

MULTIVARIATE OPTIMIZATION FOR NON-DECOMPOSABLE PERFORMANCE MEASURES

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November 25, 2016

Overview

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Problem Statement

Finding general optimization technique to maximize performance which are non-decomposable in nature. Our work will primarily consider some concave measures of performance.

- Examples: Min, G-mean, H-mean etc.
- Expressed as $f(TPR, TNR)$.
- TPR = True Positive Rate, TNR = True Negative Rate

Stochastic Primal Dual Method [NarasimhanK015]

The existing online method has following shortcomings:

- Requires performance measure function to be L-Lipschitz.
- Works with non-Lipschitz functions with some restriction.
- Example: G-mean

Decomposable vs Non-decomposable

- Misclassification rate is decomposable. Loss function:

$$\Delta(\bar{y}, \bar{y}^*) = \frac{1}{n} \sum_{i=1}^n \frac{1 - y_i y_i^*}{2}$$

- F_β score is non-decomposable. Performance measure:

$$\phi(\bar{y}, \bar{y}^*) = \frac{(1 + \beta^2) TP}{(1 + \beta^2) TP + \beta^2 FN + FP}$$

- Problem with misclassification rate?
 - class imbalanced setting

Multivariate Optimization Setting

- Hypothesis function \bar{h} maps $\bar{x} \in \bar{\mathcal{X}}$ and $\bar{x} = \{x_1, x_2, \dots, x_n\}$ to $\bar{y} \in \bar{\mathcal{Y}}$ and $\bar{y} = \{y_1, y_2, \dots, y_n\}$ where $y_i \in \{+1, -1\}$

$$\bar{h} : \bar{\mathcal{X}} \rightarrow \bar{\mathcal{Y}}$$

- We define score for a particular input-output combination as follows:

$$f_w(\bar{x}, \bar{y}) = w^T \psi(\bar{x}, \bar{y})$$

- Hypothesis function gives \bar{y} with highest score for an input \bar{x} .

$$\bar{h}_w(\bar{x}) = \arg \max_{\bar{y} \in \bar{\mathcal{Y}}} (w^T \psi(\bar{x}, \bar{y}))$$

- We use the following form of ψ

$$\psi(\bar{x}, \bar{y}) = \sum_{i=1}^n y_i^* x_i$$

Structural SVM

- Struct SVM by [Joachims:2005] used for multi-class classification.

$$\begin{aligned}
 \min_{w, \xi \geq 0} \quad & \frac{1}{2} \|w\|^2 + C\xi \\
 \text{s.t.} \quad & \forall \bar{y} \in \bar{\mathcal{Y}} \setminus \bar{y}^* : w^T [\psi(\bar{x}, \bar{y}^*) - \psi(\bar{x}, \bar{y})] \geq \Delta(\bar{y}^*, \bar{y}) - \xi \\
 & \Rightarrow \Delta(\bar{y}^*, \bar{y}) + \sum (y_i - y_i^*) w^T x_i \leq \xi
 \end{aligned}$$

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

- ξ is the upper bound of loss function.
- We substitute margin violation ξ in objective function by

$$\mathcal{L}_w(\bar{x}, \bar{y}^*) = \max_{\bar{y} \in \{1, -1\}^n} \{ \Delta(\bar{y}^*, \bar{y}) + \sum_{i=1}^n (y_i - y_i^*) w^T x_i \} \quad (1)$$

Performance measure in Fenchel Dual

- Performance measure G-mean is given by

$$\begin{aligned}\phi(P, N) &= \sqrt{PN} \\ &= \min_{\alpha, \beta} \{ \alpha P + \beta N - \phi^*(\alpha, \beta) \}\end{aligned}$$

as ϕ is a concave function. P, N stands for TPR and TNR respectively.

- We define our loss function as

$$\begin{aligned}\Delta(\bar{y}^*, \bar{y}) &= -\phi(P, N) \\ &= \max_{\alpha, \beta} \{ -\alpha P - \beta N + \phi^*(\alpha, \beta) \}\end{aligned}$$

Optimization Problem

- We can re-write equation 1 as,

$$\begin{aligned}
 & \mathcal{L}_w(\bar{x}, \bar{y}^*) \\
 &= \max_{\bar{y} \in \{1, -1\}^n} \left\{ \max_{\alpha, \beta} \{-\alpha P - \beta N + \phi^*(\alpha, \beta)\} + \frac{1}{n} \sum_{i=1}^n (y_i - y_i^*) w^T x_i \right\} \\
 &= \max_{\alpha, \beta} \left\{ \max_{\bar{y}} \{-\alpha P - \beta N + \frac{1}{n} \sum_{i=1}^n (y_i - y_i^*) w^T x_i\} + \phi^*(\alpha, \beta) \right\} \quad (2)
 \end{aligned}$$

- Express P and N as following:

$$P = \sum_{i=1}^n P_i(y_i, y_i^*) = \frac{1}{n_+} \sum_{i=1}^n \frac{(1 + y_i)(1 + y_i^*)}{4}$$

Continued...

$$N = \sum_{i=1}^n N_i(y_i, y_i^*) = \frac{1}{n_-} \sum_{i=1}^n \frac{(1 - y_i)(1 - y_i^*)}{4}$$

- Substituting, inner maximization becomes,

$$\sum_{i=1}^n \max_{y_i \in \{-1, +1\}} -\frac{\alpha}{n_+} \frac{(1 + y_i)(1 + y_i^*)}{4} - \frac{\beta}{n_-} \frac{(1 - y_i)(1 - y_i^*)}{4} + \frac{1}{n} (y_i - y_i^*) w^T x_i$$

using independence among the data points.

- Now we can perform maximization for each point separately.

