

MATH378 - Nonlinear Optimization

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§I PRELIMINARIES

§I.1 Terminology

We consider problems of the form

$$\text{minimize } f(x) \text{ subject to } x \in X, \quad (\dagger)$$

with $X \subset \mathbb{R}^n$ the *feasible region* with x a *feasible point*, and $f : X \rightarrow \mathbb{R}$ the *objective (function)*; more concisely we simply write

$$\min_{x \in X} f(x).$$

When $X = \mathbb{R}^n$, we say the problem (\dagger) is *unconstrained*, and conversely *constrained* when $X \subsetneq \mathbb{R}^n$.

⊗ **Example 1.1** (Polynomial Fit): Given $y_1, \dots, y_m \in \mathbb{R}$ measurements taken at m distinct points $x_1, \dots, x_m \in \mathbb{R}$, the goal is to find a degree $\leq n$ polynomial $q : \mathbb{R} \rightarrow \mathbb{R}$, of the form

$$q(x) = \sum_{k=0}^n \beta_k x^k,$$

“fitting” the data $\{(x_i, y_i)\}_i$, in the sense that $q(x_i) \approx y_i$ for each i . In the form of (\dagger) , we can write this precisely as

$$\min_{\beta \in \mathbb{R}^{n+1}} \frac{1}{2} \sum_{i=0}^n \left(\underbrace{\beta_n x_i^n + \dots + \beta_1 x_i + \beta_0 - y_i}_{q(x_i)} \right)^2;$$

namely, we seek to minimize the ℓ^2 -distance between $(q(x_i))$ and (y_i) . If we write

$$X := \begin{pmatrix} 1 & x_1 & \dots & x_1^n \\ \vdots & \dots & \dots & \vdots \\ 1 & x_m & \dots & x_m^n \end{pmatrix} \in \mathbb{R}^{m \times (n+1)}, \quad y := \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix} \in \mathbb{R}^m,$$

then concisely this problem is equivalent to

$$\min_{\beta \in \mathbb{R}^{n+1}} \frac{1}{2} \|X \cdot \beta - y\|_2^2,$$

a so-called *least-squares problem*.

We have two related tasks:

1. Find the optimal value asked for by (\dagger) , that is what $\inf_X f$ is;
2. Find a specific point \bar{x} such that $f(\bar{x}) = \inf_X f$, i.e. the value of a point

$$\bar{x} \in \operatorname{argmin}_X f := \left\{ x \in X \mid f(x) = \inf_X f \right\}.$$

(noting that argmin should be viewed as a set-valued function, as there may be multiple admissible minimizers) Notice that if we can accomplish 2., we’ve accomplished 1. by computing $f(\bar{x})$.

Note that $\bar{x} \in \operatorname{argmin}_X f \Rightarrow f(\bar{x}) = \inf_X f$, but $\inf_X f \in \mathbb{R}$ does not necessarily imply $\operatorname{argmin}_X f \neq \emptyset$, that is, there needn't be a feasible minimum; for instance $\inf_{x \in \mathbb{R}} e^x = 0$, but $\operatorname{argmin}_{\mathbb{R}} f = \emptyset$ (there is no x for which $e^x = 0$).

→ **Definition 1.1** (Minimizers): Let $X \subset \mathbb{R}^n$ and $f : \mathbb{R}^n \rightarrow \mathbb{R}$. Then $\bar{x} \in X$ is called a

- *global minimizer (off over X)* if $f(\bar{x}) \leq f(x) \forall x \in X$, or equivalently if $\bar{x} \in \operatorname{argmin}_X f$;
- *local minimizer (off over X)* if $f(\bar{x}) \leq f(x) \forall x \in X \cap B_\varepsilon(\bar{x})$ for some $\varepsilon > 0$.

In addition, we have *strict* versions of each by replacing “ \leq ” with “ $<$ ”.

→ **Definition 1.2** (Some Geometric Tools): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$.

- $\operatorname{gph} f := \{(x, f(x)) \mid x \in \mathbb{R}^n\} \subseteq \mathbb{R}^n \times \mathbb{R}$
- $f^{-1}(\{c\}) := \{x \mid f(x) = c\} \equiv \text{contour/level set at } c$
- $\operatorname{lev}_c f := f^{-1}((-\infty, c]) = \{x \mid f(x) \leq c\} \equiv \text{lower level/sublevel set at } c$

Remark 1.1:

- $\operatorname{lev}_{\inf f} f = \operatorname{argmin} f$
- assume f continuous; then all (sub)level sets are closed (possibly empty)

We recall the following result from calculus/analysis:

→ **Theorem 1.1** (Weierstrass): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be continuous and $X \subset \mathbb{R}^n$ compact. Then, $\operatorname{argmin}_X f \neq \emptyset$.

From, we immediately have the following:

→ **Proposition 1.1**: Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ continuous. If there exists a $c \in \mathbb{R}$ such that $\operatorname{lev}_c f$ is nonempty and bounded, then $\operatorname{argmin}_{\mathbb{R}^n} f \neq \emptyset$.

PROOF. Since f continuous, $\operatorname{lev}_c f$ is closed (being the inverse image of a closed set), thus $\operatorname{lev}_c f$ is compact (and in particular nonempty). By Weierstrass, f takes a minimum over $\operatorname{lev}_c f$, namely there is $\bar{x} \in \operatorname{lev}_c f$ with $f(\bar{x}) \leq f(x) \leq c$ for each $x \in \operatorname{lev}_c f$. Also, $f(x) > c$ for each $x \notin \operatorname{lev}_c f$ (by virtue of being a level set), and thus $f(\bar{x}) \leq f(x)$ for each $x \in \mathbb{R}^n$. Thus, \bar{x} is a global minimizer and so the theorem follows. ■

§I.2 Convex Sets and Functions

→ **Definition 1.3** (Convex Sets): $C \subset \mathbb{R}^n$ is *convex* if for any $x, y \in C$ and $\lambda \in (0, 1)$, $\lambda x + (1 - \lambda)y \in C$; that is, the entire line between x and y remains in C .

→**Definition 1.4** (Convex Functions): Let $C \subset \mathbb{R}^n$ be convex. Then, $f : C \rightarrow \mathbb{R}$ is called

1. *convex (on C)* if

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y),$$

for every $x, y \in C$ and $\lambda \in (0, 1)$;

2. *strictly convex (on C)* if the inequality \leq is replaced with $<$;

3. *strongly convex (on C)* if there exists a $\mu > 0$ such that

$$f(\lambda x + (1 - \lambda)y) + \mu\lambda(1 - \lambda)\|x - y\|^2 \leq \lambda f(x) + (1 - \lambda)f(y),$$

for every $x, y \in C$ and $\lambda \in (0, 1)$; we call μ the *modulus of strong convexity*.

Remark 1.2: 3. \Rightarrow 2. \Rightarrow 1.

Remark 1.3: A function is convex iff its epigraph is a convex set.

⊕ **Example 1.2:** $\exp : \mathbb{R} \rightarrow \mathbb{R}$, $\log : (0, \infty) \rightarrow \mathbb{R}$ are convex. A function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ of the form $f(x) = Ax - b$ for $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^m$ is called *affine linear*. For $m = 1$, every affine linear function is convex. All norms on \mathbb{R}^n are convex.

→**Proposition 1.2:**

1. (*Positive combinations*) Let f_i be convex on \mathbb{R}^n and $\lambda_i > 0$ scalars for $i = 1, \dots, m$, then $\sum_{i=1}^m \lambda_i f_i$ is convex; as long as one is strictly (resp. strongly) convex, the sum is strictly (resp. strongly) convex as well.
2. (*Composition with affine mappings*) Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex and $G : \mathbb{R}^m \rightarrow \mathbb{R}^n$ be affine. Then, $f \circ G$ is convex on \mathbb{R}^m .

§II UNCONSTRAINED OPTIMIZATION

§II.1 Theoretical Foundations

We focus on the problem

$$\min_{x \in \mathbb{R}^n} f(x),$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is continuously differentiable.

→**Definition 2.1** (Directional derivative): Let $D \subset \mathbb{R}^n$ be open and $f : D \rightarrow \mathbb{R}$. We say f directionally differentiable at $\bar{x} \in D$ in the direction $d \in \mathbb{R}^n$ if

$$\lim_{t \rightarrow 0^+} \frac{f(\bar{x} + td) - f(\bar{x})}{t}$$

exists, in which case we denote the limit by $f'(\bar{x}; d)$.

↪ **Lemma 2.1:** Let $D \subset \mathbb{R}^n$ be open and $f : D \rightarrow \mathbb{R}$ differentiable at $x \in D$. Then, f is directionally differentiable at x in every direction d , with

$$f'(x; d) = \nabla f(x)^T d = \langle \nabla f(x), d \rangle.$$

⊗ **Example 2.1** (Directional derivatives of the Euclidean norm): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ by $f(x) = \|x\|$ the usual Euclidean norm. Then, we claim

$$f'(x; d) = \begin{cases} \frac{x^T d}{\|x\|} & x \neq 0 \\ \|d\| & x = 0 \end{cases}$$

For $x \neq 0$, this follows from the previous lemma and the calculation $\nabla f(x) = \frac{x}{\|x\|}$. For $x = 0$, we look at the limit

$$\lim_{t \rightarrow 0^+} \frac{f(0 + td) - f(0)}{t} = \lim_{t \rightarrow 0^+} \frac{t\|d\| - 0}{t} = \|d\|,$$

using homogeneity of the norm.

↪ **Lemma 2.2** (Basic Optimality Condition): Let $X \subset \mathbb{R}^n$ be open and $f : X \rightarrow \mathbb{R}$. If \bar{x} is a *local minimizer* of f over X and f is directionally differentiable at \bar{x} , then $f'(\bar{x}; d) \geq 0$ for all $d \in \mathbb{R}^n$.

PROOF. Assume otherwise, that there is a direction $d \in \mathbb{R}^n$ for which the $f'(\bar{x}; d) < 0$, i.e.

$$\lim_{t \rightarrow 0^+} \frac{f(\bar{x} + td) - f(\bar{x})}{t} < 0.$$

Then, for all sufficiently small $t > 0$, we must have

$$f(\bar{x} + td) < f(\bar{x}).$$

Moreover, since X open, then for t even smaller (if necessary), $\bar{x} + td$ remains in X , thus \bar{x} cannot be a local minimizer. ■

↪ **Theorem 2.1** (Fermat's Rule): In addition to the assumptions of the previous lemma, assume further that f is differentiable at \bar{x} . Then, $\nabla f(\bar{x}) = 0$.

PROOF. From the previous, we know $0 \leq f'(\bar{x}; d)$ for any d . Take $d = -\nabla f(\bar{x})$, then using the representation of a directional derivative for a differentiable function, and the fact that norms are nonnegative,

$$0 \leq -\|\nabla f(\bar{x})\|^2 \leq 0,$$

which can only hold if $\|\nabla f(\bar{x})\| = 0$ hence $\nabla f(\bar{x}) = 0$ ■

We recall the following from Calculus:

→ **Theorem 2.2** (Taylor's, Second Order): Let $f : D \subset \mathbb{R}^n \rightarrow \mathbb{R}$ be twice continuously differentiable, then for each $x, y \in D$, there is an η lying on the line between x and y such that

$$f(y) = f(x) + \nabla f(x)^T(y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(\eta)(y - x).$$

→ **Theorem 2.3** (2nd-order Optimality Conditions): Let $X \subseteq \mathbb{R}^n$ open and $f : X \rightarrow \mathbb{R}$ twice continuously differentiable. Then, if x a local minimizer of f over X , then the Hessian matrix $\nabla^2 f(x)$ is positive semi-definite.

