Dual Relation Semi-supervised Multi-label Learning

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Multi-label Learning:

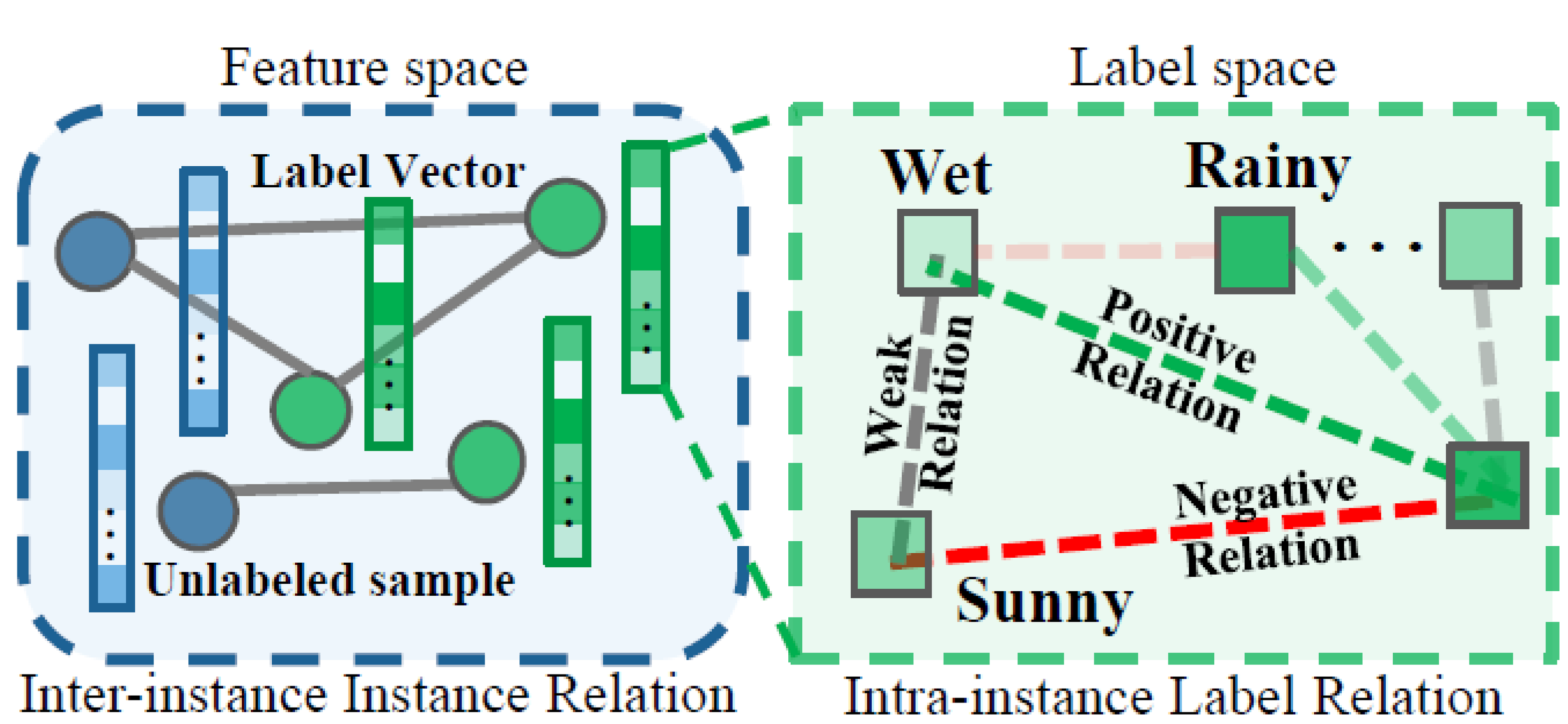
Background:

One object can be described by tens or hundreds of descriptions (e.g., color, shape, texture and category). It is critical and practical to predict all the labels from a single instance.