Continued...

Solving the above maximization, we get the following weighted hinge loss like function with some additional constants,

$$\sum_{i=1}^n \left(\frac{\alpha}{n_+} \max\{0, 1 - y_i^* \frac{2n_+}{\alpha n} w^T x_i\} - \frac{\alpha}{n_+} \right) \mathbb{I}(y_i^* = 1) \\ + \left(\frac{\beta}{n_-} \max\{0, 1 - y_i^* \frac{2n_-}{\beta n} w^T x_i\} - \frac{\beta}{n_-} \right) \mathbb{I}(y_i^* = -1)$$

Now we can re-write equation 2 as following

$$\mathcal{L}_w(\bar{x}, \bar{y}^*) = \max_{\alpha, \beta} \left\{ \frac{\alpha}{n_+} \sum_{y_i^*=1} \max\{0, 1 - y_i^* \frac{2n_+}{\alpha n} w^T x_i\} \right. \\ \left. + \frac{\beta}{n_-} \sum_{y_i^*=-1} \max\{0, 1 - y_i^* \frac{2n_-}{\beta n} w^T x_i\} \right. \\ \left. - (\alpha + \beta) + \phi^*(\alpha, \beta) \right\}$$

Objective function

We can substitute the loss in struct SVM:

$$\begin{aligned}
 & \min_w \frac{\|w\|^2}{2} + C \mathcal{L}_w(\bar{x}, \bar{y}^*) \\
 & \equiv \min_w \frac{\|w\|^2}{2} + C \max_{\alpha, \beta} \left\{ \frac{\alpha}{n_+} \sum_{y_i^*=1} \max\left\{0, 1 - y_i^* \frac{2n_+}{\alpha n} w^T x_i\right\} \right. \\
 & \quad \left. + \frac{\beta}{n_-} \sum_{y_i^*=-1} \max\left\{0, 1 - y_i^* \frac{2n_-}{\beta n} w^T x_i\right\} \right. \\
 & \quad \left. - (\alpha + \beta) + \phi^*(\alpha, \beta) \right\}
 \end{aligned}$$

Solution Steps

We perform the following steps in each iterative cycle:

- 1 Fix w
- 2 Gradient ascent on $\mathcal{L}_w(\bar{x}, \bar{y}^*)$ wrt α, β
- 3 Fix α, β
- 4 SVM wrt w
- 5 Go to step 1

We can use Liblinear solver to perform SVM.

Conjugate function of $\phi(P, N)$

For any concave ϕ

$$\phi(P, N) = \min_{\alpha, \beta} \{\alpha P + \beta N - \phi^*(\alpha, \beta)\}$$

For G-mean as ϕ

$$\phi(P, N) = \sqrt{PN}$$

$$\phi^*(\alpha, \beta) = \min_{P, N} \{\alpha P + \beta N - \sqrt{PN}\}$$

Solving for $g'(P, N) = 0$ where $g = \alpha P + \beta N - \sqrt{PN}$, we get $\alpha = \frac{1}{2}\sqrt{\frac{N}{P}}$ and $\beta = \frac{1}{2}\sqrt{\frac{P}{N}}$ giving

$$\phi^*(\alpha, \beta) = 0 \tag{3}$$

Dual feasible region

Trivial: $\alpha > 0, \beta > 0$ as $P, N \geq 0$

$$\begin{aligned} g &= \alpha P + \beta N - \sqrt{PN} \\ &= (\sqrt{\alpha P} - \sqrt{\beta N})^2 + \sqrt{PN}(2\sqrt{\alpha\beta} - 1) \end{aligned}$$

By ensuring $P = \frac{\beta N}{\alpha}$ we can show the first part to be zero. For large P, N , $g \rightarrow -\infty$ if $2\sqrt{\alpha\beta} < 1$. Hence the feasible dual region is defined by,

$$\text{dom}(\alpha, \beta) = \{\alpha, \beta | \alpha\beta \geq \frac{1}{4}, \alpha > 0, \beta > 0\}$$

Q. P, N has to be the number of true positives/negatives, not rate?

Gradient computation

- $h(\alpha) = \frac{\alpha}{n_+} \max\{0, 1 - y_i^* \frac{2n_+}{\alpha n} w^T x_i\}$. By Danskin's theorem it can be shown that,

$$h'(\alpha) = \begin{cases} 0, & \text{if } y_i^* \frac{2n_+}{\alpha n} w^T x_i \geq 1 \\ \frac{1}{n_+}, & \text{otherwise} \end{cases}$$

- Similarly for $h(\beta) = \frac{\beta}{n_-} \max\{0, 1 - y_i^* \frac{2n_-}{\beta n} w^T x_i\}$. By Danskin's theorem it can be shown that,

$$h'(\beta) = \begin{cases} 0, & \text{if } y_i^* \frac{2n_-}{\beta n} w^T x_i \geq 1 \\ \frac{1}{n_-}, & \text{otherwise} \end{cases}$$

- We have proved $\phi^*(a, b) = 0$ for G-mean, hence its derivative gives 0.

Problem with Gradient Ascent

- Unbounded increase in dual variables in \mathbb{R}_+^2

References



Joachims, Thorsten

A Support Vector Method for Multivariate Performance Measures.

Proceedings of the 22Nd International Conference on Machine Learning



Narasimhan, Harikrishna and Vaish, Rohit and Agarwal, Shivani

On the Statistical Consistency of Plug-in Classifiers for Non-decomposable Performance Measures.

Advances in Neural Information Processing Systems 27



Narasimhan, Harikrishna and Kar, Purushottam and Jain, Prateek

Optimizing Non-decomposable Performance Measures: A Tale of Two Classes.

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Thank You!