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Paired passive aggressive for ranking and classification

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Abstract

This paper describes the ....

Keywords: Passive aggressive, AUC, MAP

1. Introduction

The importance of the problem

Related work

2. Problem Setting

Notation

AUC notation $\boldsymbol{x}+$ and $\boldsymbol{x}-$....

loss

3. Average Classification Loss

Define the loss and the problem

Derive the update rule

Theorem 1: the expected loss is less than the average loss

Theorem 2: 1-AUC is bounded

Theorem 3: Show that classification is correct and $wx+ > 0$ while $wx- < 0$ after the update

4. Double-slack

Define the new problem

Derive update rules using DCA

Derive update rules by calling PA sequentially

Theorem 4: convergence of DCA

Theorem 5: classification errors –¿ number of mistakes

Theorem 6: Show that classification is correct and $wx+ > 0$ while $wx- < 0$ after the update

Theorem 7: from Theorem 5 it follows that 1-AUC is bounded

5. Calibrated Multilabel Classification and Ranking

Calibrated separation ranking loss was proposed by **?**

Derive update rule

Theorem 8: correct multilabels are above the incorrect set of labels

Can we show that 1-MAP is bounded?

6. Experiments

Synthetic data

Discriminative keyword spotting with algo 1 and algo 2

LETOR3 data for ranking with algo 1 and algo 2

multi label - Reuters

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Appendix A.

In this appendix we prove the following theorem from Section X.X:

Theorem *First we will show that the 1 - AUC is bounded by the mean of the errors in the first class and the mean number of errors in the second class.* $1 - AUC \leq E(M^{+}) + E(M^{-})$ ∎

Proof

$$\begin{aligned} 1 - AUC = \frac{1}{|X^{-}||X^{+}|} \sum_{x^{+} \in X^{+}, x^{-} \in X^{-}} \mathbb{1}_{\boldsymbol{w}^T \boldsymbol{x}^{+} \leq \boldsymbol{w}^T \boldsymbol{x}^{-}} \quad \leq \\ \frac{1}{|X^{-}||X^{+}|} \sum_{\boldsymbol{x}^{+} \in X^{+}, \boldsymbol{x}^{-} \in X^{-}} \mathbb{1}_{\boldsymbol{w}^T \boldsymbol{x}^{+} \leq 0} \; + \; \mathbb{1}_{0 \leq \boldsymbol{w}^T \boldsymbol{x}^{-}} \quad = \\ \frac{1}{|X^{+}|} \sum_{\boldsymbol{x}^{+} \in X^{+}} \mathbb{1}_{\boldsymbol{w}^T \boldsymbol{x}^{+} \leq 0} \; + \; \frac{1}{|X^{-}|} \sum_{\boldsymbol{x}^{-} \in X^{-}} \mathbb{1}_{0 \leq \boldsymbol{w}^T \boldsymbol{x}^{-}} \; = \; E(M^{+}) + E(M^{-}) \end{aligned} \tag{1}$$

and that is that.

Theorem *The sum of the average mistake in the two classes can be bounded* $E(M^{+}) + E(M^{-}) \leq \frac{1}{|X^{-}||X^{+}|}\, max\{R^2, 1/C\}(||\mathbf{u}||^2 + 2C \sum_{t=1}^{T} l_t^{*+} + l_t^{*-})$ ∎

Proof.

$$. \tag{2}$$

References