- Input: an instance
- Output: multiple predicted labels

Challenges:

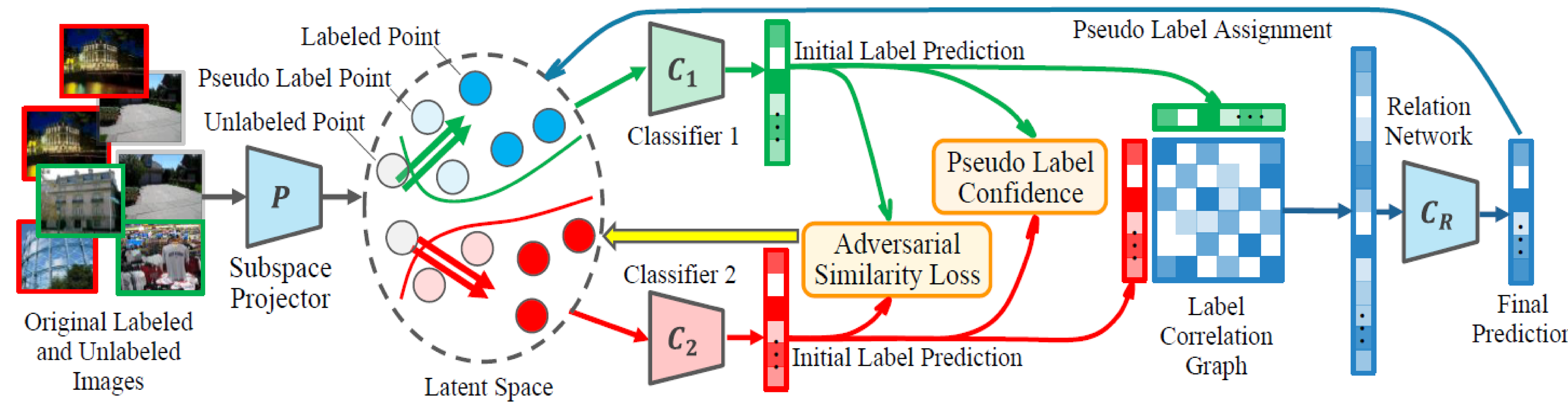
- Long-tail label distribution. The labels followed a long-tail distribution characteristic, which means some labels (e.g., *man-made*) are always show up while some labels are rarely be assigned (e.g., *fire*) .
- Distribution gaps between training and testing sets. The training sets cannot cover the entire feature space of testing.
- Label correlation is crucial for high accurate label prediction, while this knowledge is difficult, expensive, and challenging to obtain.



Insights:

- Semi-supervised multi-label learning for multi-label prediction. Unlabeled samples are explored associated with labeled samples.
- The label-level correlation of each instance is important. Meanwhile, the label correlations residing inside both labeled and unlabeled samples could also provide crucial information. To this end, we want to explore the label correlations in unlabeled samples.

Proposed Method:



- Two classifiers structure is deployed to align the distribution differences between labeled and unlabeled samples.

$$L_C(X_l, Y_l) = \frac{1}{2}\left[\|C_1(Z_l) - Y_l\|_F^2 + \|C_2(Z_l) - Y_l\|_F^2\right]$$

$$\min_{C1,C2} -L_{DA}(X_u) + \lambda L_C(X_l, Y_l) \qquad L_{DA}(X_u) = d(C_1(Z_u), C_2(Z_u))$$

$$d(f_1, f_2) = \frac{1}{d_l}\sum_{k=1}^{d_l} |f_{1k} - f_{2k}|$$

- Pseudo label is gradually assigned to unlabeled samples
- Label correlations are explored by relation networks

$$L_R = \sum_{i=1}^{n} \|y_i - C_R(C_1(P(x_i)) \cdot C_2(P(x_i))^\top)\|_2^2 \qquad \min_{P,C_1,C_2,C_R} \frac{\alpha}{2} L_C + (1-\alpha) L_R$$