PROOF. Suppose not, then there exists a d such that $d^T \nabla^2 f(x) d < 0$. By Taylor's, for every $t > 0$, there is an η_t on the line between x and $x + td$ such that

$$\begin{aligned} f(x + td) &= f(x) + \underbrace{t \nabla f(x)^T d}_{=0} + \frac{1}{2} t^2 d^T \nabla^2 f(\eta_t) d \\ &= f(x) + \frac{t^2}{d^T} \nabla^2 f(\eta_t) d. \end{aligned}$$

As $t \rightarrow 0^+$, $\nabla^2 f(\eta_t) \rightarrow \nabla^2 f(x) < 0$. By continuity, for t sufficiently small, $\frac{t^2}{d^T} d^T \nabla^2 f(\eta_t) d < 0$ for t sufficiently small, whence we find

$$f(x + td) < f(x),$$

for sufficiently small t , a contradiction. ■

→ **Lemma 2.3:** Let $X \subset \mathbb{R}^n$ open, $f : X \rightarrow \mathbb{R}$ in C^2 . If $\bar{x} \in \mathbb{R}^n$ is such that $\nabla^2 f(\bar{x}) > 0$ (i.e. is positive definite), then there exists $\varepsilon, \mu > 0$ such that $B_\varepsilon(\bar{x}) \subset X$ and

$$d^T \nabla^2 f(x) d \geq \mu \|d\|^2, \quad \forall d \in \mathbb{R}^n, x \in B_\varepsilon(\bar{x}).$$

Combining this and Taylor's Theorem, we can deduce the following (our first “sufficient” result of this section):

→ **Theorem 2.4** (Sufficient Optimality Condition): Let $X \subset \mathbb{R}^n$ open and $f \in C^2(X)$. Let \bar{x} be a stationary point of f such that $\nabla^2 f(\bar{x}) > 0$. Then, \bar{x} is a *strict* local minimizer of f .

II.1.1 Quadratic Approximation

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^2 and $\bar{x} \in \mathbb{R}^n$. By Taylor's, we can approximate

$$f(y) \approx g(y) := f(\bar{x}) + \nabla f(\bar{x})^T(y - \bar{x}) + \frac{1}{2}(y - \bar{x})^T \nabla^2 f(\bar{x})(y - \bar{x}).$$

㊂ **Example 2.2 (Quadratic Functions):** For $Q \in \mathbb{R}^{n \times n}$ symmetric, $c \in \mathbb{R}^n$ and $\gamma \in \mathbb{R}$, let

$$f : \mathbb{R}^n \rightarrow \mathbb{R}, \quad f(x) = \frac{1}{2}x^T Qx + c^T x + \gamma,$$

a typical quadratic function. Then,

$$\nabla f(x) = \frac{1}{2}(Q + Q^T)x + c = Qx + c, \quad \nabla^2 f(x) = Q.$$

We find that f has *no* minimizer if $c \notin \text{rge}(Q)$ or Q is not positive semi-definite, combining our previous two results. In turn, if Q is positive definite (and thus invertible), there is a unique local minimizer $\bar{x} = -Q^{-1}c$ (*and* global minimizer, as we'll see).

§II.2 Differentiable Convex Functions

↪ **Theorem 2.5:** Let $C \subset \mathbb{R}^n$ be open and convex and $f : C \rightarrow \mathbb{R}$ differentiable on C . Then:

1. f is convex (on C) iff

$$f(x) \geq f(\bar{x}) + \nabla f(\bar{x})^T(x - \bar{x}) \quad \star_1$$

for every $x, \bar{x} \in C$;

2. f is *strictly* convex iff same inequality as 1. with strict inequality;
3. f is *strongly* convex with modulus $\sigma > 0$ iff

$$f(x) \geq f(\bar{x}) + \nabla f(\bar{x})^T(x - \bar{x}) + \frac{\sigma}{2}\|x - \bar{x}\|^2 \quad \star_2$$

for every $x, \bar{x} \in C$.

PROOF. (1., \Rightarrow) Let $x, \bar{x} \in C$ and $\lambda \in (0, 1)$. Then,

$$f(\lambda x + (1 - \lambda)\bar{x}) - f(\bar{x}) \leq \lambda(f(x) - f(\bar{x})),$$

which implies

$$\frac{f(\bar{x} + \lambda(x - \bar{x})) - f(\bar{x})}{\lambda} \leq f(x) - f(\bar{x}).$$

Letting $\lambda \rightarrow 0^+$, the LHS \rightarrow the directional derivative of f at \bar{x} in the direction $x - \bar{x}$, which is equal to, by differentiability of f , $\nabla f(\bar{x})^T(x - \bar{x})$, thus the result.

(1., \Leftarrow) Let $x_1, x_2 \in C$ and $\lambda \in (0, 1)$. Let $\bar{x} := \lambda x_1 + (1 - \lambda)x_2$. \star_1 implies

$$f(x_i) \geq f(\bar{x}) + \nabla f(\bar{x})^T(x_i - \bar{x}),$$

for each of $i = 1, 2$. Taking "a convex combination of these inequalities", i.e. multiplying them by $\lambda, 1 - \lambda$ resp. and adding, we find

$$\lambda f(x_1) + (1 - \lambda)f(x_2) \geq f(\bar{x}) + \nabla f(\bar{x})^T(\lambda x_1 + (1 - \lambda)x_2 - \bar{x}) = f(\lambda x_1 + (1 - \lambda)x_2),$$

thus proving convexity.

(2., \Rightarrow) Let $x \neq \bar{x} \in C$ and $\lambda \in (0, 1)$. Then, by 1., as we've just proven,

$$\lambda \nabla f(\bar{x})^T(x - \bar{x}) \leq f(\bar{x} + \lambda(x - \bar{x})) - f(\bar{x}).$$

But $f(\bar{x} + \lambda(x - \bar{x})) < \lambda f(x) + (1 - \lambda)f(\bar{x})$ by strict convexity, so we have

$$\lambda \nabla f(\bar{x})^T (x - \bar{x}) < \lambda(f(x) - f(\bar{x})),$$

and the result follows by dividing both sides by λ .

(2., \Leftarrow) Same as (1., \Leftarrow) replacing " \leq " with " $<$ ".

(3.) Apply 1. to $f - \frac{\sigma}{2}\|\cdot\|^2$, which is still convex if f σ -strongly convex, as one can check. ■

↪ **Corollary 2.1:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex and differentiable. Then,

- a) there exists an *affine function* $g : \mathbb{R}^n \rightarrow \mathbb{R}$ such that $g(x) \leq f(x)$ everywhere;
- b) if f strongly convex, then it is coercive, i.e. $\lim_{\|x\| \rightarrow \infty} f(x) = \infty$.

↪ **Corollary 2.2:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex and differentiable, then TFAE:

1. \bar{x} is a global minimizer of f ;
2. \bar{x} is a local minimizer of f ;
3. \bar{x} is a stationary point of f .

PROOF. 1. \Rightarrow 2. is trivial and 2. \Rightarrow 3. was already proven and 3. \Rightarrow 1. follows from the fact that differentiability gives

$$f(x) \geq f(\bar{x}) + \underline{\nabla f(\bar{x})^T(x - \bar{x})}$$

for any $x \in \mathbb{R}^n$. ■

↪ **Corollary 2.3:** (2.2.4)

↪ **Theorem 2.6** (Twice Differentiable Convex Functions): Let $\Omega \subset \mathbb{R}^n$ open and convex and $f \in C^2(\Omega)$. Then,

1. f is convex on Ω iff $\nabla^2 f \geq 0$;
2. f is strictly convex on $\Omega \Leftrightarrow \nabla^2 f > 0$;
3. f is σ -strongly convex on $\Omega \Leftrightarrow \sigma \leq \lambda_{\min}(\nabla^2 f(x))$ for all $x \in \Omega$.

↪ **Corollary 2.4:** Let $A \in \mathbb{R}^{n \times n}$ be symmetric, $b \in \mathbb{R}^n$ and $f(x) := \frac{1}{2}x^T Ax + b^T x$. Then,

1. f convex $\Leftrightarrow A \geq 0$;
2. f strongly convex $\Leftrightarrow A > 0$.

→ **Theorem 2.7** (Convex Optimization): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex and continuous, $X \subset \mathbb{R}^n$ convex (and nonempty), and consider the optimization problem

$$\min f(x) \text{ s.t. } x \in X \quad (\star).$$

Then, the following hold:

1. \bar{x} is a global minimizer of (\star) $\Leftrightarrow \bar{x}$ is a local minimizer of (\star)
2. $\operatorname{argmin}_X f$ is convex (possibly empty)
3. f is strictly convex $\Rightarrow \operatorname{argmin}_X f$ has at *most* one element
4. f is strongly convex and differentiable, and X closed, $\Rightarrow \operatorname{argmin}_X f$ has *exactly* one element

PROOF. (1., \Rightarrow) Trivial. (1., \Leftarrow) Let \bar{x} be a local minimizer of f over X , and suppose towards a contradiction that there exists some $\hat{x} \in X$ such that $f(\hat{x}) < f(\bar{x})$. By convexity of f , X , we know for $\lambda \in (0, 1)$, $\lambda\bar{x} + (1 - \lambda)\hat{x} \in X$ and

$$f(\lambda\bar{x} + (1 - \lambda)\hat{x}) \leq \lambda f(\bar{x}) + (1 - \lambda)f(\hat{x}) < f(\bar{x}).$$

Letting $\lambda \rightarrow 1^-$, we see that $\lambda\bar{x} + (1 - \lambda)\hat{x} \rightarrow \bar{x}$; in particular, for any neighborhood of \bar{x} we can construct a point which strictly lower bounds $f(\bar{x})$, which contradicts the assumption that \bar{x} a local minimizer.

(2.) and (3.) are left as an exercise.

(4.) We know that f is strictly convex and level-bounded. By (3.) we know there is at most one minimizer, so we just need to show there exists one. Take $c \in \mathbb{R}$ such that $\operatorname{lev}_c(f) \cap X \neq \emptyset$ (which certainly exists by taking, say, $f(x)$ for some $x \in X$). Then, notice that (\star) and

$$\min_{x \in \operatorname{lev}_c(f) \cap X} f(x) \quad (\star \star)$$

have the same solutions i.e. the same set of global minimizers (noting that this remains a convex problem). Since f continuous and $\operatorname{lev}_c(f) \cap X$ compact and nonempty, f attains a minimum on $\operatorname{lev}_c(f) \cap X$, as we needed to show. ■

Remark 2.1: Note that level sets of convex functions are convex, this is left as an exercise.

III.3 Matrix Norms

We denote by $\mathbb{R}^{m \times n}$ the space of real-valued $m \times n$ matrices (i.e. of linear operators from $\mathbb{R}^n \rightarrow \mathbb{R}^m$).

→ **Proposition 2.1** (Operator Norms): Let $\|\cdot\|_*$ be a norm on \mathbb{R}^m and \mathbb{R}^n , resp. Then, the map

$$\mathbb{R}^{m \times n} \ni A \mapsto \|A\|_* := \sup_{\substack{x \in \mathbb{R}^n, \\ \|x\|_* \neq 0}} \frac{\|Ax\|_*}{\|x\|_*} \in \mathbb{R}$$

is a norm on $\mathbb{R}^{m \times n}$. In addition,

$$\|A\|_* = \sup_{\|x\|_* = 1} \|Ax\|_* = \sup_{\|x\|_* \leq 1} \|Ax\|_*.$$

PROOF. We first note that all of these sup's are truly max's since they are maximizing continuous functions over compact sets.

Let $A \in \mathbb{R}^{m \times n}$. The first "In addition" equality follows from positive homogeneity, since $\frac{x}{\|x\|_*}$ a unit vector. For the second, note that " \leq " is trivial, since we are supping over a larger (super)set. For " \geq ", we have for any x with $\|x\|_* \leq 1$,

$$\|Ax\|_* = \|x\|_* \left\| A \frac{x}{\|x\|_*} \right\|_* \leq \left\| A \frac{x}{\|x\|_*} \right\|.$$

Supping both sides over all such x gives the result. ■

We now check that $\|\cdot\|_*$ actually a norm on $\mathbb{R}^{m \times n}$.

