THU-70250403, Convex Optimization (Fall 2020)

Homework: 5

Dual Problems and Classification

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Problem 1

Considering the following optimization problem

$$\min_{\boldsymbol{x}, \boldsymbol{z} \in \mathbb{R}^n} \quad \frac{1}{2} |\boldsymbol{x}|_2^2 + \frac{1}{2} |A\boldsymbol{z} - \boldsymbol{b}|_2^2
\text{s.t.} \quad \boldsymbol{x} - \boldsymbol{z} = \boldsymbol{c} \tag{2}$$

s.t.
$$\boldsymbol{x} - \boldsymbol{z} = \boldsymbol{c}$$
 (2)

where $A \in \mathbb{R}^{m \times n}$ are known constant matrix with rank $(A) = n, b \in \mathbb{R}^m, c \in \mathbb{R}^n$ are known constant vectors.

Please derive the corresponding dual problem.

Problem 2

The sum of the largest elements of a vector.

Define $f: \mathbb{R}^n \to \mathbb{R}$ as

$$f(\boldsymbol{x}) = \sum_{i=1}^{r} \boldsymbol{x}_{[i]},$$

where r is an integer between 1 and n, and $\boldsymbol{x}_{[1]} \geqslant \boldsymbol{x}_{[2]} \geqslant \cdots \geqslant \boldsymbol{x}_{[r]}$ are the components of x sorted in decreasing order. In other words, f(x) is the sum of the r largest elements of x. In this problem we study the constraint

$$f(\boldsymbol{x}) \leqslant \alpha.$$

This is a convex constraint, and equivalent to a set of n!/(r!(n-r)!) linear inequalities

$$\boldsymbol{x}_{i_1} + \cdots + \boldsymbol{x}_{i_r} \leqslant \alpha, \quad 1 \leqslant i_1 < i_2 < \cdots < i_r \leqslant n.$$

The purpose of this problem is to derive a more compact representation.

1. Given a vector $\boldsymbol{x} \in \mathbb{R}^n$, show that $f(\boldsymbol{x})$ is equal to the optimal value of the LP

maximize
$$\boldsymbol{x}^T \boldsymbol{y}$$
 subject to $\boldsymbol{0} \leq \boldsymbol{y} \leq \boldsymbol{1}$ $\boldsymbol{1}^T \boldsymbol{y} = r$

with $\mathbf{y} \in \mathbb{R}^n$ as variable.

2. Derive the dual of the LP in part (a). Show that it can be written as

minimize
$$rt + \mathbf{1}^T \mathbf{u}$$

subject to $t\mathbf{1} + \mathbf{u} \succeq \mathbf{x}$
 $\mathbf{u} \succeq \mathbf{0}$,

where the variables are $t \in \mathbb{R}$, $\boldsymbol{u} \in \mathbb{R}^n$. By duality this LP has the same optimal value as the LP in (a), *i.e.*, f(x). We therefore have the following result: \boldsymbol{x} satisfies $f(\boldsymbol{x}) \leqslant \alpha$ if and only if there exist $t \in \mathbb{R}$, $\boldsymbol{u} \in \mathbb{R}^n$ such that

$$rt + \mathbf{1}^T \mathbf{u} \leqslant \alpha, \qquad t\mathbf{1} + \mathbf{u} \succeq \mathbf{x}, \qquad \mathbf{u} \succeq \mathbf{0}.$$

These conditions form a set of 2n+1 linear inequalities in the 2n+1 variables $\boldsymbol{x},\boldsymbol{u},t$.

Problem 3

The so called Support Vector Data Description (SVDD) [1] is a one-class classification method. Given a set of data $(\boldsymbol{x}_i), i = 1, \ldots, l, \boldsymbol{x}_i \in \mathbb{R}^n$, SVDD tries to find a closed boundary (indeed an hypersphere centered at $\boldsymbol{a} \in \mathbb{R}^n$ and has a radius $r \in \mathbb{R}$) around the data by solving the following problem

$$\min_{\boldsymbol{a},r} \quad r^2 + C \sum_{i=1}^{L} \xi_i \tag{3}$$

s.t.
$$|\mathbf{x}_i - \mathbf{a}|_2^2 \le r^2 + \xi_i, \ i = 1, \dots, L$$
 (4)

$$\xi_i \ge 0, \ i = 1, \dots, L \tag{5}$$

where C > 0 is a penalty parameter.

Please explain the geometry meaning of ξ_i above and derive the dual problem.

References

 D. M. J. Tax, R. P. W. Duin, "Support Vector Data Description," Machine Learning, vol. 54, no. 1, pp. 45-66, 2004.