Constrained optimization - theory

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What is the gradient of $\|H(x)\|^2$?

- Write $G(x) = ||H(x)||^2 = F(H(x))$, where $F(x) = ||x||^2 = x_1^2 + ... + x_n^2$.
- **2** We have that $F'(x) = (2x_1, ..., 2x_n)$, so that $F'(H(x)) = 2H(x)^T$.
- The chain rule gives that $G'(x) = F'(H(x))H'(x) = 2H(x)^TH'(x).$
- The Jacobi matrix of a real function is a row vector. The gradient is obtained by transposing this, so that ∇G(x) = 2H'(x)^TH(x).

- Define the tangent vector space, and show that all elements \boldsymbol{d} therein satsify $\nabla f(\boldsymbol{x}^*)^T \boldsymbol{d} \ge 0$.
- Optime linearized feasible directions
- Show that the tangent vector space, and the linearized feasible directions are the same when x* is regular
- O Apply Farkas lemma.

Let $C \subseteq \mathbb{R}^n$ and let $\mathbf{x} \in C$. A vector $\mathbf{d} \in \mathbb{R}^n$ is called a *tangent* (vector) to C at \mathbf{x} if there is a sequence $\{\mathbf{x}^k\}$ in C and a sequence $\{\alpha_k\}$ in \mathbb{R}_+ such that

$$\lim_{k\to\infty}(\boldsymbol{x}^k-\boldsymbol{x})/\alpha_k=\boldsymbol{d}.$$

The set of tangent vectors at \mathbf{x} is denoted by $T_C(\mathbf{x})$.

- Let C be the set of feasible solutions (those x satisfying all the equality and inequality constraints).
- **2** One shows that \mathbf{x}^* satisfies $\nabla f(\mathbf{x}^*)^T \mathbf{d} \ge 0$ for all $\mathbf{d} \in T_C(\mathbf{x}^*)$.

A linearized feasible direction at $\mathbf{x} \in C$ is a vector \mathbf{d} such that

$$egin{array}{lll} m{d} \cdot
abla h_i(m{x}) = 0 & (i \leq m) \ m{d} \cdot
abla g_j(m{x}) \leq 0 & (j \in A(m{x})). \end{array}$$

- We denote by LF_C(x) the set of all linearized feasible directions at x.
- **2** since $H'(x^*)$ is the matrix with rows $\nabla h_i(x^*)$, the first condition is the same as $H'(x^*)d = 0$.
- when all constraints are active the second condition is the same as G'(x*)d ≤ 0.

Let $\mathbf{x}^* \in C$. Then $T_C(\mathbf{x}^*) \subseteq LF_C(\mathbf{x}^*)$. If \mathbf{x}^* is a regular point, then $T_C(\mathbf{x}^*) = LF_C(\mathbf{x}^*)$.

Putting these things together, when \mathbf{x}^* is regular, $\nabla f(\mathbf{x}^*)^T \mathbf{d} \ge 0$ for all $\mathbf{d} \in LF_C(\mathbf{x}^*)$.

Farkas lemma

If *B* and *C* are matrices with *n* rows, and *K* is the cone defined by $K = \{B\mathbf{y} + C\mathbf{w}, \text{ with } \mathbf{y} \ge \mathbf{0}\}$, then exactly one of the following two alternatives are true:

 $\bullet g \in K$

2 There exists a $\boldsymbol{d} \in \mathbb{R}^n$ so that $\boldsymbol{g}^T \boldsymbol{d} < 0$, $B^T \boldsymbol{d} \ge 0$, and $C^T \boldsymbol{d} = 0$.

Now, do the following:

0 Set
$$\boldsymbol{g} =
abla f(\boldsymbol{x}^*), \ B = -\boldsymbol{G}'(\boldsymbol{x}^*)^T$$
, and $C = -\boldsymbol{H}'(\boldsymbol{x}^*)^T$,

2 $B^T \boldsymbol{d} \ge 0$, and $C^T \boldsymbol{d} = 0$ simply says that $\boldsymbol{d} \in LF_C(\boldsymbol{x}^*) = T_C(\boldsymbol{x}^*)$.

③ For all
$$\boldsymbol{d} \in T_C(\boldsymbol{x}^*)$$
 we have proved that $\boldsymbol{g}^T \boldsymbol{d} = \nabla f(\boldsymbol{x}^*)^T \boldsymbol{d} \ge 0$, so that point 2 of Farkas lemma does not hold for $\boldsymbol{g} = \nabla f(\boldsymbol{x}^*)$.

• We conclude that
$$\boldsymbol{g} = \nabla f(\boldsymbol{x}^*) \in K$$
.

This means that we can find $y \ge 0$ and w so that

$$\boldsymbol{g} = \nabla f(\boldsymbol{x}^*) = -\boldsymbol{H}'(\boldsymbol{x}^*)^T \boldsymbol{w} - \boldsymbol{G}'(\boldsymbol{x}^*)^T \boldsymbol{y} = B\boldsymbol{y} + C \boldsymbol{w}.$$

But this states exactly what we want to prove:

- **1** that $\nabla f(x^*) + H'(x^*)^T w + G'(x^*)^T y = 0$,
- **2** that **w** contains the Lagrange multipliers λ_i ,
- **(3)** that **y** contains the μ_i , and that they must be non-negative.