1. $\|A\|_* = 0 \Leftrightarrow \sup_{\|x\|_*=1} \|Ax\|_* = 0 \Leftrightarrow \|Ax\|_* = 0 \forall \|x\|_* = 1 \Leftrightarrow Ax = 0 \forall \|x\|_* = 1 \Leftrightarrow A = 0$
2. For $\lambda \in \mathbb{R}, A \in \mathbb{R}^{m \times n}, \|\lambda A\|_* = \sup \|\lambda Ax\|_* = |\lambda| \cdot \sup \|Ax\|_* = |\lambda| \|A\|_*$
3. For $A, B \in \mathbb{R}^{m \times n}, \|A + B\|_* \leq \|A\|_* + \|B\|_*$ using properties of sups of sums

→ **Proposition 2.2:** Let $A = (a_{ij})_{i=1,\dots,m, j=1,\dots,n} \in \mathbb{R}^{m \times n}$, then:

1. $\|A\|_1 = \max_{j=1}^n \sum_{i=1}^m |a_{ij}|$
2. $\|A\|_2 = \sqrt{\lambda_{\max}(A^T A)} = \sigma_{\max}(A)$
3. $\|A\|_\infty = \max_{i=1}^m \sum_{j=1}^n |a_{ij}|$

→ **Proposition 2.3:** Let $\|\cdot\|_*$ be a norm on $\mathbb{R}^n, \mathbb{R}^m$, and \mathbb{R}^p . For $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$,

1. $\|Ax\|_* \leq \|A\|_* \cdot \|x\|_*$
2. $\|AB\|_* \leq \|A\|_* \cdot \|B\|_*$

→ **Proposition 2.4 (Banach Lemma):** Let $C \in \mathbb{R}^{n \times n}$ with $\|C\| < 1$, where $\|\cdot\|$ submultiplicative. Then, $I + C$ is invertible, and

$$\|(I + C)^{-1}\| \leq \frac{1}{1 - \|C\|}.$$

PROOF. We have for any m ,

$$\left\| \sum_{i=1}^m (-C)^i \right\| \leq \sum_{i=1}^m \|C\|^i \xrightarrow{m \rightarrow \infty} \frac{1}{1 - \|C\|}.$$

Hence, $A_m := \sum_{i=1}^m (-C)^i$ a sequence of matrices with bounded norm uniformly in m , and thus has a converging subsequence, so wlog $A_m \rightarrow A \in \mathbb{R}^{n \times n}$ (by relabelling).

Moreover, observe that

$$A_m \cdot (I + C) = \sum_{i=0}^m (-C)^i (I + C) = \sum_{i=0}^m [(-C)^i - (-C)^{i+1}] = (-C)^0 - (-C)^{m+1} = I - (-C)^{m+1}.$$

Now, $\|C^{m+1}\| \leq \|C\|^{m+1} \rightarrow 0$, since $\|C\| < 1$, thus $C \rightarrow 0$. Hence, taking limits in the line above implies

$$A(I + C) = \lim_{m \rightarrow \infty} A_m(I + C) = I,$$

implying A the inverse of $(I + C)$, proving the proposition. ■

→ **Corollary 2.5:** Let $A, B \in \mathbb{R}^{n \times n}$ with $\|I - BA\| < 1$ for $\|\cdot\|$ submultiplicative. Then, A and B are invertible, and $\|B^{-1}\| \leq \frac{\|A\|}{1 - \|I - BA\|}$.

§II.4 Descent Methods

II.4.1 A General Line-Search Method

We deal with the unconstrained problem

$$\min_{x \in \mathbb{R}^n} f(x) \quad (\star).$$

→ **Definition 2.2** (Descent Direction): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $x \in \mathbb{R}^n$. $d \in \mathbb{R}^n$ is a *descent direction* of f at x if there exists a $\bar{t} > 0$ such that $f(x + td) < f(x)$ for all $t \in (0, \bar{t})$.

→ **Proposition 2.5:** If $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is directionally differentiable at $x \in \mathbb{R}^n$ in the direction d with $f'(x; d) < 0$, then d a descent direction of f at x ; in particular if f differentiable at x , then true for d if $\nabla f(x)^T d < 0$.

→ **Corollary 2.6:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ differentiable, $B \in \mathbb{R}^{n \times n}$ positive definite, and $x \in \mathbb{R}^n$. Then $\nabla f(x) \neq 0 \Rightarrow -B\nabla f(x)$ is a descent direction of f at x .

PROOF. $\nabla f(x)^T (-B\nabla f(x)) = -\nabla f(x)^T B\nabla f(x) < 0$. ■

A generic method/strategy for solving (\star) :

- S1. (Initialization) Choose $x^0 \in \mathbb{R}^n$ and set $k := 0$
- S2. (Termination) If x^k satisfies a “termination criterion”, STOP
- S3. (Search direction) Determine d^k such that $\nabla f(x^k)^T d^k < 0$
- S4. (Step-size) Determine $t_k > 0$ such that $f(x^k + t_k d^k) < f(x^k)$
- S5. (Update) Set $x^{k+1} := x^k + t_k d^k$, iterate k , and go back to step 2.

Remark 2.2: a) The generic choice for d^k in 3. is just $d^k := -B_k \nabla f(x^k)$ for some $B_k > 0$. We focus on:

- $B_k = I$ (*gradient-descent*)
- $B_k = \nabla^2 f(x^k)^{-1}$ (*Newton's method*)
- $B_k \approx \nabla^2 f(x^k)^{-1}$ (*quasi Newton's method*)

b) Step 4. is called *line-search*, since $t_k > 0$ determined by looking at

$$0 < t \mapsto f(x^k + td^k),$$

i.e. along the (half)line $t > 0$.

c) Executing Step 4. is a trade-off between

- (i) decreasing f along $x^k + td^k$ as much as possible;
- (ii) keeping computational efforts low.

For instance, the *exact minimization rule* $t_k = \operatorname{argmin}_{t>0} f(x^k + td^k)$ overemphasizes (i) over (ii).

→ **Definition 2.3** (Step-size rule): Let $f \in C^1(\mathbb{R}^n)$ and

$$\mathcal{A}_f := \{(x, d) \mid \nabla f(x)^T d < 0\}.$$

A (possible set-valued) map

$$T : (x, d) \in \mathcal{A}_f \mapsto T(x, d) \in \mathbb{R}_+$$

is called a *step-size rule* for f .

If T is well-defined for all C^1 -functions, we say T well-defined.

II.4.1.1 Global Convergence of Algorithm 2.1

→ **Definition 2.4** (Efficient step-size): Let $f \in C^1(\mathbb{R}^n)$. The step-size rule T is called *efficient* for f if there exists $\theta > 0$ such that

$$f(x + td) \leq f(x) - \theta \left(\frac{\nabla f(x)^T d}{\|d\|} \right)^2, \quad \forall t \in T(x, d), (x, d) \in \mathcal{A}_f.$$

→ **Theorem 2.8:** Let $f \in C^1(\mathbb{R}^n)$. Let $\{x^k\}, \{d^k\}, \{t_k\}$ be generated by Algorithm 2.1. Assume the following:

1. $\exists c > 0$ such that $-\left(\nabla f(x^k)^T d^k\right) / (\|\nabla f(x^k)\| \cdot \|d^k\|) \geq c$ for all k (this is called the *angle condition*), and
2. there exists $\theta > 0$ such that $f(x^k + t_k d^k) \leq f(x^k) - \theta \cdot \left(\nabla f(x^k)^T d^k / \|d^k\|\right)^2$ for all k (which is satisfied if $t_k \in T(x^k, d^k)$ for an efficient T).

Then, every cluster point of $\{x^k\}$ is a stationary point of f .

PROOF. By condition 2., there is $\theta > 0$ such that

$$f(x^{k+1}) \leq f(x^k) - \theta \left(\frac{\nabla f(x^k)^T d^k}{\|d^k\|} \right)^2,$$

for all $k \in \mathbb{N}$. By 1., we know

$$\left(\frac{\nabla f(x^k)^T d^k}{\|d^k\|} \right)^2 \geq c^2 \|\nabla f(x^k)\|^2.$$

Put $\kappa := \theta c^2$, then these two inequalities imply

$$f(x^{k+1}) \leq f(x^k) - \kappa \cdot \|\nabla f(x^k)\|^2. \quad (*)$$

Let \bar{x} be a cluster point of $\{x^k\}$. As $\{f(x^k)\}$ is monotonically decreasing (by construction in the algorithm), and has cluster point $f(\bar{x})$ by continuity, it follows that $f(x_k) \rightarrow f(\bar{x})$ along the whole sequence. In particular, $f(x^{k+1}) - f(x^k) \rightarrow 0$; thus, from $(*)$,

$$0 \leq \kappa \|\nabla f(x^k)\|^2 \leq f(x^k) - f(x^{k+1}) \rightarrow 0,$$

and thus $\nabla f(x^k) \rightarrow \nabla f(\bar{x}) = 0$, so indeed \bar{x} a stationary point of f . ■

II.4.2 The Gradient Method

We specialize Algorithm 2.1 here. Specifically, we'll take

$$d^k := -\nabla f(x^k);$$

it's known that

$$\frac{-\nabla f(x^k)}{\|\nabla f(x^k)\|} = \operatorname{argmin}_{d: \|d\| \leq 1} \nabla f(x^k)^T d,$$

with $\|\cdot\|$ the 2 norm.

We use a step-size rule called "Armijo rule". Choose parameters $\beta, \sigma \in (0, 1)$. For $(x, d) \in \mathcal{A}_f$, we define our step-size rule by

$$T_A(x, d) := \max_{\ell \in \mathbb{N}_0} \left\{ \beta^\ell \underbrace{|f(x + \beta^\ell d) \leq f(x) + \beta^\ell \sigma \nabla f(x)^T d}_{\text{"Armijo condition"}} \right\}.$$

For instance, consider $f(x) = (x - 1)^2 - 1$. The minimum of this function is $f^* = -1$. Choose $x^k := \frac{1}{k}$, then

$$f(x^k) = \frac{2k + 1}{k^2} \rightarrow 0 \neq f^*,$$

even though $f(x^{k+1}) - f(x^k) < 0$; we don't actually reach the right stationary point with our chosen step size.

④ **Example 2.3** (Illustration of Armijo Rule): For $(x, d) \in \mathcal{A}_f$ and f smooth on \mathbb{R}^n , defined $\phi : \mathbb{R} \rightarrow \mathbb{R}$, $\phi(t) := f(x + td)$. The map $t \mapsto \sigma\varphi'(0)t + \varphi(0) = \sigma t \nabla f(x)^T d + \varphi(0)$

→ **Proposition 2.6:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be differentiable with $\beta, \sigma \in (0, 1)$. Then for $(x, d) \in \mathcal{A}_f$, there exists $\ell \in \mathbb{N}_0$ such that

$$f(x + \beta^\ell d) \leq f(x) + \beta^\ell \sigma \nabla f(x)^T d,$$

i.e. $T_A(x, d) \neq \emptyset$.

PROOF. Suppose not, i.e.

$$\frac{f(x + \beta^\ell d) - f(x)}{\beta^\ell} > \sigma \nabla f(x)^T d, \forall \ell \in \mathbb{N}_0.$$

Letting $\ell \rightarrow \infty$, the left-hand side converges to $\nabla f(x)^T d$, so

$$\nabla f(x)^T d \geq \sigma \nabla f(x)^T d.$$

But $(x, d) \in \mathcal{A}_f$, so $\nabla f(x)^T d < 0$ so dividing both sides of this inequality by this quantity, this implies $\sigma \leq 0$, which is a contradiction. ■

We now prove convergence of an algorithm based on the Armijo Rule:

Gradient Descent with Armijo Rule
S0. Choose $x^0 \in \mathbb{R}^n, \sigma, \beta \in (0, 1), \varepsilon \geq 0$, and set $k := 0$
S1. If $\ \nabla f(x^k)\ \leq \varepsilon$, STOP
S2. Set $d^k := -\nabla f(x^k)$
S3. Determine $t_k > 0$ by
$t_k = T_A(x, d)$
as defined above.
S4. Set $x^{k+1} = x^k + t_k d^k$, iterate k and go to S1.

→ **Lemma 2.4:** Let $f \in C^1(\mathbb{R}^n)$, $x^k \rightarrow x, d^k \rightarrow d$ and $t_k \downarrow 0$. Then

$$\lim_{k \rightarrow \infty} \frac{f(x^k + t_k d^k) - f(x^k)}{t_k} = \nabla f(x)^T d.$$

PROOF. Left as an exercise. ■

→ **Theorem 2.9:** Let $f \in C^1(\mathbb{R}^n)$. Then every cluster point of a sequence $\{x^k\}$ generated by Algorithm 2.2 is a stationary point of f .

