Supplemental Material of "Adaptive Graph Guided Disambiguation for Partial Label Learning"

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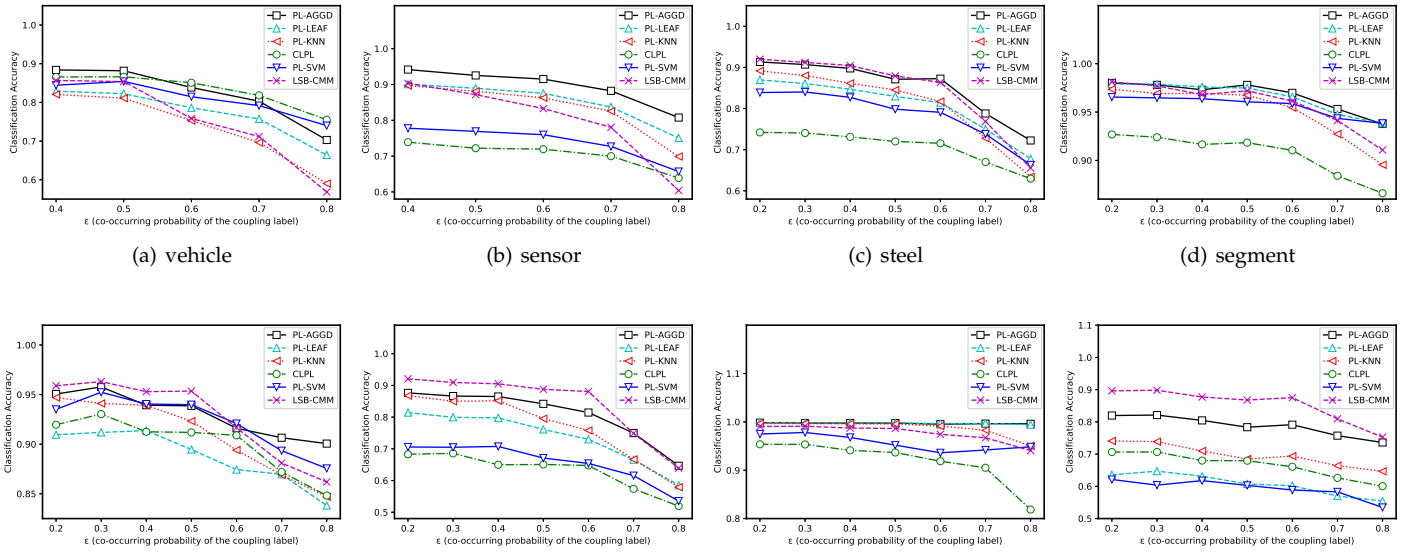
DETAILED TRANSDUCTIVE RESULTS ON CONTROLLED UCI DATA SETS

Table 8 summarizes the win/tie/loss counts of transductive accuracy between PL-AGGD and each comparing algorithm of the 139 statistical tests on all 8 UCI data sets. Here we report the detailed comparison results of transductive accuracy of each algorithm on controlled UCI data sets. The same experiment setups of Section 4.1 are used for conducting the transductive performance[1]. Fig. 1 illustrates the transductive accuracy of each comparing algorithm on the controlled UCI data sets with the varying co-occurring probability ϵ. Fig. 2 illustrates transductive accuracy of each comparing algorithm on the controlled UCI data sets with the varying proportion p of partially labeled examples. Table 1 shows the transductive performance with varying the ambiguity size r.



(a) vehicle (b) sensor (c) steel (d) segment

(e) ecoli (f) winerate (g) pendigits (h) abalone

Fig. 1. Transductive performance of each comparing algorithm with the varying ϵ (co-occurring probability of the coupling label) and fixed r and p ($r = 1, p = 1$).

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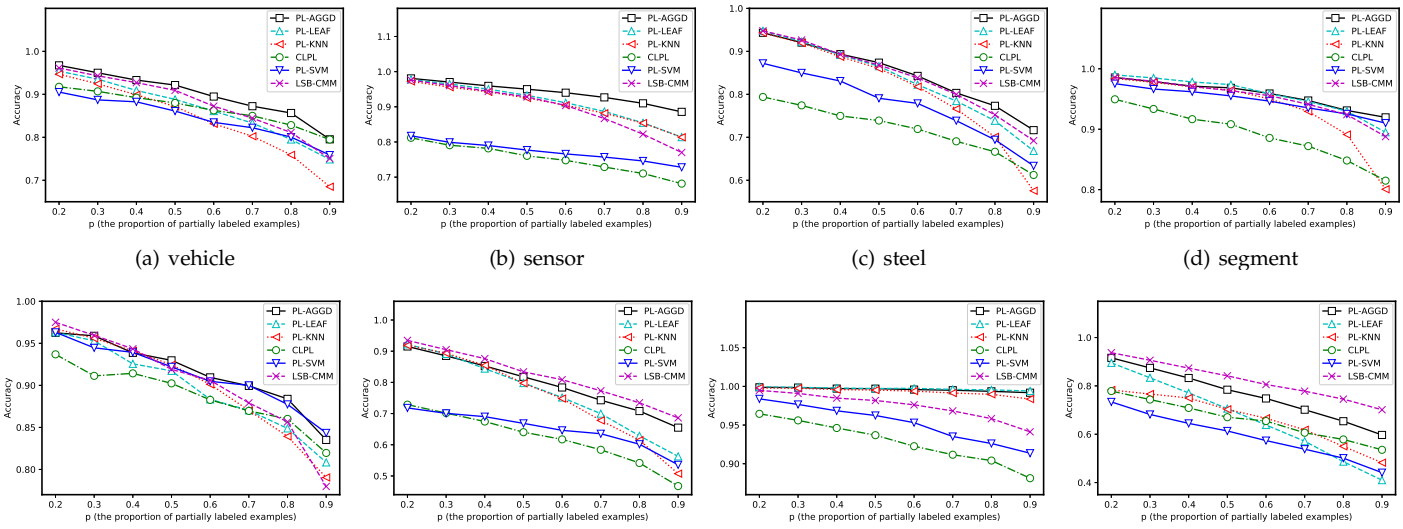
[1]For `vehicle` and `sensor`, there are only 4 labels in each of these two data sets, and the minimum ambiguity degree of all label pairs is $1/3$, therefore we vary label co-occurring probability ϵ from 0.4 to 0.8 with step size 0.1 for these two data sets. And for other data sets, we vary ϵ from 0.1 to 0.8. In the experiments with varying p, we set $r = 2$ for `vehicle` and `sensor` and $r = 5$ for other data sets.