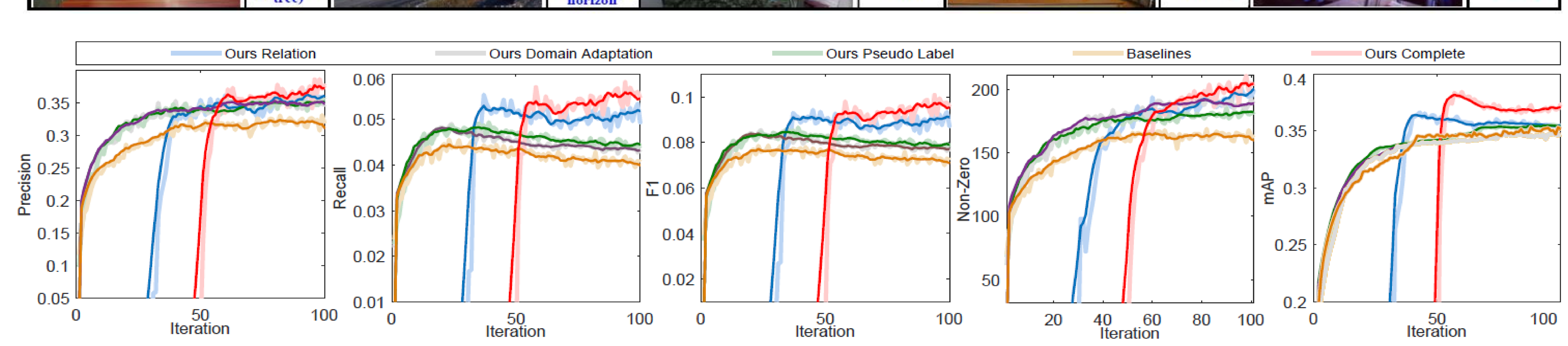
Experiments:

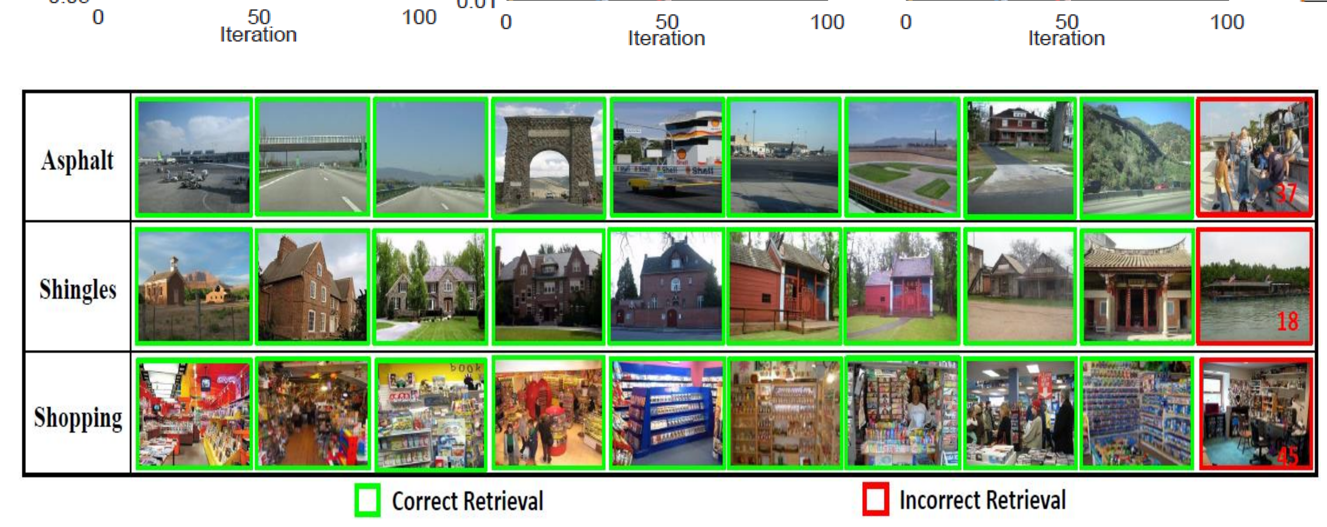
- ➢ Six datasets are used: MAD, Keck and Weizmann datasets.
- ➢ One is set as dictionary and another one is set as target dataset.