PROOF. Let \bar{x} be a cluster point of $\{x^k\}$ and let $x^k \xrightarrow{k \in K} \bar{x}$, K an infinite subset of \mathbb{N} . Assume towards a contradiction $\nabla f(\bar{x}) \neq 0$. As $f(x^k)$ is monotonically decreasing with cluster point $f(\bar{x})$, it must be that $f(x^k) \rightarrow f(\bar{x})$ along the whole sequence so $f(x^{k+1}) - f(x^k) \rightarrow 0$. Thus,

$$0 \leq t_k \|\nabla f(x^k)\|^2 \stackrel{S2}{=} -t_k \nabla f(x^k)^T d^k \stackrel{S3}{\leq} \frac{f(x^k) - f(x^{k+1})}{\sigma} \rightarrow 0.$$

Thus, $0 = \lim_{k \in K} t_k \|\nabla f(x^k)\| = \|\nabla f(\bar{x})\| \lim_{k \in K} t_k$. We assumed \bar{x} not a stationary point, so it follows that $t_k \xrightarrow{k \in K} 0$. By S3, for $\beta^{\ell_k} = t_k$,

$$\frac{f(x^k + \beta^{\ell_k-1} d^k) - f(x^k)}{\beta^{\ell_k-1}} > \sigma \nabla f(x^k)^T d^k.$$

Letting $k \rightarrow \infty$ along K , the LHS converges to, by the previous lemma, to

$$\nabla f(\bar{x})^T d = -\nabla f(\bar{x})^T \nabla f(\bar{x}) = -\|\nabla f(\bar{x})\|^2,$$

and the RHS converges to $\sigma \|\nabla f(\bar{x})\|^2$, which implies

$$-\|\nabla f(\bar{x})\|^2 \geq \sigma \|\nabla f(\bar{x})\|^2,$$

which implies σ negative, a contradiction. ■

Remark 2.3: The proof above shows, the following: Let $\{x^k\}$ such that $x^{k+1} := x^k + t_k d^k$ for $d^k \in \mathbb{R}^n, t_k > 0$, and let $f(x^{k+1}) \leq f(x^k)$ and $x^k \xrightarrow{K} \bar{x}$ such that $d^k = -\nabla f(x^k), t_k = T_A(x^k, d^k)$ for all $k \in K$. Then $\nabla f(\bar{x}) = 0$; i.e., all of the “focus” is on the subsequence along K . The only time we needed the whole sequence was to use the fact that $f(x^k) \rightarrow f(\bar{x})$ along the whole sequence.

II.4.3 Newton-Type Methods

II.4.3.1 Convergence Rates and Landau Notation

→ **Definition 2.5:** Let $\{x^k \in \mathbb{R}^n\}$ converge to \bar{x} . Then, $\{x^k\}$ converges:

1. *linearly* to \bar{x} if there exists $c \in (0, 1)$ such that

$$\|x^{k+1} - \bar{x}\| \leq c \|x^k - \bar{x}\|, \forall k;$$

2. *superlinearly* to \bar{x} if

$$\lim_{k \rightarrow \infty} \frac{\|x^{k+1} - \bar{x}\|}{\|x^k - \bar{x}\|} = 0;$$

3. *quadratically* to \bar{x} if there exists $C > 0$ such that

$$\|x^{k+1} - \bar{x}\| \leq C \|x^k - \bar{x}\|^2, \forall k.$$

Remark 2.4: 3. \Rightarrow 2. \Rightarrow 1.

Remark 2.5: We needn't assume $x^k \rightarrow \bar{x}$ for the first two definitions; their statements alone imply convergence. However, the last does not; there exists sequences with this property that do not converge.

→ **Definition 2.6** (Landau Notation): Let $\{a_k\}, \{b_k\}$ be positive sequences $\downarrow 0$. Then,

1. $a_k = o(b_k) \Leftrightarrow \lim_{k \rightarrow \infty} \frac{a_k}{b_k} = 0$;
2. $a_k = O(b_k) \Leftrightarrow \exists C > 0 : a_k \leq C b_k$ for all k (sufficiently large).

Remark 2.6: If $x^k \rightarrow \bar{x}$, then

1. the convergence is superlinear $\Leftrightarrow \|x^{k+1} - \bar{x}\| = o(\|x^k - \bar{x}\|)$;
2. the convergence is quadratic $\Leftrightarrow \|x^{k+1} - \bar{x}\| = O(\|x^k - \bar{x}\|^2)$.

II.4.3.2 Newton's Method for Nonlinear Equations

We consider the nonlinear equation

$$F(x) = 0, \quad (*)$$

where $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is smooth (continuously differentiable). Our goal is to find a numerical scheme that can determine approximate zeros of F , i.e. solutions to (*). The idea of Newton's method for such a problem, is, given $x^k \in \mathbb{R}^n$, to consider the (affine) linear approximation of F about x^k ,

$$F_k : x \mapsto F(x^k) + F'(x^k)(x - x^k),$$

where F' the Jacobian of F . Then, we compute x^{k+1} as a solution of $F_k(x) = 0$. Namely, if $F'(x^k)$ invertible, then solving for $F_k(x^{k+1}) = 0$, we find

$$x^{k+1} = x^k - F'(x^k)^{-1} F(x^k).$$

More generally, one solves $F'(x^k)d = -F(x^k)$ and sets $x^{k+1} := x^k + d^k$.

Specifically, we have the following algorithm:

Newton's Method (Local Version)
S0. Choose $x^0 \in \mathbb{R}^n, \varepsilon > 0$, and set $k := 0$.
S1. If $\ F(x^k)\ < \varepsilon$, STOP.
S2. Compute d^k as a solution of <i>Newton's equation</i>
$F'(x^k)d = -F(x^k).$
S3. Set $x^{k+1} := x^k + d^k$, increment k and go to S1.

→ **Lemma 2.5:** Let $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be C^1 , and $\bar{x} \in \mathbb{R}^n$ such that $F'(\bar{x})$ is invertible. Then, there exists $\varepsilon > 0$ such that $F'(x)$ remains invertible for all $x \in B_\varepsilon(\bar{x})$, and there exists $C > 0$ such that

$$\|F'(x)^{-1}\| \leq C, \quad \forall x \in B_\varepsilon(\bar{x}).$$

PROOF. Since F' continuous at \bar{x} , there exists $\varepsilon > 0$ such that $\|F'(\bar{x}) - F'(x)\| \leq \frac{1}{2\|F'(\bar{x})^{-1}\|}$ for all $x \in B_\varepsilon(\bar{x})$. Then, for all $x \in B_\varepsilon(\bar{x})$,

$$\begin{aligned}\|I - F'(x)F'(\bar{x})^{-1}\| &= \|(F'(\bar{x}) - F'(x))F'(\bar{x})^{-1}\| \\ &\leq \|F'(\bar{x}) - F'(x)\|\|F'(\bar{x})^{-1}\| \leq \frac{1}{2} < 1.\end{aligned}$$

By a corollary of the Banach lemma, $F'(x)$ invertible over $B_\varepsilon(\bar{x})$, and

$$\|F'(x)^{-1}\| \leq \frac{\|F'(\bar{x})^{-1}\|}{1 - \|I - F'(x)F'(\bar{x})^{-1}\|} \leq 2\|F'(\bar{x})^{-1}\| =: C.$$

■

Remark 2.7: Observe $F : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is differentiable at \bar{x} if and only if $\|F(x^k) - F(\bar{x}) - F'(\bar{x})(x^k - \bar{x})\| = o(\|x^k - \bar{x}\|)$ for every $x^k \rightarrow \bar{x}$.

This can be sharpened if F' is continuous or even locally Lipschitz.

↪**Lemma 2.6:** Let $F : \mathbb{R}^n \rightarrow \mathbb{R}$ be continuously differentiable and $x^k \rightarrow \bar{x}$, then:

1. $\|F(x^k) - F(\bar{x}) - F'(x^k)(x^k - \bar{x})\| = o(\|x^k - \bar{x}\|);$
2. if F' locally Lipschitz at \bar{x} , then $\|F(x^k) - F(\bar{x}) - F'(x^k)(x^k - \bar{x})\| = O(\|x^k - \bar{x}\|^2)$.

PROOF.

1. Observe that

$$\begin{aligned}&\|F(x^k) - F(\bar{x}) - F'(x^k)(x^k - \bar{x})\| \\ &\leq \|F(x^k) - F(\bar{x}) - F(\bar{x})(x^k - \bar{x})\| + \|F'(\bar{x})(x^k - \bar{x}) - F'(\bar{x})(x^k - \bar{x})\| \\ &\leq \|F(x^k) - F(\bar{x}) - F(\bar{x})(x^k - \bar{x})\| + \|F'(\bar{x}) - F(\bar{x})\|\|x^k - \bar{x}\|.\end{aligned}$$

The left-hand term is $o(\|x^k - \bar{x}\|)$ by our observations previously, and the right-hand term is as well by continuity of F' , thus so is the sum.

2. Let $L > 0$ be a local Lipschitz constant of F' at \bar{x} . Then,

$$\begin{aligned}\|F(x^k) - F(\bar{x}) - F'(x^k)(x^k - \bar{x})\| &= \left\| \int_0^1 F'(\bar{x} + t(x^k - \bar{x})) dt (x^k - \bar{x}) - F'(x^k)(x^k - \bar{x}) \right\| \\ &\leq \int_0^1 \|F'(\bar{x} + t(x^k - \bar{x})) - F'(x^k)\| dt \cdot \|x^k - \bar{x}\| \\ &\leq L \int_0^1 |1-t| \|x^k - \bar{x}\| dt \cdot \|x^k - \bar{x}\| \\ &= L \|x^k - \bar{x}\|^2 \int_0^1 (1-t) dt = \frac{L}{2} \|x^k - \bar{x}\|^2,\end{aligned}$$

which implies the result.

■

→ **Theorem 2.10:** Let $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be continuously differentiable, $\bar{x} \in \mathbb{R}^n$ such that $F(\bar{x}) = 0$ and $F'(\bar{x})$ is invertible. Then, there exists an $\varepsilon > 0$ such that for every $x^0 \in B_\varepsilon(\bar{x})$, we have:

1. Algorithm 2.3 is well-defined and generates a sequence $\{x^k\}$ which converges to \bar{x} ;
2. the rate of convergence is (at least) linear;
3. if F' is locally Lipschitz at \bar{x} , then the rate is quadratic.

PROOF.

1. By the previous lemma, we know there is $\varepsilon_1, c > 0$ such that $\|F'(x)^{-1}\| \leq c$ for all $x \in B_{\varepsilon_1}(x)$. Further, there exists an $\varepsilon_2 > 0$ such that $\|F(x) - F(\bar{x}) - F'(x)(x - \bar{x})\| \leq \frac{1}{2c}\|x - \bar{x}\|$ for all $x \in B_{\varepsilon_2}(\bar{x})$. Take $\varepsilon = \min\{\varepsilon_1, \varepsilon_2\}$ and pick $x^0 \in B_\varepsilon(\bar{x})$. Then, x^1 is well-defined, since $F'(x^0)$ is invertible, and so

$$\begin{aligned} \|x^1 - \bar{x}\| &= \left\| x^0 - F'(x^0)^{-1}F(x^0) - \bar{x} \right\| \\ &= \left\| F'(x^0)^{-1} \left(F(x^0) - \underbrace{F(\bar{x})}_{=0} - F'(x^0)(x^0 - \bar{x}) \right) \right\| \\ &\leq \|F'(x^0)^{-1}\| \|F(x^0) - F(\bar{x}) - F'(x^0)(x^0 - \bar{x})\| \\ &\leq c \cdot \frac{1}{2c} \|x^0 - \bar{x}\| \\ &= \frac{1}{2} \|x^0 - \bar{x}\| < \frac{\varepsilon}{2}, \end{aligned}$$

so in particular, $x^1 \in B_{\varepsilon/2}(\bar{x}) \subset B_\varepsilon(\bar{x})$. Inductively,

$$\|x^k - \bar{x}\| \leq \left(\frac{1}{2}\right)^k \|x^0 - \bar{x}\|,$$

for every $k \in \mathbb{N}$. Thus, x^k well-defined and converges to \bar{x} .

