# 6.252 NONLINEAR PROGRAMMING 

## LECTURE 20: STRONG DUALITY

## LECTURE OUTLINE

- Strong Duality Theorem
- Linear equality constraints. Fenchel Duality.
********************************
- Consider the problem
minimize $f(x)$
subject to $x \in X, \quad g_{j}(x) \leq 0, \quad j=1, \ldots, r$,
assuming $-\infty<f^{*}<\infty$.
- $\mu^{*}$ is a Lagrange multiplier if $\mu^{*} \geq 0$ and $f^{*}=$ $\inf _{x \in X} L\left(x, \mu^{*}\right)$.
- Dual problem: Maximize $q(\mu)=\inf _{x \in X} L(x, \mu)$ subject to $\mu \geq 0$.


## DUALITY THEOREM FOR INEQUALITIES

- Assume that $X$ is convex and the functions $f: \Re^{n} \mapsto \Re, g_{j}: \Re^{n} \mapsto \Re$ are convex over $X$. Furthermore, the optimal value $f^{*}$ is finite and there exists a vector $\bar{x} \in X$ such that

$$
g_{j}(\bar{x})<0, \quad \forall j=1, \ldots, r .
$$

- Strong Duality Theorem: There exists at least one Lagrange multiplier and there is no duality gap.



## PROOF OUTLINE

- Show that $A$ is convex. [Consider vectors $(z, w) \in$ $A$ and $(\tilde{z}, \tilde{w}) \in A$, and show that their convex combinations lie in A.]
- Observe that $\left(0, f^{*}\right)$ is not an interior point of $A$. - Hence, there is hyperplane passing through $\left(0, f^{*}\right)$ and containing $A$ in one of the two corresponding halfspaces; i.e., a $(\mu, \beta) \neq(0,0)$ with

$$
\beta f^{*} \leq \beta w+\mu^{\prime} z, \quad \forall(z, w) \in A
$$

This implies that $\beta \geq 0$, and $\mu_{j} \geq 0$ for all $j$.

- Prove that hyperplane is nonvertical, i.e., $\beta>0$.
- Normalize $(\beta=1)$, take the infimum over $x \in X$, and use the fact $\mu \geq 0$, to obtain

$$
f^{*} \leq \inf _{x \in X}\left\{f(x)+\mu^{\prime} g(x)\right\}=q(\mu) \leq \sup _{\mu \geq 0} q(\mu)=q^{*} .
$$

Using the weak duality theorem, $\mu$ is a Lagrange multiplier and there is no duality gap.

## LINEAR EQUALITY CONSTRAINTS

- Suppose we have the additional constraints

$$
e_{i}^{\prime} x-d_{i}=0, \quad i=1, \ldots, m
$$

- We need the notion of the affine hull of a convex set $X$ [denoted $a f f(X)$ ]. This is the intersection of all hyperplanes containing $X$.
- The relative interior of $X$, denoted $r i(X)$, is the set of all $x \in X$ s.t. there exists $\epsilon>0$ with

$$
\{z \mid\|z-x\|<\epsilon, z \in a f f(X)\} \subset X,
$$

that is, $r i(X)$ is the interior of $X$ relative to $a f f(X)$. - Every nonempty convex set has a nonempty relative interior.

## DUALITY THEOREM FOR EQUALITIES

- Assumptions:
- The set $X$ is convex and the functions $f, g_{j}$ are convex over $X$.
- The optimal value $f^{*}$ is finite and there exists a vector $\bar{x} \in \operatorname{ri}(X)$ such that

$$
\begin{aligned}
g_{j}(\bar{x})<0, & j=1, \ldots, r, \\
e_{i}^{\prime} \bar{x}-d_{i}=0, & i=1, \ldots, m .
\end{aligned}
$$

- Under the preceding assumptions there exists at least one Lagrange multiplier and there is no duality gap.


## COUNTEREXAMPLE

- Consider
minimize $f(x)=x_{1}$
subject to $x_{2}=0, \quad x \in X=\left\{\left(x_{1}, x_{2}\right) \mid x_{1}^{2} \leq x_{2}\right\}$.
- The optimal solution is $x^{*}=(0,0)$ and $f^{*}=0$.
- The dual function is given by

$$
q(\lambda)=\inf _{x_{1}^{2} \leq x_{2}}\left\{x_{1}+\lambda x_{2}\right\}= \begin{cases}-\frac{1}{4 \lambda}, & \text { if } \lambda>0, \\ -\infty, & \text { if } \lambda \leq 0 .\end{cases}
$$

- No dual optimal solution and therefore there is no Lagrange multiplier. (Even though there is no duality gap.)
- Assumptions are violated (the feasible set and the relative interior of $X$ have no common point).


## FENCHEL DUALITY FRAMEWORK

- Consider the problem

$$
\begin{aligned}
& \operatorname{minimize} \quad f_{1}(x)-f_{2}(x) \\
& \text { subject to } x \in X_{1} \cap X_{2},
\end{aligned}
$$

where $f_{1}$ and $f_{2}$ are real-valued functions on $\Re^{n}$, and $X_{1}$ and $X_{2}$ are subsets of $\Re^{n}$.

- Assume that $-\infty<f^{*}<\infty$.
- Convert problem to
minimize $f_{1}(y)-f_{2}(z)$
subject to $z=y, \quad y \in X_{1}, \quad z \in X_{2}$,
and dualize the constraint $z=y$.

$$
\begin{aligned}
q(\lambda) & =\inf _{y \in X_{1}, z \in X_{2}}\left\{f_{1}(y)-f_{2}(z)+(z-y)^{\prime} \lambda\right\} \\
& =\inf _{z \in X_{2}}\left\{z^{\prime} \lambda-f_{2}(z)\right\}-\sup _{y \in X_{1}}\left\{y^{\prime} \lambda-f_{1}(y)\right\} \\
& =g_{2}(\lambda)-g_{1}(\lambda)
\end{aligned}
$$

## DUALITY THEOREM



- Assume that
- $X_{1}$ and $X_{2}$ are convex
- $f_{1}$ and $f_{2}$ are convex and concave over $X_{1}$ and $X_{2}$, respectively
- The relative interiors of $X_{1}$ and $X_{2}$ intersect
- The duality theorem for equalities applies and shows that

$$
f^{*}=\max _{\lambda \in \Re^{n}}\left\{g_{2}(\lambda)-g_{1}(\lambda)\right\}
$$

and that the maximum above is attained.

