# 1. Parameter Optimization Problems: 

# 1.3. Inequality Constrained Optimization 

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## 1 Kuhn-Tucker Problem

We will now develop the necessary conditions for $y^{*} \in \mathbf{R}^{n}$ to be a local minimum for the function $L(y)$, with the $p$-dimensional constraint $f(y) \leq 0$. We denote by $x \leq 0$, for a vector $x$, the scalar conditions $x_{i} \leq 0, i=1, \ldots p$.

If for some of the constraints $f_{1}\left(y^{*}\right)<0$, we say that the corresponding constraint is inactive, and it may be eliminated from the set. If on the other hand $f_{i}(y)=0$, then this constraint is said to be active. Clearly if at $y^{*}$ all constraints are inactive, the necessary condition for optimality is that $L_{y}=0$ as before.

Consider the more interesting case where $0<m \leq p$ of the $p$ given constraints are active. Consequently, we'll only look at these $m$ constraints, and with some abuse of notation, we'll denote this $m$-vector of constraints again by $f(y)$. At this point $m$ may be larger or smaller than $n$. We will also assume that the rank of $f$ at $y^{*}$ is $r$. This means that at the point $y *$, the $m \times n$ gradient matrix satisfies

$$
\operatorname{rank} f_{y}\left(y^{*}\right)=r \leq \min (m, n)
$$

Equivalently, this expresses that the gradients of the effective constraints span an $r$-dimensional subspace of $\mathbf{R}^{n}$.
In what follows we shall also make use of the class of selection matrices. An $r-m$ selection matrix $\Gamma$ is an $r \times m$ matrix whose rows are arbitrarily chosen from the $m \times m$ identity matrix. There always exists a selection matrix $\Gamma$ such that rank $\Gamma f_{y} f_{y}^{\prime} \Gamma^{\prime}=r$.
If $r<n$, denote by $\Gamma^{c}$ the complementary selection matrix, so that the rows of $f$ are a permutation of the rows of $\left[\begin{array}{c}\Gamma f_{y} \\ \Gamma^{c} f_{y}\end{array}\right]$.

[^0]First we will derive the set of admissible perturbations $d y$. A suitable basis for the tangent space at $y^{*}$, i.e., the vector space attached at $y^{*}$ (or with origin at $y^{*}$ ), are the $r$ selected gradients (the rows of $\Gamma f_{y}$ ) augmented (if $r<n$ ) with $n-r$ independent row vectors $\eta$ in the orthogonal complement of the rowspace of $\Gamma f_{y}$. Denoting this space by $f_{y}^{\perp}$, we also have that $f_{y}^{\perp}=\left[\Gamma f_{y}\right]^{\perp}$. Recall that vectors in the tangent space are row vectors. These rows, $\eta$, satisfy $\Gamma f_{y} \eta^{\prime}=0$. Changing back to columns (more precisely: the dual space), any arbitrary (column)-vector $d y$ of dimension $n$ can then be expressed as

$$
\begin{equation*}
d y=\left(\Gamma f_{y}\right)^{\prime}\left(\Gamma f_{y} f_{y}^{\prime} \Gamma^{\prime}\right)^{-1} \epsilon+\eta^{\prime} \quad ; \quad \Gamma f_{y} \eta^{\prime}=0 \tag{1}
\end{equation*}
$$

where $\epsilon \in \mathbf{R}^{r}$. Note that $\left(\Gamma f_{y} f_{y}^{\prime} \Gamma^{\prime}\right)^{-1} \epsilon$ selects a particular linear combination of the columns of $\left(\Gamma f_{y}\right)^{\prime}$. The vector $\eta$ may also be expressed as

$$
\begin{equation*}
\eta=f_{y}^{\perp^{\prime}} \nu, \tag{2}
\end{equation*}
$$

with $\nu \in \mathbf{R}^{n-r}$. If $r=n$, then $f_{y}^{\perp}=0$. This may seem like a strange parametrization, but the reason will become clear shortly. Admissibility of the perturbation, requires that the corresponding changes in $f$ satisfy the constraint, or $d f \leq 0$. Thus

$$
\begin{equation*}
d f=f_{y} d y=f_{y}\left(\Gamma f_{y}\right)^{\prime}\left(\Gamma f_{y} f_{y}^{\prime} \Gamma^{\prime}\right)^{-1} \epsilon+f_{y} f_{y}^{\perp^{\prime}} \nu \tag{3}
\end{equation*}
$$

from which:

$$
\begin{align*}
\Gamma d f & =\epsilon  \tag{4}\\
\Gamma^{c} d f & =0, \tag{5}
\end{align*}
$$

since $f_{y} f_{y}^{\perp^{\prime}}=0$ by definition. The condition for admissibility is thus $\epsilon \leq 0$.
What is now the effect on $d L$ of such an admissible perturbation? We express the gradient $L_{y}$ also in terms of the basis in the tangent space. Let thus for some row vectors $\lambda$ and $\mu$

$$
\begin{equation*}
L_{y}=-\lambda \Gamma f_{y}+\mu f_{y}^{\perp} \tag{6}
\end{equation*}
$$

be the expansion of the gradient $L_{y}$ in the chosen basis for the tangent space. Then the change in $L$ due to the admissible perturbation $d y$ is

$$
\begin{align*}
d L & =L_{y} d y=\left[-\lambda \Gamma f_{y}+\mu f_{y}^{\perp}\right]\left[\left(\Gamma f_{y}\right)^{\prime}\left(\Gamma f_{y} f_{y}^{\prime} \Gamma^{\prime}\right)^{-1} \epsilon+\eta^{\prime}\right] \\
& =-\lambda \epsilon+\mu f_{y}^{\perp} \eta^{\prime} \\
& =-\lambda \epsilon+\mu f_{y}^{\perp} f_{y}^{\perp^{\prime}} \nu \tag{7}
\end{align*}
$$

The two other terms vanish because $f_{y} f_{y}^{\perp}=0$. As $\nu$ is arbitrary, the second term can have either sign unless $\mu=0$. If $y^{*}$ is a stationary solution to the problem $I C$, then at $y^{*}, d L$ is necessarily nonnegative for all admissible excursions. The increment $d L$ is positive for all admissible excursions $d y$ if $\lambda \geq 0$ and $\mu=0$. The second condition is equivalent to $L_{y} \in \operatorname{rowspan} f_{y}$, while the first further restricts $L_{y}$ to be in the cone spanned by the rows of $-f_{y}$ (the negative gradients of the constraints). This means that $L_{y}=-\lambda f_{y}$, where $\lambda$
cannot have negative components. This proves the following.

## Kuhn-Tucker Theorem

The necessary conditions for $y^{*}$ to minimize $L(y)$, subject to the $m$ constraints, $f_{y} \leq 0$, are that

$$
\begin{aligned}
L_{y}\left(y^{*}\right)+\lambda f_{y}\left(y^{*}\right) & =0 \\
\lambda f\left(y^{*}\right) & =0 \\
\lambda & \geq 0 \text { with } \lambda_{i}=0 \text { if } f_{i}\left(y^{*}\right)<0 .
\end{aligned}
$$


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