2., 3. Analogous to 1.,

$$\begin{aligned} \|x^{k+1} - \bar{x}\| &= \|x^k - d^k - \bar{x}\| \\ &= \|x^k - F'(x^k)^{-1}F(x^k) - \bar{x}\| \\ &\leq \|F'(x^k)^{-1}\| \|F(x^k) - F(\bar{x}) - F'(x^k)(x^k - \bar{x})\| \\ &\leq c \|F(x^k) - F(\bar{x}) - F'(x^k)(x^k - \bar{x})\|. \end{aligned}$$

This final line is little o of $\|x^k - \bar{x}\|$ or this quantity squared by the previous lemma, which proves the result depending on the assumptions of 2., 3..

■

II.4.3.3 Newton's Method for Optimization Problem

Consider

$$\min_{x \in \mathbb{R}^n} f(x),$$

with $f : \mathbb{R}^n \rightarrow \mathbb{R}$ twice continuously differentiable. Recall that if \bar{x} a local minimizer of f , $\nabla f(\bar{x}) = 0$. We'll now specialize Newton's to $F := \nabla f$:

Newton's Method for Optimization (Local Version)
S0. Choose $x^0 \in \mathbb{R}^n, \varepsilon > 0$, and set $k := 0$.
S1. If $\ \nabla f(x^k)\ < \varepsilon$, STOP.
S2. Compute d^k as a solution of <i>Newton's equation</i>
$\nabla^2 f(x^k) d = -\nabla f(x^k).$
S3. Set $x^{k+1} := x^k + d^k$, increment k and go to S1.

We then have an analogous convergence result to the previous theorem by simply applying $F := \nabla f$; in particular, if f thrice continuously differentiable, we have quadratic convergence.

⊕ **Example 2.4:** Let $f(x) := \sqrt{x^2 + 1}$. Then $f'(x) = \frac{x}{\sqrt{x^2 + 1}}, f''(x) = \frac{1}{(x^2 + 1)^{3/2}}$. Newton's equation (i.e. Algorithm 2.4, S2) reads in this case:

$$\frac{1}{(x_k^2 + 1)^{3/2}} d = -\frac{x_k}{\sqrt{x_k^2 + 1}}.$$

This gives solution $d_k = -(x_k^2 + 1)x_k$, so $x_{k+1} = -x_k^3$. Then, notice that if:

$$|x_0| < 1 \Rightarrow x_k \rightarrow 0, \text{ quadratically}$$

$$|x_0| > 1 \Rightarrow x_k \text{ diverges}$$

$$|x_0| = 1 \Rightarrow |x_k| = 1 \forall k,$$

so the convergence is truly local; if we start too far from 0, we'll never have convergence.

We can see from this example that this truly a local algorithm. A general globalization strategy is to:

- if Newton's equation has no solution, or doesn't provide sufficient decay, set $d^k := -\nabla f(x^k)$;
- introduce a step-size.

Newton's Method (Global Version)
S0. Choose $x^0 \in \mathbb{R}^n, \varepsilon > 0, \rho > 0, p > 2, \beta \in (0, 1), \sigma \in (0, 1/2)$ and set $k := 0$
S1. If $\ \nabla f(x^k)\ < \varepsilon$, STOP
S2. Determine d^k as a solution of
$\nabla^2 f(x^k) d = -\nabla f(x^k).$
If no solution exists, or if $\nabla f(x^k)^T d^k \leq -\rho \ d^k\ ^p$, is violated, set $d^k := -\nabla f(x^k)$
S3. Determine $t_k > 0$ by the Armijo back-tracking rule, i.e.
$t_k := \max_{\ell \in \mathbb{N}_0} \left\{ \beta^\ell \mid f(x^k + \beta^\ell d^k) \leq f(x^k) + \beta^\ell \sigma \nabla f(x^k)^T d^k \right\}$
S4. Set $x^{k+1} := x^k + t_k d^k$, increment k to $k + 1$, and go back to S1.

Remark 2.8: S3. well-defined since in either choice of d^k in S2., we will have a descent direction so the choice of t_k in S3. is valid; i.e. $(x^k, d^k) \in \mathcal{A}_f$ for every k .

→ **Theorem 2.11** (Global convergence of Algorithm 2.5): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be twice continuously differentiable. Then every cluster point of $\{x^k\}$ generated by Algorithm 2.5 is a stationary point of f .

Remark 2.9: Note that we didn't impose any invertibility condition on the Hessian of f ; indeed, if say the hessian was nowhere invertible, then Algorithm 2.5 just becomes the gradient method with Armijo back-tracking, for which have already established this result.

PROOF. Let $\{x^k\}$ be generated by Algorithm 2.5, with $\{x^k\}_K \rightarrow \bar{x}$. If $d^k := -\nabla f(x^k)$ for infinitely many $k \in K$ (i.e. along a subsubsequence of $\{x^k\}$), then we have nothing to prove by the previous remark.

Otherwise, assume wlog (by passing to a subsubsequence again if necessary) that d^k is determined by the Newton equation for all $k \in K$. Suppose towards a contradiction that $\nabla f(\bar{x}) \neq 0$. By Newton's equation,

$$\|\nabla f(x^k)\| = \|\nabla^2 f(x^k)d^k\| \leq \|\nabla^2 f(x^k)\| \|d^k\|, \quad \forall k \in K.$$

By assumption $\|\nabla^2 f(x^k)\| \neq 0$; if it were, then by assumption $\nabla f(x^k) = 0$, i.e. we'd have already reached our stationary point, which we assumed doesn't happen. So, we may write $\frac{\|\nabla f(x^k)\|}{\|\nabla^2 f(x^k)\|} \leq \|d^k\|$ for all $k \in K$. We claim that there exists $c_1, c_2 > 0$ such that

$$0 < c_1 \leq \|d^k\| \leq c_2, \quad \forall k \in K.$$

We have existence of c_1 since, if it didn't, we could find a subsequence of the d^k 's such that $d^k \rightarrow 0$ along this subsequence; but by our bound above and the fact that $\|\nabla^2 f(x^k)\|$ uniformly bounded (by continuity), then $\|\nabla f(x^k)\|$ would converge to zero along the subsequence too, a contradiction.

The existence of c_2 follows from the sufficient decrease condition. Indeed, suppose such a c_2 didn't exist; by the condition

$$\nabla f(x^k)^T \frac{d^k}{\|d^k\|} \leq -\rho \|d^k\|^{p-1};$$

the left-hand side is bounded (since $\nabla f(x^k) \rightarrow \nabla f(\bar{x})$ and $\frac{d^k}{\|d^k\|}$ lives on the unit sphere). Since c_2 assumed not to exist, there is a subsequence $\|d^k\| \rightarrow \infty$, but then $-\rho \|d^k\|^{p-1} \rightarrow -\infty$, contradicting the fact that the LHS is bounded. Hence, there also exists such a c_2 as claimed.

As $\{f(x^k)\}$ is monotonically decreasing (by construction in S3) and converges along a subsequence K to $f(\bar{x})$, then $f(x^k)$ converges along the whole sequence to $f(\bar{x})$. In particular, $f(x^{k+1}) - f(x^k) \rightarrow 0$. Then,

$$\frac{f(x^{k+1}) - f(x^k)}{\sigma} \leq t_k \nabla f(x^k)^T d^k \leq -\rho t_k \|d^k\|^p \leq 0.$$

Taking $k \rightarrow \infty$ along K , we see that $t_k \|d^k\|^p \rightarrow 0$ along K as well. We show now that $\{t_k\}_K$ actually uniformly bounded away from zero. Suppose not. Then, along a sub(sub)sequence, $t_k \rightarrow 0$. By the Armijo rule, $t_k = \beta^{\ell_k}$, for $\ell_k \in \mathbb{N}_0$, uniquely determined. Since $t_k \rightarrow 0$, then $\ell_k \rightarrow \infty$. On the other hand, by S3,

$$\frac{f(x^k + \beta^{\ell_k-1} d^k) - f(x^k)}{\beta^{\ell_k-1}} > \sigma \nabla f(x^k)^T d^k.$$

Suppose $d^k \rightarrow \bar{d} \neq 0$ (by again passing to a subsequence if necessary), which we may assume by boundedness. Taking $k \rightarrow \infty$, the LHS converges to $\nabla f(\bar{x})^T \bar{d}$ and the RHS converges to $\sigma \nabla f(\bar{x})^T \bar{d}$ so $\nabla f(\bar{x})^T \bar{d} \geq \sigma \nabla f(\bar{x})^T \bar{d}$, which implies since $\sigma \in (0, \frac{1}{2})$ that $\nabla f(\bar{x})^T \bar{d} \geq 0$. Taking $k \rightarrow \infty$ in the sufficient decrease condition statement shows that this is a contradiction. Hence, t_k uniformly bounded away from 0. Hence, there exists a $\bar{t} > 0$ such that $t_k \geq \bar{t}$ for all $k \in K$. But we had that $t^k \nabla f(x^k)^T d^k \rightarrow 0$, so by boundedness of t_k it must be that $\nabla f(x^k)^T d^k \rightarrow 0$ along the subsequence; by the sufficient decrease condition again, it must be that $d^k \rightarrow 0$, which it can't, as we showed it was uniformly bounded away, and thus we have a contradiction. ■

→ **Theorem 2.12** (Fast local convergence of Algorithm 2.5): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be twice continuously differentiable, $\{x^k\}$ generated by Algorithm 2.5. If \bar{x} is a cluster point of $\{x^k\}$ with $\nabla^2 f(\bar{x}) > 0$. Then:

1. $\{x^k\} \rightarrow \bar{x}$ along the *whole* sequence, so \bar{x} is a strict local minimizer of f ;
2. for $k \in \mathbb{N}$ sufficiently large, d^k will be determined by the Newton equation in S2;
3. $\{x^k\} \rightarrow \bar{x}$ at least superlinearly;
4. if $\nabla^2 f$ locally Lipschitz, $\{x^k\} \rightarrow \bar{x}$ quadratically.

II.4.4 Quasi-Newton Methods

In Newton's, in general we need to find

$$d^k \text{ solving } \nabla^2 f(x^k) d = -\nabla f(x^k).$$

Advantages/disadvantages:

- (+) Global convergence with fast local convergence
- (-) Evaluating $\nabla^2 f$ can be expensive/impossible.

Dealing with the second, there are two general approaches:

- *Direct Methods*: replace $\nabla^2 f(x^k)$ with some matrix H_k approximating it;
- *Indirect Methods*: replace $\nabla^2 f(x^k)^{-1}$ by B_k approximating it;

where H_k, B_k reasonably computational, and other convergence results are preserved.

II.4.4.1 Direct Methods

The typical conditions we put on H_{k+1} as described above are:

1. H_{k+1} symmetric

2. H_{k+1} satisfies the *Quasi-Newton equation* (QNE)

$$H_{k+1}s^k = y^k, \quad s^k := x^{k+1} - x^k, \quad y^k := \nabla f(x^{k+1}) - \nabla f(x^k)$$

3. H_{k+1} can be achieved from H_k “efficiently”

4. The result method has strong local convergence properties

Remark 2.10: Suppose x^k a current iterate for an algorithm to minimize $f : \mathbb{R}^n \rightarrow \mathbb{R}$ for $f \in C^2$.

1. $\nabla^2 f(x^k)$ does not generally satisfy QNE;
2. condition 1 above is motivated by the fact that Hessians are symmetric;
3. the QNE is motivated by the mean-value theorem for vector-valued functions,

$$\nabla f(x^{k+1}) - \nabla f(x^k) = \int_0^1 \nabla^2 f(x^k + t(x^{k+1} - x^k)) dt \cdot (x^{k+1} - x^k);$$

we can think of the integrated term as an averaging of the Hessian along the line between x^k, x^{k+1} .

We follow a so-called *symmetric rank-2 approach*; given H_k , we update

$$H_{k+1} = H_k + \gamma uu^T + \delta vv^T, \quad \gamma, \delta \in \mathbb{R}; u, v \in \mathbb{R}^n. \quad (1)$$

Note that if we put $S := uu^T$ for $u \neq 0$, $\text{rank}(S) = 1$ and $S^T = S$.

