

Abstract

Multi-label learning is useful in object recognition when several objects are present in an image. Conventional approaches implement multi-label learning as a set of binary classification problems, but they suffer from imbalanced data distributions when the number of classes is large. We address multi-label learning via a ranking approach. Given a test image, the proposed scheme aims to order all the object classes such that the relevant classes are ranked higher than the irrelevant ones. We present an efficient algorithm for multi-label ranking based on block coordinate descent.

Maximum margin multi-label ranking

$$\min_{\{f_k \in \mathcal{H}_k\}_{k=1}^K} \frac{1}{2} \sum_{k=1}^K \|f_k\|_{\mathcal{H}_k}^2 + C \sum_{i=1}^n \sum_{k,l=1}^K \varepsilon_i^{k,l} \quad (1)$$

f_k : classifier of the class c_k

K : the number of classes

C : regularization parameter

$\varepsilon_i^{k,l}$: loss in ranking classes c_k and c_l

$$\varepsilon_i^{k,l} = I(y_i^k \neq y_i^l) l \left(\frac{y_i^k - y_i^l}{2} (f_k(x_i) - f_l(x_i)) \right)$$

✓ Challenge in solving (1)

- ✓ Solutions for $f_i(x)$, $i=1, 2, \dots, K$ depend on each other, making it difficult to find optimal solutions for all classifiers

✓ Our strategy

- ✓ Convert the problem into its dual form
- ✓ Simplify the dependence among classifiers by relaxing the solution domains

Efficient Algorithm For Multiple Ranking

1. Dual Formulation for multiple ranking

$\{f_k(x)\}_{k=1}^K$ that optimize (1) admit the following form

$$f_k(x) = \sum_{i=1}^n y_i^k \alpha_i^k \kappa(x_i, x),$$

where α_i^k are solutions to the following problem

$$\max_{\alpha_i \in \Delta} \sum_{i=1}^n \sum_{k=1}^K \alpha_i^k - \frac{1}{2} \sum_{k=1}^K \sum_{i,j=1}^n \kappa(x_i, x_j) y_i^k y_j^k \alpha_i^k \alpha_j^k \quad (2)$$

- ✓ Δ captures the dependence among classes
- ✓ Structure in Δ makes it difficult to solve efficiently

Efficient Algorithm For Multiple Ranking

2. Relaxing Domain Δ

$$\hat{\Delta} = \left\{ \alpha_i \in [0, C]^K : \sum_{k=1}^a \alpha_i^k = \sum_{k=a+1}^K \alpha_i^k \right\}$$

- ✓ Property: $\hat{\Delta} \subseteq \Delta$

- ✓ Simplify (2) as follows

$$\max_{\alpha_i \in \hat{\Delta}} \sum_{i=1}^n \sum_{k=1}^K \alpha_i^k - \frac{1}{2} \sum_{k=1}^K \sum_{i,j=1}^n \kappa(x_i, x_j) y_i^k y_j^k \alpha_i^k \alpha_j^k$$

- ✓ More challenging than SVM; can be solved efficiently

Experiments

Datasets:

- ✓ VOC-06: 10 classes, 5304 images & VOC-07: 20 classes, 9963 images - %50 train - %50 test (10 random runs)

Baseline methods:

- ✓ Ova SVM (LIBSVM and SVMperf)
- ✓ MLSSM (Ji et al. 2008)

Table 1. Mean and standard deviation of AUC (%)

VOC 2006	Proposed	LIBSVM	SVM-perf	MLSSM
Overall	76.8 ± 0.4	76.4 ± 0.6	74.2 ± 0.8	75.8 ± 0.6
multi-obj	81.2 ± 0.9	74.3 ± 0.7	74.0 ± 0.1	77.8 ± 0.7
single-obj	74.4 ± 1.0	76.8 ± 0.7	75.6 ± 0.7	75.6 ± 0.7
VOC 2007	Proposed	LIBSVM	SVM-perf	MLSSM
Overall	76.0 ± 0.2	74.8 ± 0.1	68.2 ± 0.6	74.7 ± 0.2
multi-obj	79.4 ± 0.7	77.9 ± 0.2	69.4 ± 0.8	78.6 ± 0.1
single-obj	73.1 ± 0.5	72.2 ± 0.2	67.9 ± 0.2	71.3 ± 0.1

Table 2. Mean and standard deviation for running times (sec)

	Proposed	LIBSVM	SVM-perf	MLSSM
VOC 2006	43.2 ± 1.4	1147.5 ± 349.7	673.7 ± 65.8	324.2 ± 16.9
VOC 2007	447.3 ± 0.3	7720.7 ± 34.2	1597.3 ± 3.21	1821.04 ± 5.1

Conclusions

- ✓ Overall, the proposed method is more effective for object recognition compared to baselines.
- ✓ The performance gain is larger for images with multiple objects labeled. This shows the benefit of our ranking approach versus binary decomposition.
- ✓ The proposed algorithm is computationally more efficient than the three baseline methods.



True objects	People, motorbike, car	Car, people, dog	People, motorbike, car
Proposed	People, motorbike, car	Car, people, dog	People, motorbike, car
LIBSVM	People, car, bus	People, car, horse	People, cow, motorbike
SVM-perf	People, horse, car	Car, people, cat	People, cat, car
MLSSM	People, car, bus	People, dog, cat	People, car, bus