



Northeastern
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Dual Relation Semi-supervised Multi-label Learning

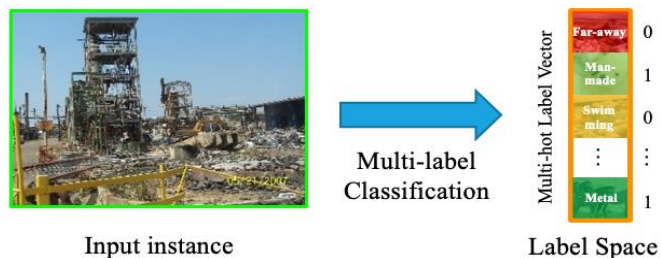
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Multi-label learning:

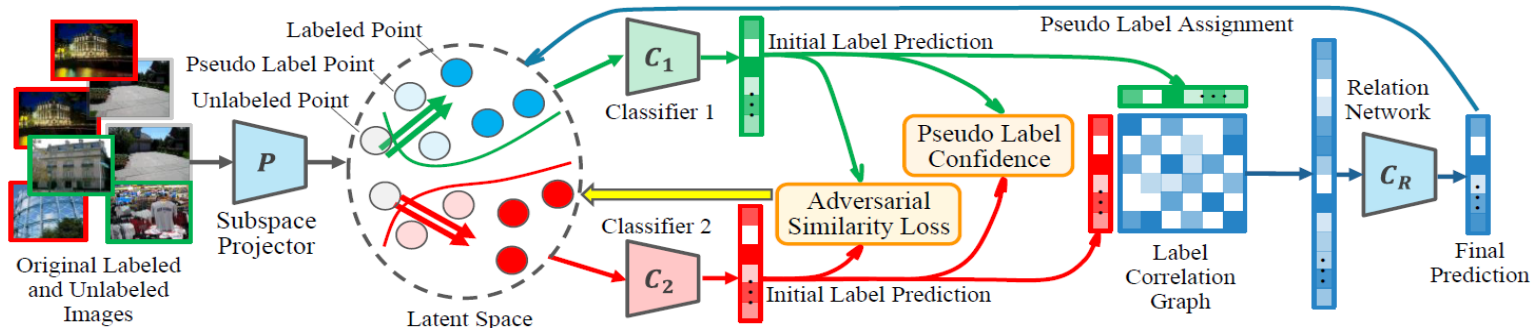
Predict multiple labels from a single instance.



Difficulties & insights:

- Multi-label follows long-tail label distribution. No enough samples to well train all labels.
- Semi-supervised approach is deployed to utilize unlabeled samples
- Label correlations are crucial information
- Label-correlation graph and co-training strategy is proposed to explore label relation from both labeled and unlabeled samples.

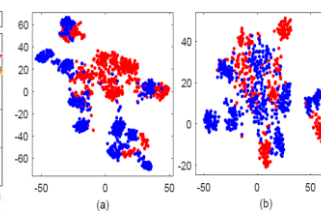
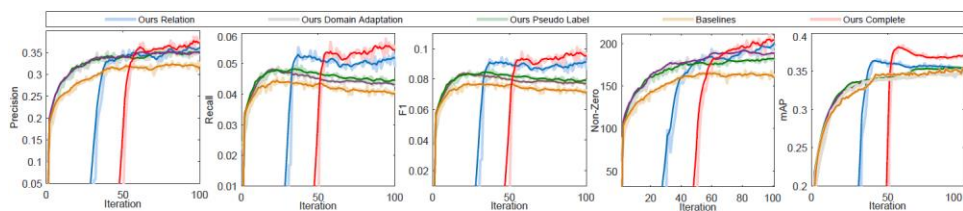
Our model:



- Two-classifier structure is utilized to align distributions of labeled and unlabeled samples.
- A co-training strategy is specifically designed which gradually assigns labels to unlabeled samples.
- A label-correlation graph is utilized to explore the label relations from labeled and unlabeled samples.

Experiments:

- Six datasets, four experimental settings, and ablation studies



SUN	LR	0.6209	0.1473	0.2457	102	0.6807
	SSMLDR	0.6879	0.1700	0.2726	102	0.6723
	FastTag	0.6816	0.1473	0.2457	102	0.6914
	ML-PGD	0.7110	0.1614	0.2631	101	0.7087
	SAE	0.7183	0.1638	0.2668	98	0.7012
CUB	AGZE	0.7685	0.1765	0.2871	99	0.6778
	Ours	0.7906	0.1793	0.2923	102	0.6800
	LR	0.2010	0.0239	0.0428	157	0.0638
	SSMLDR	0.3410	0.0473	0.0832	178	0.2329
	FastTag	0.2147	0.0359	0.0615	167	0.3144
AWA	ML-PGD	0.3334	0.0451	0.0794	155	0.3288
	SAE	0.3383	0.0514	0.0908	196	0.3255
	AGZE	0.3499	0.0531	0.0911	190	0.3106
	Ours	0.3714	0.0548	0.0955	202	0.3542
	LR	0.8798	0.0821	0.1500	75	0.8626
AWA	SSMLDR	0.7812	0.0858	0.1546	67	0.8346
	FastTag	0.7861	0.0949	0.1694	72	0.8791
	ML-PGD	0.5395	0.0635	0.1136	57	0.9121
	SAE	0.9683	0.0957	0.1742	73	0.9397
	AGZE	0.8483	0.0827	0.1507	73	0.9033
	Ours	0.8689	0.0835	0.1523	75	0.9441



Correct Retrieval

Incorrect Retrieval