Supplementary Material: Diverse Image Annotation

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1. Evaluation Results by Conventional Metrics

Here we present the results of different methods, evaluated by conventional metrics, including precision (P), recall (R) and F1 score, on ESP Game and IAPRTC-12, as shown in Table 2. ML-MG shows the best performance in all cases, which has also verified in [1]. In contrast, DPP-S-sampling gives the worst performance in all cases. The obvious reason is MLMG picks the most representative tags in top-k tags, such that more positive tags could be retrieved. In contrast, the diversity encourages DPP-S-sampling to cover tags from different semantic paths, such that some negative labels maybe included. However, as shown in the main manuscript, the conventional metrics are much less consistent with human evaluation than the semantic metrics.

2. Combining Our Sampling with Traditional Methods

Here we add an experiment combining our sampling algorithm (see Algorithm 1 in the main manuscript) with the compared traditional image annotation methods, i.e., ML-MG and LEML [2]. The results are presented in Table 2. Our sampling is based on a DPP distribution, so the quality score in DPP should be replaced by the square root of the posterior score produced by ML-MG or LEML. The results of ML-MG are in the range [0, 1], thus they can be directly used as the quality score. The results of LEML range from large negative to large positive values, so we normalize them to [0, 1]. As shown in Table 2, in most cases ML-MG + sampling improves over ML-MG without sampling. Also, the value changes of different metrics are reasonable according to the characteristics of the original ML-MG scores. Specifically, the improvements of Rsp are 10.58% and 7.74% in the case of 3 tags and 5 tags respectively. The reason is that ML-MG puts the most representative but redundant tags in the top-k tag list, thus its Rsp value is lower than the one of other methods. With our sampling, the redundant tags will be removed, giving the chance to add other tags from different semantic paths, leading to the increase of Rsp. The improvements of Psp is relatively small, and even negative in the case of 5 tags. This is not strange, because the removed redundant tags is likely to be relevant, while the new added tags may be irrelevant. Then the precision Psp could decrease. This comparison could demonstrate that our sampling algorithm could help other traditional image annotation methods to increase the diversity. Besides, the performance of ML-MG + sampling is still worse than our DPP-S-sampling. This verifies that both our model learning and sampling contribute to the diversity performance. LEML performs worse in most cases. We find that lots of normalized scores of LEML are round 0.5, which should be the main reason for poor sampling.

3. Quality Results

Some quality results are shown in Figure 1 and 2. For each image, we provide the complete tags, and the predicted
Figure 1. Some quality results on ESP Game data. For each image, we present the ground-truth tag subset, the tag subsets with 3 and 5 tags produced by three methods, and the $F_{1-sp}$ scores.

Figure 2. Some quality results on IAPRTC-12 data. For each image, we present the ground-truth tag subset, the tag subsets with 3 and 5 tags produced by three methods, and the $F_{1-sp}$ scores.

tags of ML-MG, LEML and DPP-S-sampling in both cases of 3 and 5 tags, as well as their $F_{1-sp}$ values. We can see that in most cases DPP-S-sampling produces more representative and diverse tags than ML-MG and LEML, with the larger $F_{1-sp}$ values.

References
