Constrained Optimization I

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Lagrangian and Duality

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Lectures heavily inspired by the Maths for Machine learning book

Minimax Inequality

- Minimax inequality states:$\max_{\boldsymbol{y}} \min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y}) \leqslant \min_{\boldsymbol{x}} \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$

Minimax Inequality

- Minimax inequality states:$\max_{\boldsymbol{y}} \min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y}) \leqslant \min_{\boldsymbol{x}} \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$
- We first prove For all $\boldsymbol{x}, \boldsymbol{y}$ $\quad \min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y}) \leqslant \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$

Minimax Inequality

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x $\Downarrow$				
1	1	2	3	4
2	2	4	6	8
3	3	6	9	12
4	4	8	12	16
	1	2	3	4

$y \Rightarrow$

Minimax Inequality

- For each value of x, we find y that maximizes $q(x, y)$

x ⇓					
	1	1	2	3	4
	2	2	4	6	8
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$y \Rightarrow$

Minimax Inequality

- For each value of x, we find y that maximizes $q(x, y)$
- $y = 4$ maximizes $q(x, y)$ $\forall x$

x	1	1	2	3	4
$\Downarrow$	2	2	4	6	8
	3	3	6	9	12
	4	4	8	12	16
		1	2	3	4
		y	$\Rightarrow$		

Minimax Inequality

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Minimax Inequality

- For each value of y, we find x that minimizes $q(x, y)$
- $x = 1$ minimizes $q(x, y)\ \forall y$

x	1	1	2	3	4
$\Downarrow$	2	2	4	6	8
	3	3	6	9	12
	4	4	8	12	16
		1	2	3	4
		y	$\Rightarrow$		

Minimax Inequality

- We just showed For all $\boldsymbol{x}, \boldsymbol{y}$ $\min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y}) \leqslant \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$

x	1	1	2	3	4
$\Downarrow$	2	2	4	6	8
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		1	2	3	4
		y	$\Rightarrow$		

Minimax Inequality

- We just showed For all $\boldsymbol{x}, \boldsymbol{y}$ $\min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y}) \leqslant \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$
- The equality occurs at $x = 1, y = 4$

$x \Downarrow$				
1	1	2	3	4
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$y \Rightarrow$

Minimax Inequality

- Let us now find $\max_{\boldsymbol{y}} \min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y})$

x $\Downarrow$					
	1	1	2	3	**4**
	2	2	4	6	8
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$y \Rightarrow$

Minimax Inequality

- Similarly, let us now find $\min_{\boldsymbol{x}} \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$

x	1	1	2	3	**4**
$\Downarrow$	2	2	4	6	8
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	4	4	8	12	16
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Minimax Inequality

- Similarly, let us now find $\min_{\boldsymbol{x}} \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$
- We can thus see our Minimax inequality $\max_{\boldsymbol{y}} \min_{\boldsymbol{x}} q(\boldsymbol{x}, \boldsymbol{y}) \leqslant \min_{\boldsymbol{x}} \max_{\boldsymbol{y}} q(\boldsymbol{x}, \boldsymbol{y})$

x					
$x \Downarrow$	1	1	2	3	**4**
	2	2	4	6	8
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Revisiting the Lagrange multipliers

Our problem is of the form

$$\begin{array}{lll} \min_{\boldsymbol{x}} & f(\boldsymbol{x}) & \\ \text{subject to} & g_i(\boldsymbol{x}) \leqslant 0 \quad \text{for all} & i = 1, \ldots, m \end{array}$$

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Idea: Convert constrained problem to an unconstrained problem

$$J(\boldsymbol{x}) = f(\boldsymbol{x}) + \sum_{i=1}^{m} \mathbf{1}\left(g_i(\boldsymbol{x})\right)$$

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where $1(z)$ is an infinite step function

$$\mathbf{1}(z) = \begin{cases} 0 & \text{if } z \leqslant 0 \\ \infty & \text{otherwise} \end{cases}$$

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This would give infinte penalty if constraint is not satisfied. But, this formulation is hard to solve too.

Revisiting the Lagrange multipliers

Idea: Introduce Lagrange multipliers ($\lambda_i \geq 0$) to "approximate" $J(x)$

$$\mathfrak{L}(\boldsymbol{x}, \boldsymbol{\lambda}) = f(\boldsymbol{x}) + \sum_{i=1}^{m} \lambda_i g_i(\boldsymbol{x})$$

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What is the relationship between $\mathfrak{L}(\boldsymbol{x}, \boldsymbol{\lambda})$ and $J(\boldsymbol{x})$ given $\lambda_i \geq 0$?

When $\lambda \geqslant 0$, the Lagrangian $\mathcal{L}(x, \lambda)$ is a lower bound of $J(\boldsymbol{x})$. Hence, the maximum of $\mathfrak{L}(\boldsymbol{x}, \boldsymbol{\lambda})$ with respect to $\boldsymbol{\lambda}$ is

$$J(\boldsymbol{x}) = \max_{\boldsymbol{\lambda} \geqslant 0} \mathfrak{L}(\boldsymbol{x}, \boldsymbol{\lambda})$$

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But, our original problem was minimizing $J(\boldsymbol{x})$, which is equivalent to:

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We can write the dual objective as a function of λ as $\mathfrak{D}(\boldsymbol{\lambda}) = \min_{\boldsymbol{x} \in \mathbb{R}^d} \mathfrak{L}(\boldsymbol{x}, \boldsymbol{\lambda})$

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- Primal objective:

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- Or, primal objective (in terms of x) $\geq$ dual objective (in terms of λ)
- For SVM like formulations, primal objective is the same as dual objective (strong duality)
- For some problems, there is a "daulity-gap" between the two objectives