So, the ansatz we take is

$$y^k = H_{k+1}s^k = H_k s^k + \gamma uu^T s^k + \delta vv^T s^k. \quad (2)$$

If $H_k > 0$ and $(y^k)^T s^k \neq 0$, then taking $u := y^k, v := H_k s^k, \gamma := \frac{1}{(y^k)^T s^k}$ and $\delta := -\frac{1}{(s^k)^T H_k s^k}$ will solve (2), and gives the formula

$$H_{k+1}^{\text{BFGS}} := H_k - \frac{(H_k s^k)(H_k s^k)^T}{(s^k)^T H_k s^k} + \frac{y^k (y^k)^T}{(y^k)^T s^k} \quad (3),$$

the so-called “BFGS” formula. Another update formula that can be obtained that solves (2) is

$$H_{k+1}^{\text{DFP}} := H_k + \frac{(y^k - H_k s^k)(y^k)^T + y^k (y^k - H_k s^k)^T}{(y^k)^T s^k} - \frac{(y^k - H_k s^k)^T s^k}{[(y^k)^T s^k]^2} y^k (y^k)^T.$$

Note that any convex combination of formulas that satisfy (2) also satisfy (2); thus, we define the so-called *Broyden class* by the family of convex combinations of the above two formula,

$$H_{k+1}^\lambda := (1 - \lambda)H_{k+1}^{\text{DFP}} + \lambda H_{k+1}^{\text{BFGS}}, \quad \forall \lambda \in [0, 1].$$

Algorithmically, for $f \in C^1$;

Globalized BFGS Method

S0. Choose $x^0 \in \mathbb{R}^n$, $H_0 \in \mathbb{R}^{n \times n}$ symmetric positive definite, $\sigma \in (0, \frac{1}{2})$, $\rho \in (\sigma, 1)$, $\varepsilon \geq 0$ and set $k := 0$.

S1. If $\|\nabla f(x^k)\| \leq \varepsilon$, STOP.

S2. Determine d^k as a solution to the QNE,

$$H_k d = -\nabla f(x^k).$$

S3. Determine $t_k > 0$ such that

$$f(x^k + t_k d^k) \leq f(x^k) + \sigma t_k \nabla f(x^k)^T d^k,$$

(this is just the Armijo condition), AND

$$\nabla f(x^k + t_k d^k)^T d^k \geq \rho \nabla f(x^k)^T d^k,$$

call the *Wolfe-Powell rule*.

S4. Set

$$\begin{aligned} x^{k+1} &:= x^k + t_k d^k, \\ s^k &:= x^{k+1} - x^k, \\ y^k &:= \nabla f(x^{k+1}) - \nabla f(x^k), \\ H_{k+1} &:= H_{k+1}^{\text{BFGS}}. \end{aligned}$$

S5. Increment k and go to S1.

We use the *Wolfe-Powell rule*; i.e., for $f : \mathbb{R}^n \rightarrow \mathbb{R}$ differentiable, $\sigma \in (0, \frac{1}{2})$, $\rho \in (\sigma, 1)$,

$$T_{\text{WP}} : \mathcal{A}_f \ni (x, d) \mapsto \left\{ t > 0 \mid \begin{array}{l} f(x + td) \leq f(x) + \sigma t \nabla f(x)^T d \\ \nabla f(x + td)^T d \geq \rho \nabla f(x)^T d \end{array} \right\} \subset \mathbb{R}_+.$$

↪ **Lemma 2.7:** For $f \in C^1$ and $(x, d) \in \mathcal{A}_f$, assume that f is bounded from below on $\{x + td \mid t > 0\}$. Then, $T_{\text{WP}}(x, d) \neq \emptyset$.

Remark 2.11: Note that we didn't need any boundedness restriction for the well-definedness of the Armijo rule.

↪ **Lemma 2.8:** For $f \in C^1$, bounded from below with ∇f Lipschitz continuous on $\mathcal{L} := \text{lev}_{f(x^0)} f$. Then, T_{WP} restricted to $\mathcal{A}_f \cap (\mathcal{L} \times \mathbb{R}^n)$ is *efficient*, i.e. there exists a $\theta > 0$ such that $f(x + td) \leq f(x) - \theta \left(\frac{\nabla f(x)^T d}{\|\nabla f(x)\| \|d\|} \right)^2$ for every $(x, d) \in \mathcal{A}_f \cap (\mathcal{L} \times \mathbb{R}^n)$ and $t \in T_{\text{WP}}(x, d)$.

Remark 2.12: Note that, generally x^k will be in the level set at $f(x^0)$ for every $k \geq 0$ when x^k defined by a descent method. So in the context of this lemma, we will have the efficient bound at every iterate.

We turn to analyze Algorithm 2.6.

↪**Lemma 2.9:** Let $y^k, s^k \in \mathbb{R}^n$ such that $(y^k)^T s^k > 0$ and $H_k > 0$. Then,

$$H_{k+1}^{\text{BFGS}} > 0.$$

PROOF. For fixed k , set $H_+ := H_{k+1}$, $H := H_k$, $s := s^k$ and $y := y^k$ for notational convenience. As $H > 0$, there exists a $W > 0$ such that $W^2 = H$. Let $d \in \mathbb{R}^n - \{0\}$ and set $z := Ws$, $v := Wd$. Then

$$\begin{aligned} d^T H_+ d &= d^T \left(H + \frac{yy^T}{y^T s} - \frac{Hss^T H}{s^T H s} \right) d \\ &= d^T Hd + d^T \frac{yy^T}{y^T s} d - d^T \frac{Hss^T H}{s^T H s} d \\ &= d^T Hd + \frac{(y^T d)^2}{y^T s} - \frac{(d^T H s)^2}{s^T H s} \\ &= \|v\|^2 + \frac{(y^T d)^2}{y^T s} - \frac{(v^T z)^2}{\|z\|^2} \\ &\geq \|v\|^2 + \frac{(y^T d)^2}{y^T s} - \|v\|^2 \\ &= \frac{(y^T d)^2}{y^T s} \geq 0, \end{aligned}$$

using Cauchy-Schwarz. In particular, equality (to zero) holds throughout iff v and z are linearly dependent and $y^T d = 0$. Suppose this is the case. In particular, there is an $\alpha \in \mathbb{R}$ for which $v = \alpha z$. Then, $d = W^{-1}v = \alpha W^{-1}z = \alpha s$, thus $0 = d^T y = \alpha s^T y$, hence α must equal zero, since we assumed $y^T s > 0$. Thus, $d = 0$, which we also assumed wasn't the case. Thus, we can never have equality here, and thus $d^T H_+ d > 0$, and so $H_+ > 0$. ■

↪**Lemma 2.10:** If in the k th iteration of Algorithm 2.6 we have $H_k > 0$ and there exists $t_k \in T_{\text{WP}}(x^k, d^k)$, then $(s^k)^T y^k > 0$.

PROOF. We have

$$\begin{aligned}
(s^k)^T y^k &= (x^{k+1} - x^k)^T (\nabla f(x^{k+1}) - \nabla f(x^k)) \\
&= t_k (d^k)^T (\nabla f(x^{k+1}) - \nabla f(x^k)) \\
&\stackrel{\text{WP}}{\geq} t_k (\rho - 1) \nabla f(x^k)^T d^k \\
&= \underbrace{t_k (1 - \rho) \left(\underbrace{\frac{\nabla f(x^k)}{\neq 0}}_{>0} \right)^T}_{>0} H_k^{-1} \nabla f(x^k) \\
&> 0,
\end{aligned}$$

since $H_k^{-1} > 0$ and $t_k > 0$ and $0 < \rho < 1$. ■

↪ **Theorem 2.13:** Let $f \in C^1(\mathbb{R}^n)$ and bounded from below. Then, the following hold for the iterates generated by Algorithm 2.6:

1. $(s^k)^T y^k > 0$;
2. $H_k > 0$;
3. thus, Algorithm 2.6 is well-defined, i.e. at each iteration, each step generates a valid value.

PROOF. We prove inductively on k , with the fact that $H_0 > 0$ already establishing 2. for the base step. $H_k > 0$ implies the existence of a unique solution $d^k = -H_k^{-1} \nabla f(x^k)$ to QNE. Because $\nabla f(x^k) \neq 0$, $\nabla f(x^k)^T d^k < 0$ so $(x^k, d^k) \in \mathcal{A}_f$. By [Lem. 2.7](#), there exists a $t_k \in T_{\text{WP}}(x^k, d^k)$. Thus, by [Lem. 2.10](#), $(y^k)^T s^k > 0$ and so by [Lem. 2.9](#) $H_{k+1} > 0$. Since this holds for any k this proves the result. ■

↪ **Theorem 2.14:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be continuously differentiable, and $\{x^k\}, \{d^k\}, \{t_k\}$ be generated by Algorithm 2.6. assume that ∇f is Lipschitz on $\mathcal{L} := \text{lev}_{f(x^0)} f$, and that there exists a $c > 0$ such that $\text{cond}(H_k) := \frac{\lambda_{\max}(H_k)}{\lambda_{\min}(H_k)} \leq \frac{1}{c}$ for all $k \in \mathbb{N}$. Then every cluster point of $\{x^k\}$ is a stationary point of f .

PROOF. For all $k \in \mathbb{N}$,

$$\begin{aligned}
-\nabla f(x^k)^T d^k &= (d^k)^T H_k d^k \geq \lambda_{\min}(H_k) \|d^k\|^2 \\
&= \lambda_{\min}(H_k) \|H_k^{-1} \nabla f(x^k)\| \|d^k\| \\
&= \frac{\lambda_{\min}(H_k)}{\|H_k\|} \|H_k\| \|H_k^{-1} \nabla f(x^k)\| \|d^k\| \\
&\geq \frac{\lambda_{\min}(H_k)}{\lambda_{\max}(H_k)} \|\nabla f(x^k)\| \|d^k\| \\
&= \frac{1}{\text{cond}(H_k)} \|\nabla f(x^k)\| \|d^k\| \\
&\geq c \|\nabla f(x^k)\| \|d^k\|,
\end{aligned}$$

and thus $-\frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\| \|d^k\|} \geq c$ for all $k \in \mathbb{N}$ (this is the so-called “angle condition”).

Moreover, under the assumptions on f , the Wolfe-Powell rule (restricted to $\mathcal{A}_f \cap \mathcal{L} \times \mathbb{R}^n$, in which we always stay) is efficient, so by the previously established global convergence of Algorithm 2.1, we have convergence of this algorithm as well. ■

Remark 2.13: We cited the convergence of Algorithm 2.1, which we couldn't do when proving convergence of the gradient, since the step size in that case was *not* efficient.

Remark 2.14:

1. The assumption that ∇f is Lipschitz on $\text{lev}_{f(x^0)} f$ is satisfied under either of the following conditions,
 - (i) $f \in C^2$ and $\|\nabla^2 f(x)\|$ bounded on a convex superset of \mathcal{L} ;
 - (ii) $f \in C^2$ and \mathcal{L} is bounded (hence compact).

An example of a C^1 function that is not C^2 but still globally Lipschitz is $f(x) := \frac{1}{2} \text{dist}_C^2(x)$ where C a convex set, and $\nabla f(x) = x - P_C(x)$ where P_C the projection onto C .

2. The BFGS method is regarded as one of the most robust methods for smooth, unconstrained optimization up to medium scale. For large-scale, there is a method called “limited memory BFGS”. Surprisingly, BFGS can be modified to work well for nonsmooth functions with a special line search method.

II.4.4.2 Inexact Methods

The local Newton's method involves finding d^k such that $\nabla^2 f(x^k) d^k = -\nabla f(x^k)$. Quasi-Newton methods replace the Hessian with an approximation, and indirect methods further allow the flexibility to let d^k approximately solve this equation (since solving this equation exactly can be costly). The goal is to find d^k such that

$$\frac{\|\nabla^2 f(x^k) d + \nabla f(x^k)\|}{\|\nabla f(x^k)\|} \leq \eta_k$$

for a prescribed tolerance η_k . This is called the *inexact Newton's equation*.

Remark 2.15: Dividing by $\|\nabla f(x^k)\|$ here enforces the idea that the closer x^k is to a stationary point, the higher accuracy we require.

