A New Convex Loss Function For Multiple Instance Support Vector Machines

I INTRODUCTION

❑ Multiple Instance Learning (MIL)
- Weakly Supervised Learning
- Training instances are arranged in sets, called bags
- Labels are provided for entire bags, not for instances
- Task: Find a bag classifier to predict the labels of unseen bags

❑ Applications of MIL
- Drug Activity Prediction Problem: the first MIL Model
- Computer Aided Diagnosis (from images)
- Anomaly Detection in Videos
- Video Classification

❑ SVM Formulations od MIL
- mi-SVM/MI-SVM, ∝SVM, RMI-SVM

❑ WR-SVM
- A New SVM based on the Witness Rate(WR) of a positive bag
- Maximizing the minimum WR among positive bags
- Estimation of WR of a positive bag using tanh(·) for unknown labels

❑ Contributions of WR-SVM
- Proposing a new convex loss function for MIL
- Providing a very simple NN framework for MIL

Ⅱ MATHEMATICAL MODELS

❑ Binary MIL Model: Training dataset: $\{(X_i, Y_i)\}_{i=1}^{N}$
- $X_i = \{x_1^i, x_2^i, \ldots, x_{M_i}^i\}$: bag i
- $x_j^i \in R^d$: instances of bag i
- $Y_i \in \mathcal{Y} = \{-1,1\}$ is the known label of the bag X_i.
- The label y_j^i of an instance x_j^i is unknown, $y_j^i \in \{-1,1\}$

❑ Standard MIL Assumptions
- If $Y_i = 1$, then $y_j^i = 1$ for at least one $j \in \{1, \cdots, M_i\}$.
- If $Y_i = -1$, then $y_j^i = -1$ for all $j \in \{1, \cdots, M_i\}$.

❑ WR-SVM
- The Witness Rate (WR) ρ_i of the i-th positive bag is defined by

$$\rho_i = \frac{1}{M_i} \sum_{j=1}^{M_i} \mathbb{1}_{\{y_j^i = 1\}}$$

- WR-SVM maximizes $\min_{i:Y_i=1} \{\rho_i\}$:

$$\min_{y_j^i, w, b, \xi_j^i} \frac{\lambda}{2}\|w\|^2 + \frac{1}{N}\sum_{i:Y_i=-1} \xi_j^i + \frac{1}{N}\frac{1}{\min_{i:Y_i=1}\{\rho_i\}}$$

subject to

$$-w^T x_j^i - b \geq 1 - \xi_j^i, \quad \forall i: Y_i = -1$$

$$\sum_j \frac{y_j^i + 1}{2} \geq 1, \ \forall i: Y_i = 1$$

$$y_j^i \in \{-1,1\}, \ \forall j, i: Y_i = 1$$

$$\xi_j^i \geq 0, \ \forall i: Y_i = -1$$

❑ Relax the integer variable y_j^i to be a real variable
- Approximate the label y_j^i of an instance x_j^i in positive bags with a real variable $z_j^i = \tanh(w^T x_j^i + b) \in (-1,1)$
- Using this relaxation, WR can be approximated as:

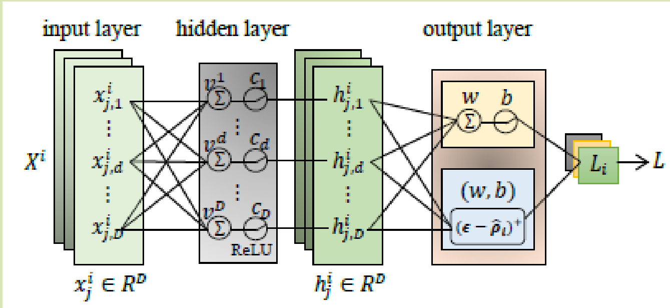
$$\hat{\rho}_i = \frac{1}{M_i} \sum_{j=1}^{M_i} \mathbb{1}_{\{z_j^i \geq z_0\}} z_j^i$$

- Loss function L of WR-SVM:

$$L = \frac{\lambda}{2}\|w\|^2 + \frac{1}{N}\sum_{i:Y_i=-1} \sum_{j=1}^{M_i} \left(1 + w^T x_j^i + b\right)_+ + \frac{1}{N}\sum_{i:Y_i=1} (\epsilon - \hat{\rho}_i)_+$$

Ⅲ EXPERIMENTS

❑ DNN architecture of WR-SVM
- The loss function L is convex.
- MIL pooling function for WR-SVM is $\hat{\rho}_i > 0$.
- Deep WR-SVM need not the MIL Pooling Layer
- The first Deep MIL without MIL Pooling Layer



❑ Video Datasets (30 classes)
- WIDER bags: sampled WIDER images from 30 classes (class 0class 29) to make artificial video bags
- CCV + WIDER bags
- HMDB51
- UCF-101

❑ Performance of WR-SVM

Classifier	Accuracy(%)			
	WIDER	CCV+	HMDB51	UCF-101
mi-SVM	25.42	23.24	21.33	19.41
MI-SVM	27.73	28.45	25.46	23.72
alter ∝SVM	35.33	31.35	29.37	33.30
Single-granular ∝SVM	37.45	34.85	31.65	28.75
RMI-SVM	37.10	38.15	35.78	34.26
Ensemble of CNNs	68.32	58.42	64.75	66.37
AWR-SVM	71.65	69.53	68.71	65.66

IV CONCLUSIONS

❑ Contributions of Our Works
- We introduce a new convex formulation, WR-SVM, of the MIL problem based on the WRs of positive bags.
- Our NN framework of WR-SVM is one of the simplest NN models for MIL.

❑ Further Research
- Test WR-SVM for larger classes and develop efficient bag generators
- Optimal DNN architectures (i.e., depths and widths) for WR-SVM