NON-DECOMPOSABLE PERFORMANCE MEASURES

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Overview

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- Some Terminologies
- Existing Solutions
- Problems in Existing Solutions
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Problem Statement

Finding general optimization techniques which can work on all non-decomposable performance measures.

Misclassification

• Can be represented as -

$$\sum \frac{1-y_iy_i^*}{2}$$

• Decomposable.

Multivariate

$$\overline{h}: \overline{\mathcal{X}} \to \overline{\mathcal{Y}}
\overline{h}_w(\overline{x}) = \underset{\overline{y}^* \in \mathcal{Y}}{\operatorname{arg\,max}} (w^T \psi(\overline{x}, \overline{y}^*))
\psi(\overline{x}, \overline{y}^*) = \sum_{i=1}^n y_i^* x_i$$

Non-decomposable Performance Measures

- Performance Measures which do not decompose linearly.
- In classification problems, error rates are generally used.
- But not useful in case of class imbalance.
- So, measures like -
 - F-measure is used for text retrieval.
 - A continuous function of TPR and TNR is used in class imbalanced classification settings.

Examples

G-mean:

$$\sqrt{pq}$$

Min

H-mean:

$$\frac{2PN}{P+N}$$

Problems in Non-decomposable Performance Measures

- Non-convex.
- Require an approximate upper bound on the raw performance measure curve given by some (surrogate) convex function which can be optimized easily.

Training Sample

$$S = ((x_1, y_1), \cdots, (x_n, y_n)) \in (\mathcal{X} \times \mathcal{Y})^n$$

drawn i.i.d. according to some unknown probability distribution.

• Find a rule $h \in \mathcal{H}$ from hypothesis space \mathcal{H} such that it optimizes the expected prediction performance

$$R^{\Delta}(h) = \int \Delta((h(x_1), \cdots, h(x_n)), (y_1, \cdots, y_n)) dPr(S)$$

- Loss function Δ is not decomposable.
- ullet Optimize the empirical loss function Δ over the entire sample set.

$$\hat{R}_{S}^{\Delta}(h) = \Delta((h(x_1), \cdots, h(x_n)), (y_1, \cdots, y_n))$$

• For such problems, structural SVM is used.

General approach to this problem based on SVM

$$\min_{w,\zeta \geq 0} \frac{1}{2} ||w||^2 + C\xi$$

$$s.t \quad \forall \overline{y}^* \in \overline{\mathcal{Y}} \setminus \overline{y} : w^T [\psi(\overline{x}, \overline{y}) - \psi(\overline{x}, \overline{y}^*)] \geq \Delta(\overline{y}^*, \overline{y}) - \xi$$

$$\Rightarrow \Delta(\overline{y}^*, \overline{y}) + w^T (\Sigma x_i y_i^* - \Sigma x_i y_i) \leq \xi$$

$$\Rightarrow \Delta(\overline{y}^*, \overline{y}) + (\Sigma (y_i^* - y_i) w^T x_i) \leq \xi$$

where $\Delta(\overline{y}^*, \overline{y})$ is loss function.

Considering concave performance measures

$$P_{\psi} = \psi(TPR, TNR)$$

• For any concave function ψ and $\alpha, \beta \in \mathbb{R}$

$$\psi^*(\alpha, \beta) = \inf_{u, v \in \mathcal{R}} \{ \alpha u + \beta v - \psi(u, v) \}$$

By concavity,

$$\psi(\mathbf{u}, \mathbf{v}) = \inf_{\alpha, \beta \in \mathcal{R}} \{ \alpha \mathbf{u} + \beta \mathbf{v} - \psi^*(\alpha, \beta) \}$$

SPADE Algorithm

- Requires link functions to be L-Lipschitz.
- Works with non-Lipschitz functions when some restrictions are imposed on them.

Our Solution

Trying to remove the restrictions to give a general solution.

$$\begin{split} \hat{R}_{S}^{\Delta}(h) &= \Delta((h(x_{1}), \cdots, h(x_{n})), (y_{1}, \cdots, y_{n})) \\ h(x, w) &= \underset{y \in \mathcal{Y}}{\text{arg max}} \, F(x, y; w) \\ F(x, y; w) &= \langle w, \psi(x, y) \rangle \\ h_{w}(\overline{x}, w) &= \underset{\overline{y} \in \mathcal{Y}}{\text{arg max}} (w^{T} \psi(\overline{x}, \overline{y})) \\ \min_{\overline{y} \in \mathcal{Y}} &= \frac{1}{2} \|w\|^{2} + C\zeta \\ s.t \quad \forall \overline{y}' \in \overline{\mathcal{Y}} \setminus \overline{y}^{*} : w^{T} [\psi(\overline{x}, \overline{y}) - \psi(\overline{x}, \overline{y}^{*})] \geq \Delta(\overline{y}^{*}, \overline{y}) - \zeta \end{split}$$

References



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Questions?