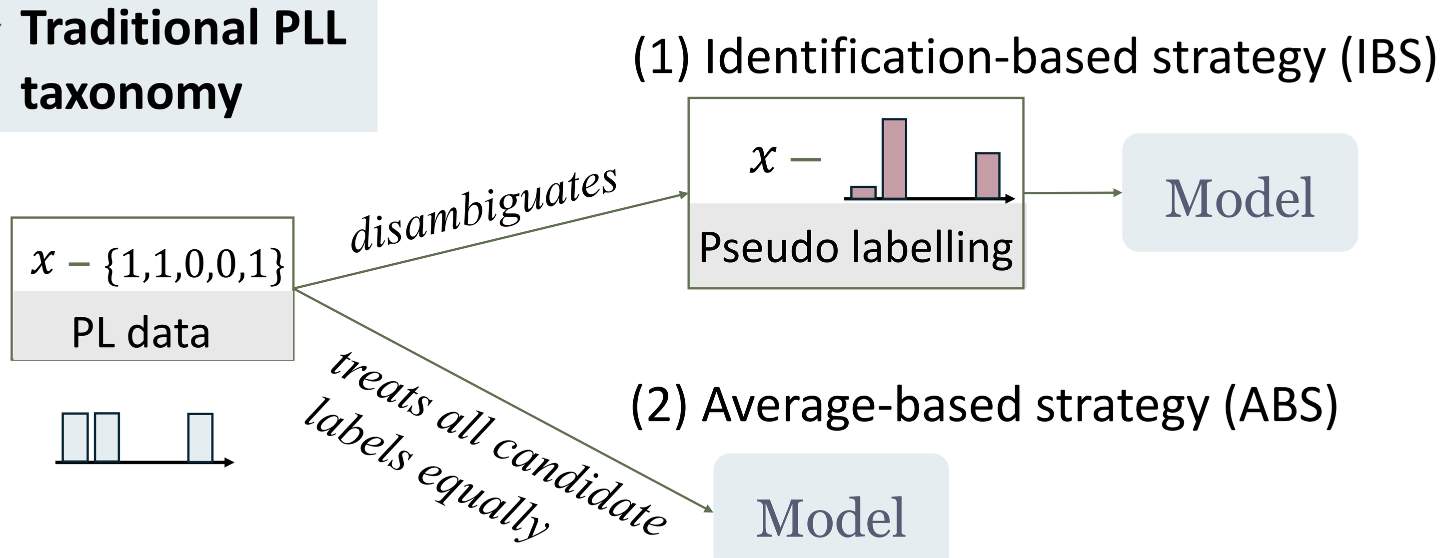
- Reducing labeling costs is a significant challenge
- Weakly supervised learning emerges as a crucial branch

Partial-Label Data:

Partial label:
Husky, Alaskan, Eurasian gray wolf

- Partial Label Learning (PLL) is a typical weakly supervised classification problem
- Each instance is labeled with a partial label, where a fixed but unknown label is true

◆ Traditional PLL taxonomy



◆ SOTA PLL methods with quite different technical routes

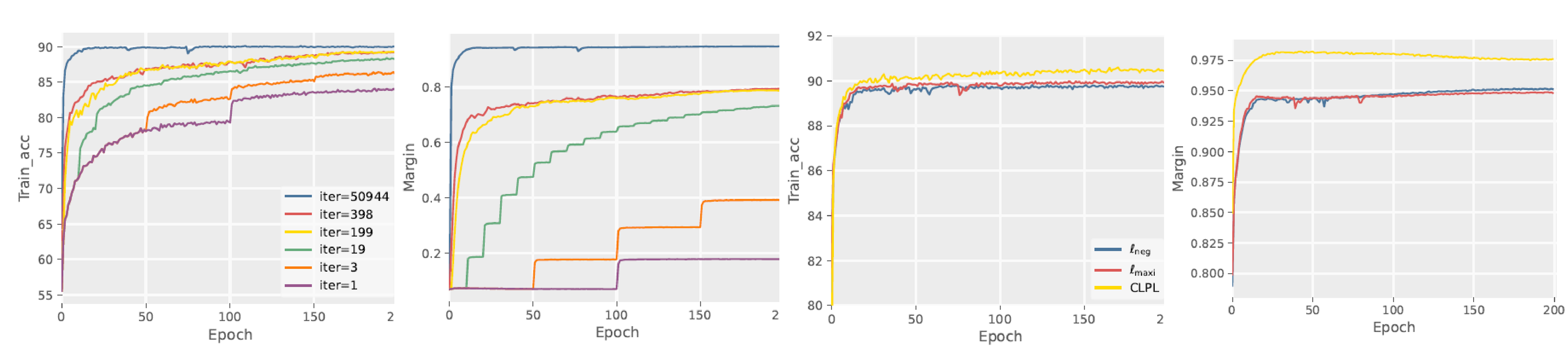
Table 1: Comparison of techniques used in eight prominent PLL methods. ✓/× indicates whether a technique is used, and an underline denotes the key components of the respective methods.

