L_1 Graph Based Sparse Model for Label De-noising

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We aim to learn recognition models from widespread user-provided social media tags, rather than costly purpose created annotations. To address this challenge, we propose a label de-noising algorithm to rectify noisy (incorrect and missing) labels. Subsequent supervised learning tasks then benefit from using the de-noised labels rather than the original noisy ones.

Our model is based on two intuitions: learning the typical noise pattern between observed noisy labels and latent true labels, and exploiting the expected smoothness true labels with regards to the image manifold. Notably, we handle both visual and label outliers with robust L_1-norm based regularisers. Our L_1 Graph based Sparse model with explicit noise pattern model (L_1GSP) is shown in Eq. (1), with two key components: the robust L_1 visual similarity graph regulariser ($||S\hat{Y}||_1$) and the robust L_1 label regulariser with explicit label noise pattern modelling ($||\hat{Y}-YQ||_1$):

$$\min_{\hat{Y},Q} ||S\hat{Y}||_1 + \gamma||\hat{Y}-YQ||_1 + \frac{\beta}{2}||Q||_F^2, \qquad (1)$$

where S encodes the visual similarity graph, Y and $\hat{Y}$ represent observed noisy labels and latent de-noised labels respectively, and Q the learned noise pattern transition matrix. The optimisation of Eq. (1) is non-trivial because the two L_1 norm terms make it significantly harder than the more common case of a single L1 norm. Therefore, multiple stages of alternating optimisation procedures are formulated in order to break it into more tractable sub-problems.

Our experiments apply label de-noising algorithms to train sets and evaluate de-noising performance. The cleaned labels are then used for classifier learning, and performance is evaluated on test sets. L_1GSP achieves better performance than its competitors on both label de-noising and follow-up classification tasks across datasets, as shown in Table 1 and 2. Qualitative label de-noising results are shown in Fig. 1. The first example shows that incorrect labels can be eliminated from the top ranking predictions of our de-noising model. The effectiveness of the proposed model to recover missing labels is illustrated in the second image of Fig. 1. The last image of Fig. 1 shows a failure case using our model, which is mainly due to the unconventional appearance of toys.

		GT	NL	L_2VG	L_2VGLG	RPCA	L_1GSP
Denoising	mAP	-	-	52.21	55.01	56.39	**60.09**
Testing	mAP	71.98	42.34	40.33	41.10	53.54	**58.66**

Table 1: Pascal VOC 2007 de-noising performance and testing performance (mAP, %). GT for Ground-truth; NL for Noisy Labels.

	De-noising		Testing	
	mAPc	mAPi	mAPc	mAPi
GT	-	-	47.76	74.31
NL	-	-	30.07	47.88
L_2VG	52.39	57.45	33.81	48.52
L_2VGLG	53.02	59.68	34.69	49.45
RPCA	48.89	64.10	31.20	54.21
L_1GSP	**58.46**	**66.98**	**35.70**	**57.84**

Table 2: De-noising (left) and testing (right) performance (mAP, %) on NUS-WIDE. GT for Ground-truth; NL for Noisy Labels.

Figure 1: Illustrations of label de-noising results on NUS-WIDE (top 3 scoring of the de-noised labels by L_1GSP are shown). Red indicates incorrect labels, green for missing labels and blue for correct labels. Failure case in red dashed line.

[1] Baoyuan Wu, Siwei Lyu, and Bernard Ghanem. Ml-mg: Multi-label learning with missing labels using a mixed graph. In *ICCV*, 2015.

[2] Wenxuan Xie, Zhiwu Lu, Yuxin Peng, and Jianguo Xiao. Graph-based multimodal semi-supervised image classification. *Neurocomputing*, 2014.