Local Inexact Newton's Method
S0. Choose $x^0 \in \mathbb{R}^n, \varepsilon \geq 0$ and set $k := 0$.
S1. If $\ \nabla f(x^k)\ \leq \varepsilon$, STOP.
S2. Choose $\eta_k \geq 0$ and determine d^k such that
$\frac{\ \nabla^2 f(x^k) d + \nabla f(x^k)\ }{\ \nabla f(x^k)\ } \leq \eta_k.$
S3. Set $x^{k+1} = x^k + d^k$, increment k and go to S1.

→ **Theorem 2.15:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^2 , let \bar{x} be a stationary point of f such that $\nabla^2 f(\bar{x})$ is invertible. Then there exists $\varepsilon > 0$ such that for all $x^0 \in B_\varepsilon(\bar{x})$:

1. If $\eta_k \leq \bar{\eta}$ for all $k \in \mathbb{N}$ for some $\bar{\eta} > 0$ sufficiently small, then Algorithm 2.7 is well-defined and generates a sequence that converges at least linearly to \bar{x} .
2. If $\eta_k \downarrow 0$, the rate of convergence is superlinear.
3. If $\nabla^2 f$ is locally Lipschitz (for instance, if $f \in C^3$) and $\eta_k = O(\|\nabla f(x^k)\|)$, then the rate is quadratic.

Remark 2.16: For $\eta_k = 0$, we just recover the local Newton's method. 2. and 3. strongly point their fingers at how to choose η_k . 1. is theoretically important, but practically useless since $\bar{\eta}$ is generally unknown.

Globalized Inexact Newton's Method

S0. Choose $x^0 \in \mathbb{R}^n, \varepsilon \geq 0, \rho > 0, p > 2, \beta \in (0, 1), \sigma \in (0, \frac{1}{2})$ and set $k := 0$.

S1. If $\|\nabla f(x^k)\| \leq \varepsilon$ STOP.

S2. Choose $\eta_k \geq 0$ and determine d^k by

$$\|\nabla^2 f(x^k) d + \nabla f(x^k)\| \leq \eta_k \|\nabla f(x^k)\|.$$

If this is not possible, or not feasible, i.e. $\nabla f(x^k)^T d^k \leq -\rho \|d^k\|^p$ is violated, then set $d^k := -\nabla f(x^k)$.

S3. Determine $t_k > 0$ by Armijo, $t_k := \max_{\{\ell \in \mathbb{N}_0\}} \left\{ \beta^\ell \mid f(x^k + \beta^\ell d^k) \leq f(x^k) + \beta^\ell \sigma \nabla f(x^k)^T d^k \right\}$.

S4. Set $x^{k+1} = x^k + t_k d^k$, increment k and go to S1.

→ **Theorem 2.16:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^2 and let $\{x^k\}$ be generated by Algorithm 2.8 with $\eta_k \downarrow 0$.

0. If \bar{x} is a cluster point of $\{x^k\}$ with $\nabla^2 f(\bar{x}) > 0$, then the following hold:

1. $\{x^k\}$ converges along the whole sequence to \bar{x} , which is a strict locally minimizer of f .
2. For all k sufficiently large, d^k will be given by the inexact Newton equation.
3. For all k sufficiently large, the full step-size $t_k = 1$ will be accepted.
4. The convergence is at least superlinear.

II.4.5 Conjugate Gradient Methods for Nonlinear Optimization

II.4.5.1 Prelude: Linear Systems

Remark that, for $A > 0$ and $b \in \mathbb{R}^n$,

$$Ax = b \quad \Leftrightarrow \quad x \text{ minimizes } f(x) := \frac{1}{2} x^T A x - b^T x.$$

→ **Definition 2.7** (A -conjugate vectors): Let $A > 0$ and $x, y \in \mathbb{R}^n \setminus \{0\}$ are called A -conjugate if

$$x^T A y = 0$$

(i.e. x, y are orthogonal in the inner product induced by A , denoted $\langle \cdot, \cdot \rangle_A$).

→ **Lemma 2.11:** Let $A > 0, b \in \mathbb{R}^n$, and $f(x) := \frac{1}{2}x^T Ax - b^T x$. Let d^0, d^1, \dots, d^{n-1} be (pairwise) A -conjugate. Let $\{x^k\}$ be generated by $x^{k+1} = x^k + t_k d^k, x^0 \in \mathbb{R}^n$, where $t_k := \operatorname{argmin}_{t>0} f(x^k + t_k d^k)$. Then, after at most n iterations, x^n is the (unique) global minimizer \bar{x} ($= A^{-1}b$) of f . Moreover, with $g^k := \nabla f(x^k)$ ($= Ax^k - b$), we have

$$t_k = -\frac{(g^k)^T d^k}{(d^k)^T Ad^k} > 0,$$

and $(g^{k+1})^T d^j = 0$ for all $j = 0, \dots, k$.

PROOF. The formula for t_k was proven in an exercise. To prove the latter statement, note that

$$\begin{aligned} (g^{k+1})^T d^k &= (Ax^{k+1} - b)^T d^k \\ &= (Ax^k - b + t_k Ad^k)^T d^k \\ &= (g^k)^T d^k + t_k (d^k)^T Ad^k \\ &= (g^k)^T d^k - (g^k)^T d^k = 0. \end{aligned}$$

Moreover, for all $i, j = 0, \dots, k$ with $i \neq j$, we have that

$$(g^{i+1} - g^i)^T d^j = (Ax^{i+1} - Ax^i)^T d^j = t_i (d^i)^T Ad^j = 0,$$

hence for all $j = 0, \dots, k$,

$$(g^{k+1})^T d^j = (g^{j+1})^T d^j + \sum_{i=j+1}^k (g^{i+1} - g^i)^T d^j = 0.$$

Thus, g^n is orthogonal to the n linearly independent vectors $\{d^0, \dots, d^{n-1}\}$, which implies $g^n = 0$, thus proving the conclusion. ■

We want to obtain these A -conjugate vectors, while simultaneously ensuring that they are descent directions at each step, i.e. that $\nabla f(x^k)^T d^k < 0$ for all $k = 0, \dots, n-1$. We do this algorithmically.

Assume $\nabla f(x^0) \neq 0$ (else we are done), and take $d^0 := -\nabla f(x^0)$. Suppose then we have $l+1$ A -conjugate vectors d^0, \dots, d^l with $\nabla f(x^i)^T d^i < 0$ for each i . Suppose

$$d^{l+1} := -g^{l+1} + \sum_{i=0}^l \beta_{il} d^i,$$

where g^{l+1} is “valid” to be used since it is not in the span of $\{d^0, \dots, d^l\}$, and $\{\beta_{il}\}$ are scalars to be determined. The condition $(d^{l+1})^T Ad^j = 0$ readily implies that

$$\beta_{jl} := \frac{(g^{l+1})^T Ad^j}{(d^j)^T Ad^j}, \quad j = 0, \dots, l.$$

Then, it follows that $(g^{l+1})^T d^{l+1} = -\|g^{l+1}\|^2 < 0$, and since $g^{l+1} = \nabla f(x^{l+1})$ by definition, it follows d^{l+1} a descent direction. Thus, it must be that

$$g^{j+1} - g^j = Ax^{j+1} - Ax^j = t_j Ad^j,$$

and so with $t_j > 0$,

$$(g^{l+1})^T Ad^j = \frac{1}{t_j} (g^{l+1})^T (g^{j+1} - g^j),$$

and thus

$$\beta_{jl} = \begin{cases} 0 & j = 0, \dots, l-1 \\ \frac{\|g^{j+1}\|^2}{\|g^l\|^2} & j = l \end{cases},$$

and thus our update of d^{l+1} reduces to

$$d^{l+1} := -g^{l+1} + \beta_l d^l, \quad \beta_l := \beta_{ll}.$$

In summary, this gives the following algorithm.

CG method for linear equations
S0. Choose $x^0 \in \mathbb{R}^n$ and $\varepsilon \geq 0$, set $g^0 := Ax^0 - b$, $d^0 := -g^0$ and initiate $k = 0$.
S1. If $\ g^k\ \leq \varepsilon$, STOP.
S2. Put
$t_k := \frac{\ g^k\ ^2}{(d^k)^T Ad^k}.$
S3. Set
$x^{k+1} = x^k + t_k d^k$
$g^{k+1} = g^k + t_k Ad^k$
$\beta_k = \frac{\ g^{k+1}\ ^2}{\ g^k\ ^2}$
$d^{k+1} = -g^{k+1} + \beta_k d^k.$
S4. Increment k and go to S1.

↪ **Theorem 2.17** (Convergence of CG Method): Let $A \in \mathbb{R}^{n \times n}$ be symmetric positive definite, $b \in \mathbb{R}^n$ and $f(x) := \frac{1}{2}x^T Ax - b^T x$. Then, Algorithm 2.9 will produce the global minimum \bar{x} of f after at most n iterations. If $m \in \{0, \dots, n\}$ is the smallest number such that $x^m = \bar{x}$, then the following hold as well:

$$(d^k)^T Ad^j = 0, (g^k)^T g^j = 0, (g^k)^T d^j = 0, \quad (k = 1, \dots, m, j = 0, \dots, k-1),$$

$$(g^k)^T d^k = -\|g^k\|^2 \quad (k = 0, \dots, m).$$

II.4.6 The Fletcher-Reeves Method

We want to apply the same method as the previous section for non-quadratic and non-convex functions. The issue we need to resolve, though, is that the step-size rule in S2. of Algorithm 2.9 is no longer appropriate. To resolve, we introduce the *Strong Wolfe-Powell rule*. Choose $\sigma \in (0, 1), \rho \in (\sigma, 1)$. The strong WP rule for a differentiable $f : \mathbb{R}^n \rightarrow \mathbb{R}$ reads

$$T_{\text{SWP}} : (x, d) \in \mathcal{A}_f \mapsto \left\{ t > 0 \mid \begin{array}{l} f(x + td) \leq f(x) + \sigma t \nabla f(x)^T d \\ |\nabla f(x + td)^T d| \leq -\rho \nabla f(x)^T d \end{array} \right\},$$

noting that clearly $T_{\text{SWP}}(x, d) \subset T_{\text{WP}}(x, d)$.

Fletcher-Reeves
S0. Choose $x^0 \in \mathbb{R}^n, \varepsilon \geq 0, 0 < \sigma < \rho < \frac{1}{2}$, set $d^0 := -\nabla f(x^0)$ and $k = 0$.
S1. If $\ \nabla f(x^k)\ \leq \varepsilon$, STOP.
S2. Determine $t_k > 0$ such that
$f(x^k + t_k d^k) \leq f(x^k) + \sigma t_k \nabla f(x^k)^T d^k,$
$ \nabla f(x^k + t_k d^k)^T d^k \leq -\rho \nabla f(x^k)^T d^k.$
S3. Set
$x^{k+1} = x^k + t_k d^k$
$\beta_k^{\text{FR}} = \frac{\ \nabla f(x^{k+1})\ ^2}{\ \nabla f(x^k)\ ^2}$
$d^{k+1} = -\nabla f(x^{k+1}) + \beta_k^{\text{FR}} d^k.$
S4. Increment k and go to S1.

↪ **Lemma 2.12:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^1 and bounded from below and $(x, d) \in \mathcal{A}_f$. Then $T_{\text{SWP}}(x, d) \neq \emptyset$.

PROOF. Define $\varphi, \psi : \mathbb{R} \rightarrow \mathbb{R}$ by

$$\varphi(t) := f(x + td), \quad \psi(t) = f(x) + \sigma t \nabla f(x)^T d,$$

noting that ψ affine linear with negative slope. We need to show, then, that $\varphi(t) \leq \psi(t)$ and $|\varphi'(t)| \leq -\rho \varphi'(0)$ for some $t > 0$. Now, $\varphi(0) = \psi(0)$, and $\varphi'(0) < \psi'(0)$. By Taylor's theorem, $\varphi(t) < \psi(t)$ for all $t > 0$ sufficiently small. Define

$$t^* = \min\{t > 0 \mid \varphi(t) = \psi(t)\}.$$

This exists, since $\psi(t) \rightarrow -\infty$ as $t \rightarrow \infty$, and $\varphi(t)$ is bounded from below; for small t , $\varphi(t) < \psi(t)$, so by continuity there must exist $t > 0$ for which $\varphi(t) = \psi(t)$, so t^* well-defined. Moreover, we have then that $\varphi'(t^*) \geq \psi'(t^*)$, which we can see by Taylor/ graphically.