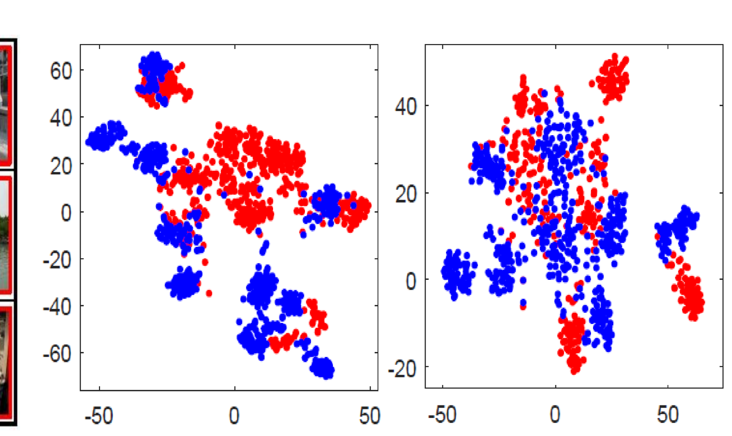
Data	Method	Pre	Rec	F1	N-R	mAP
Corel	LR	0.2859	0.3211	0.3025	128	0.3630
	SSMLDR	0.2741	0.3366	0.3022	143	0.3410
	FastTag	0.3123	0.3657	0.3369	143	0.3871
	ML-PGD	0.2575	0.2911	0.2732	122	0.3727
	SAE	0.2962	0.3442	0.3184	141	0.3823
	AG2E	0.3011	0.3520	0.3245	**157**	0.3568
	Ours	**0.3154**	**0.3775**	**0.3437**	148	**0.4127**
ESP	LR	0.3793	0.2038	0.2653	215	0.3440
	SSMLDR	0.3298	0.1885	0.2399	226	0.3156
	FastTag	0.4011	0.1927	0.2617	208	0.3904
	ML-PGD	0.3239	0.2012	0.2482	210	0.4077
	SAE	0.3861	0.1743	0.2402	194	0.3842
	AG2E	0.3548	0.1525	0.2133	213	0.3730
	Ours	**0.4373**	**0.2189**	**0.2918**	**227**	**0.4105**
IAP	LR	0.4287	0.2041	0.2765	199	0.4211
	SSMLDR	0.3491	0.2520	0.2927	229	0.3981
	FastTag	0.4346	0.2267	0.2980	227	0.4596
	ML-PGD	0.4132	0.2441	0.3011	230	0.4674
	SAE	0.3537	0.2282	0.2774	213	0.4309
	AG2E	0.3829	0.2330	0.2897	229	0.4353
	Ours	**0.4570**	**0.2531**	**0.3258**	**230**	**0.5148**

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
	AG2E	0.7685	0.1765	0.2871	99	0.6778
	Ours	**0.7906**	**0.1793**	**0.2923**	**102**	0.6800
CUB	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
	ML-PGD	0.3334	0.0451	0.0794	155	0.3288
	SAE	0.3383	0.0514	0.0908	196	0.3255
	AG2E	0.3409	0.0531	0.0911	190	0.3106
	Ours	**0.3714**	**0.0548**	**0.0955**	**202**	**0.3542**
AWA	LR	0.8798	0.0821	0.1500	75	0.8626
	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
	AG2E	0.8483	0.0827	0.1507	73	0.9033
	Ours	0.8689	0.0835	0.1523	**75**	**0.9441**

Data	Method	Pre	Rec	F1	N-R	mAP
SUN	LR	0.7047	0.1548	0.2539	97	0.6616
	SSMLDR	0.6637	0.1481	0.2422	95	0.6581
	FastTag	0.6906	0.1522	0.2494	90	0.6706
	ML-PGD	0.7037	0.1471	0.2433	95	0.6829
	SAE	0.6978	0.1710	0.2747	**100**	0.6513
	AG2E	0.7125	0.1618	0.2637	88	0.6693
	Ours	**0.7512**	**0.1794**	**0.2896**	97	**0.6924**
CUB	LR	0.2600	0.0307	0.0549	160	0.2693
	SSMLDR	0.2926	0.0383	0.0677	166	0.2329
	FastTag	0.2231	0.0434	0.0726	143	0.2967
	ML-PGD	0.2392	0.0365	0.0635	117	0.3178
	SAE	0.2552	0.0469	0.0798	**167**	0.3102
	AG2E	0.2808	0.0481	0.0821	163	0.2693
	Ours	**0.2981**	**0.0486**	**0.0835**	153	**0.3338**
AWA	LR	0.7555	0.0766	0.1392	66	0.8809
	SSMLDR	0.7017	0.0764	0.1378	66	0.7858
	FastTag	0.8610	0.0912	0.1649	81	0.8918
	ML-PGD	0.4338	0.0623	0.1091	49	0.8677
	SAE	0.9015	**0.0926**	**0.1679**	78	0.8918
	AG2E	0.8247	0.0811	0.1476	71	0.8874
	Ours	**0.9023**	0.0832	0.1524	**81**	**0.8985**







Conclusion:

We proposed a novel Dual Relation Semi-supervised Multi-label Learning approach. Unlabeled samples are utilized to improve model robustness. The label correlations from both labeled and unlabeled samples are explored.