(a) vehicle (b) sensor (c) steel (d) segment

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Fig. 2. Transductive performance of each comparing algorithm with the varying p (the proportion of examples which are partially labeled) and fixed r and ϵ ($r = 2$ for `vehicle` and `sensor`, $r = 5$ for others, $\epsilon = \frac{1}{r}$).

TABLE 1
Transductive performance of each comparing algorithm on the controlled UCI data sets with the varying r (false positive candidate label). In addition, •/○ indicates whether the transductive performance of PL-AGGD is statistically superior/inferior to the comparing algorithm on each data set (pairwise t-test at 0.05 significance level).

	r	PL-AGGD	PL-KNN	CLPL	PL-SVM	LSB-CMM	PL-LEAF
vehicle	1	0.892±0.013	0.817±0.019•	0.862±0.029•	0.849±0.021•	0.863±0.017•	0.831±0.025•
	2	0.744±0.046	0.626±0.039•	0.774±0.026○	0.728±0.032	0.678±0.044•	0.692±0.036•
sensor	1	0.941±0.004	0.900±0.004•	0.740±0.010•	0.780±0.007•	0.900±0.008•	0.907±0.008•
	2	0.857±0.008	0.766±0.006•	0.664±0.014•	0.703±0.031•	0.725±0.012•	0.766±0.013•
steel	1	0.911±0.010	0.890±0.010•	0.740±0.018•	0.840±0.010•	0.922±0.008○	0.873±0.010•
	3	0.768±0.011	0.709±0.014•	0.639±0.020•	0.673±0.025•	0.768±0.014	0.702±0.013•
	5	0.606±0.031	0.379±0.028•	0.533±0.018•	0.504±0.056•	0.560±0.020•	0.538±0.031•
segment	1	0.978±0.002	0.973±0.006•	0.923±0.005•	0.964±0.004•	0.977±0.005	0.979±0.004
	3	0.978±0.003	0.975±0.003•	0.924±0.005•	0.963±0.005•	0.974±0.004•	0.982±0.004○
	5	0.977±0.004	0.976±0.003•	0.923±0.007•	0.960±0.005•	0.977±0.004	0.978±0.005
ecoli	1	0.958±0.019	0.945±0.014•	0.929±0.026•	0.950±0.016	0.963±0.013	0.924±0.024•
	3	0.889±0.031	0.848±0.022•	0.860±0.036•	0.876±0.033	0.860±0.030•	0.825±0.037•
	5	0.754±0.064	0.661±0.054•	0.749±0.076	0.702±0.123	0.661±0.080•	0.704±0.082•
winerate	1	0.881±0.011	0.863±0.008•	0.680±0.015•	0.719±0.025•	0.922±0.010○	0.812±0.015•
	3	0.725±0.016	0.631±0.036•	0.534±0.024•	0.603±0.022•	0.773±0.014○	0.549±0.018•
	5	0.579±0.025	0.386±0.026•	0.419±0.036•	0.470±0.053•	0.639±0.017○	0.447±0.030•
pendigits	1	0.998±0.001	0.997±0.001•	0.953±0.002•	0.972±0.008•	0.991±0.001•	0.999±0.000○
	3	0.995±0.001	0.991±0.002•	0.910±0.005•	0.925±0.002•	0.962±0.001•	0.995±0.001
	5	0.990±0.002	0.977±0.001•	0.875±0.006•	0.897±0.011•	0.914±0.004•	0.991±0.001
abalone	1	0.827±0.008	0.748±0.010•	0.718±0.013•	0.637±0.029•	0.910±0.007○	0.643±0.014•
	4	0.575±0.009	0.485±0.010•	0.543±0.018•	0.397±0.043•	0.718±0.007○	0.368±0.011•
	7	0.437±0.010	0.334±0.012•	0.436±0.012	0.325±0.045•	0.578±0.011○	0.262±0.013•
	10	0.369±0.014	0.237±0.017•	0.357±0.019•	0.321±0.031•	0.467±0.014○	0.198±0.012•