PLL methods	Mini-b. purif.	Mixup	Data augment.	Exp.Mov Average	Match DA	Match DM	Main assumption
PRODEN [25]	$\underline{\checkmark}$	×	×	×	×	$\underline{\checkmark}$	DNNs learn pattern first
CC [12]	✓	×	×	×	×	×	$\underline{\text{PLs are generated uniformly}}$
LWC [37]	✓	×	×	×	×	✓	$\underline{\text{PLs are class-dependent}}$
PiCO [34]	✓	×	✓	✓	$\underline{\checkmark}$	$\underline{\checkmark}$	Same class representations cluster
DPLL [38]	✓	×	✓	×	$\underline{\checkmark}$	×	Input is invarient to the translations
SoLar [33]	✓	✓	✓	✓	✓	×	$\underline{\text{High-confid. sample is likely correct}}$
PaPi [40]	✓	✓	✓	✓	✓	$\underline{\checkmark}$	Same class representations cluster
CroSel [30]	✓	✓	✓	✓	✓	$\underline{\checkmark}$	$\underline{\text{Stable high-confid. sample is correct}}$

Main Question: What makes PLL algorithms effective?

- Past intuition: (1) IBS is more effective; (2) Stronger tricks lead to better performance
- This understanding is vital for choosing the best direction for future algorithm design
- It also can act as a conclusive work to prevent redundant efforts in future research

Observation and Answer 1

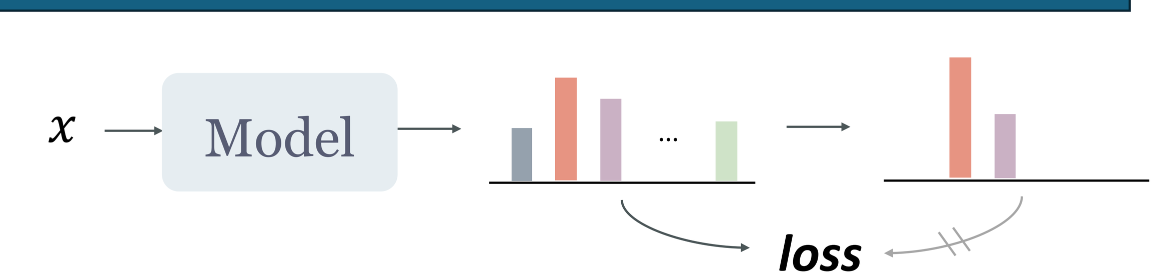


(a) Acc of IBS (b) Margin of IBS (c) Acc of ABS (d) Margin of ABS

- Observation 1: IBS and ABS often overlap in the dynamic characteristics of their implementations
- Our Answer 1: There is no need to predefine a method's category based on traditional taxonomy and then judge its utility by that classification

Observation and Answer 2

- An IBS method:



- An ABS method: optimizes $\ell_{\text{maxi}}(\boldsymbol{x}, f) = -\log \sum_{i \in S} f_i(\boldsymbol{x})$

- Observation 2: An ABS method has exactly the same optimization goals as a representative IBS algorithm
- Our Answer 2: PLL must use supervision, and supervision can be used in two ways: directly within the loss function or to manipulate pseudo-labels on-the-fly

Observation and Answer 3

Table 1: Conceptual and empirical comparisons (%) of various simplifications of DPLL. ✓/× indicates whether a technique is used.

Methods	Mini-b. purif.	ABS loss	Data augment.	DA	FMNIST 0.3	FMNIST 0.7	CIFAR-100 0.05	CIFAR-100 0.1	mini-I.Net ins.-dep.
Eq. 4+6 DPLL	✓	✓	✓	✓	93.82	**92.68**	76.81	75.93	52.22
Eq. 4+7	✓	✓	✓	✓	93.80	92.44	79.35	78.85	53.40
Eq. 8+6	✓	✓	✓	✓	93.49	92.19	**79.75**	78.87	53.78
Eq. 8+7	✓	✓	✓	✓	93.57	92.20	79.53	78.85	54.09
Eq. 6	×	✓	✓	×	93.58	92.12	76.96	75.94	44.69
Eq. 8 DASM	✓	×	✓	✓	93.89	92.85	79.70	**79.62**	54.71
DASM-H	×	×	✓	✓	93.86	92.37	78.25	33.22	34.59
DASM-S	×	×	✓	✓	93.28	90.75	78.65	76.22	36.71
DASM-E	×	×	✓	×	93.80	92.35	79.30	79.11	53.44
SASM	✓	×	✓	×	**93.83**	92.18	79.38	78.19	**55.45**
DASM w/o.aug	✓	×	×	✓	90.86	89.60	60.18	56.39	30.85

- Observation 3: By dissecting SOTA PLL algorithms with quite different technical routes, we find the common elements contributing to success
- Mini-batch PL purification is a minimal design principles in PLL
- Mini-batch PL purification is a process where for each mini-batch B selected at iteration t, the weights are updated such that the distinction among candidate labels' contributions increases over iterations:

$$w_{t+1}(\boldsymbol{x}; f, S) = g(\text{model's confidence for } \boldsymbol{x} \text{ based on current and previous iterations})$$

with g being a strictly increasing function that increases the weight for more likely candidate labels according to the model's confidence

A Step Forward: StreamPurify