Now, we consider two cases. Suppose first that $\varphi'(t^*) < 0$. Then,

$$|\varphi'(t^*)| = -\varphi'(t^*) \leq -\psi'(t^*) = -\sigma \nabla f(x)^T d.$$

We know $\sigma < \rho$, so we're done, so this is further upper bounded by $-\rho \nabla f(x)^T d = -\rho \varphi'(0)$, so we're done in this case with t^* .

Next, suppose $\varphi'(t^*) \geq 0$. t^* won't cut it in this case, but we can see that there exists $t^{**} \in (0, t^*]$, by intermediate value theorem, for which $\varphi'(t^{**}) = 0$. Since t^* the first time φ, ψ are equal (being the minimum) and $t^{**} \leq t^*$, it follows that we have $\varphi(t^{**}) < \psi(t^{**})$. Also trivially,

$$|\varphi'(t^{**})| = 0 \leq -\rho \varphi'(0),$$

since $\varphi'(0) < 0$, and thus t^{**} provides the appropriate t value for the claims, so we're done. ■

Remark 2.17: In particular, this immediately gives the well-definedness of Algorithm 2.10, assuming $\{x^k\} \times \{d^k\} \in \mathcal{A}_f$.

→ **Lemma 2.13:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^1 and bounded from below. Let $\{x^k\}, \{d^k\}$ be generated by Algorithm 2.10. Then,

$$-\sum_{j=0}^k \rho^j \leq \frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\|^2} \leq -2 + \sum_{j=0}^k \rho^j,$$

for all $k \in \mathbb{N}$.

PROOF. We induct on k . For $k = 0$, the claim reads

$$-1 \leq -1 \leq -2 + (1) = -1,$$

since $d^0 = -\nabla f(x^0)$, so it holds trivially.

Suppose the claim for some fixed $k \in \mathbb{N}$. We have

$$\rho \nabla f(x^k)^T d^k \leq \nabla f(x^{k+1})^T d^k \leq -\rho \nabla f(x^k)^T d^k$$

by (S2), which implies by a little algebraic manipulation

$$-1 + \rho \frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\|^2} \leq -1 + \frac{\nabla f(x^{k+1})^T d^k}{\|\nabla f(x^k)\|^2} \leq -1 - \rho \frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\|^2}. \quad (*)$$

In addition, by (S3), we know

$$\begin{aligned}
\frac{\nabla f(x^{k+1})^T d^{k+1}}{\|\nabla f(x^{k+1})\|^2} &= \frac{\nabla f(x^{k+1})^T (-\nabla f(x^{k+1}) + \beta_k d^k)}{\|\nabla f(x^{k+1})\|^2} \\
&= -\frac{\nabla f(x^{k+1})^T \nabla f(x^{k+1})}{\|\nabla f(x^{k+1})\|^2} + \beta_k \frac{\nabla f(x^{k+1})^T d^k}{\|\nabla f(x^{k+1})\|^2} \\
&= -1 + \frac{\nabla f(x^{k+1})^T d^k}{\|\nabla f(x^k)\|^2},
\end{aligned}$$

thus

$$\frac{\nabla f(x^{k+1})^T d^{k+1}}{\|\nabla f(x^{k+1})\|^2} = -1 + \frac{\nabla f(x^{k+1})^T d^k}{\|\nabla f(x^k)\|^2} \quad (\star \star)$$

thus

$$\begin{aligned}
-\sum_{j=0}^{k+1} \rho^j &= -1 - \sum_{j=1}^{k+1} \rho^j \\
&= -1 + \rho \left(-\sum_{j=0}^k \rho^j \right) \\
(\text{induction hypothesis}) \quad &\leq -1 + \rho \frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\|^2} \\
(\star) \quad &\leq -1 + \frac{\nabla f(x^{k+1})^T d^k}{\|\nabla f(x^k)\|^2} \quad (\dagger) \\
(\star) \quad &\leq -1 - \rho \frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\|^2} \\
(\text{induction hypothesis}) \quad &\leq -1 + \rho \sum_{j=0}^k \rho^j = -2 + \sum_{j=0}^{k+1} \rho^j.
\end{aligned}$$

But by $(\star \star)$, the line $(\dagger) = \frac{\nabla f(x^{k+1})^T d^{k+1}}{\|\nabla f(x^{k+1})\|^2}$, so we've shown the claim. ■

↪ **Theorem 2.18:** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^1 and bounded from below, and let $\{x^k\}, \{d^k\}$ be generated by Algorithm 2.10. Then,

1. Algorithm 2.10 is well-defined,
2. $\nabla f(x^k)^T d^k < 0$ for all $k \in \mathbb{N}$ (it is a descent method).

PROOF. By the previous lemma,

$$\frac{\nabla f(x^k)^T d^k}{\|\nabla f(x^k)\|^2} \leq -2 + \sum_{j=0}^k \rho^j \leq -2 + \sum_{j=0}^{\infty} \rho^j = -2 + \frac{1}{1-\rho} = \frac{2\rho-1}{1-\rho} < 0,$$

since $\rho < \frac{1}{2}$. Multiplying both sides by $\|\nabla f(x^k)\|^2$ gives 2. Combining 2. with the previous previous lemma and the accompanying remarks, 1. follows. ■

→ **Theorem 2.19** (Al-Baali): Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be C^1 and bounded from below, such that f is Lipschitz on $\text{lev}_{f(x_0)} f$, and let $\{x^k\}, \{d^k\}$ be generated by Algorithm 2.10. Then,

$$\lim_{k \rightarrow \infty} \|\nabla f(x^k)\| = 0.$$

§II.5 Least-Squares Problems

Supposing we wish to find the root of a function $F : \mathbb{R}^n \rightarrow \mathbb{R}^m$, we know that when $m = n$, then Newton's method is applicable. More generally, though, for $m \neq n$, such methods are not available. However, we can approach this by equivalently considering the optimization problem

$$\min_x \frac{1}{2} \|F(x)\|^2.$$

Such a problem, i.e. “minimizing the square of the norm”, will be considered here. Naturally, since this is now a real-valued objective function, we could just apply Newton's method to it, but we'll do things a little more interesting.

II.5.1 Linear Least-Squares

Suppose $F(x) = Ax - b$ an affine linear function for $A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$; the least-squares problem just becomes

$$\min_x \frac{1}{2} \|Ax - b\|^2. \quad (\dagger)$$

→ **Theorem 2.20:**

1. \bar{x} solves $(\dagger) \Leftrightarrow \bar{x}$ solves $A^T A x = A^T b$.
2. (\dagger) always has a solution.
3. (\dagger) has a unique solution $\Leftrightarrow \text{rank}(A) = n$.

PROOF.

1. With $f(x) := \frac{1}{2} \|Ax - b\|^2$ the function of interest, one readily checks $\nabla f(x) = A^T A x - A^T b$ (by chain rule, or by expanding f as a “proper” quadratic) and $\nabla^2 f(x) = A^T A$. Thus, since $A^T A \geq 0$ always, f is convex so stationary points are equivalent to minimization points, and thus we need $\nabla f(x) = 0 \Leftrightarrow A^T A x = A^T b$.
2. By 1., we have a solution $\Leftrightarrow A^T b$ in the image of $A^T A$; but this is equal to the image of A^T , and obviously $A^T b$ in the image of A^T .
3. Similarly to the previous, we will have a unique solution to $A^T A x = A^T b$ iff $A^T A$ has full rank $\Leftrightarrow A$ has full rank.

II.5.2 Gauss-Newton for Nonlinear Least-Squares

Suppose $F \in C^1$. Inspired by Newton's method, we will, instead of linearizing $f(x) := \frac{1}{2} \|F(x)\|^2$, we will linearize $F(x)$; plugging this linearization back into the norm squared, we

expect a quadratic function. Indeed, suppose we have an iterate $x^k \in \mathbb{R}^n$; then, the linearization of F about x^k is given by

$$F_k(x) = F(x^k) + F'(x^k)(x - x^k).$$

Then,

$$q(x) := \frac{1}{2}\|F_k(x)\|^2 = \dots = \frac{1}{2}x^T \left(F'(x^k)^T F'(x^k) \right) x + \left[F'(x^k)^T F(x^k) - F'(x^k)^T F'(x^k)x^k \right]^T x + \text{const},$$

where const independent of x . Assume $F'(x^k)$ of full rank n . Then, $F'(x^k)^T F'(x^k) > 0$, and so by the previous section,

$$\begin{aligned} x^+ \in \operatorname{argmin}(q) &\Leftrightarrow \nabla q(x^+) = 0 \\ &\Leftrightarrow F'(x^k)^T F'(x^k)x^+ + F'(x^k)^T F(x^k) - F'(x^k)^T F'(x^k)x^k = 0 \\ &\Leftrightarrow x^+ = x^k - \underbrace{\left(F'(x^k)^T F'(x^k) \right)^{-1} F'(x^k)^T F(x^k)}_{:=d^k}. \end{aligned}$$

Thus, this inspires the Gauss-Newton Method; supposing we can find d as a solution to the *Gauss-Newton Equations* (GNE),

$$F'(x^k)^T F(x^k)d = -F'(x^k)^T F(x^k),$$

then we update $x^{k+1} = x^k + d^k$. In particular, with this choice,

$$\nabla f(x)^T d^k = -\underbrace{\left(F'(x^k)^T F(x^k) \right)^T}_{=:u} \underbrace{\left(F'(x^k)^T F'(x^k) \right)^{-1}}_{\geq 0} \underbrace{\left(F'(x^k)^T F(x^k) \right)}_{=:u} < 0,$$

i.e., if $\nabla f(x^k) \neq 0$ and $F'(x^k)$ of rank n , then d^k a descent direction.

The Newton's Equation for the same function f would read

$$\left(F'(x^k)^T F'(x^k) + S(x^k) \right) d = -F'(x^k)^T F(x^k),$$

where

$$S(x^k) = \sum_{i=1}^m F_i(x^k) \nabla^2 F_i(x^k);$$

if S were zero, then this the same as the GNE (though of course, this will not hold in general).

§III CONSTRAINED OPTIMIZATION

§III.1 Optimality Conditions for Constrained Problems

Consider

$$\min f(x) \text{ s.t. } \begin{array}{l} g_i(x) \leq 0 \forall i = 1, \dots, m, \\ h_j(x) = 0 \forall j = 1, \dots, p \end{array}$$

where we will assume $f, g_i, h_j : \mathbb{R}^n \rightarrow \mathbb{R}$ are continuously differentiable. We call such a problem a *nonlinear program*. We put as before the *feasible set*

$$X := \{x \mid g_i(x) \leq 0 \forall_{i=1}^m, h_j(x) = 0 \forall_{j=1}^p\}.$$

We'll also define the index sets

$$I := \{1, \dots, m\}, \quad J := \{1, \dots, p\},$$

and the *active indices* for a point \bar{x} by

$$I(\bar{x}) := \{i \in I \mid g_i(\bar{x}) = 0\} \subset I.$$

III.1.1 First-Order Optimality Conditions

Consider the slightly more abstract problem

$$\min_x f(x) \text{ s.t. } x \in S \quad (\dagger),$$

with $f : \mathbb{R}^n \rightarrow \mathbb{R}$ in C^1 and $S \subset \mathbb{R}^n$ closed and nonempty.

→ **Definition 3.1** (Cones): A nonempty set $K \subset \mathbb{R}^n$ is said to be a *cone* if

$$\lambda v \in K \quad \forall v \in K, \lambda \geq 0,$$

i.e. K is closed under positive scalings of vectors in K .

Remark 3.1: We can in fact replace \mathbb{R}^n with any real vector space V , for a cone living in V .

We have that

- any vector space;
- the nonnegative reals;
- $\Lambda := \{(x, y)^T \mid x, y \in K, x^T y = 0\}$, where K a given cone;
- and $S_+^n := \{A \in \mathbb{R}^{n \times n} \mid A \geq 0\}$ (embedded in an appropriate space of matrices)

are all cones, for instance.

→ **Definition 3.2:** Let $S \subset \mathbb{R}^n, \bar{x} \in S$. Then

$$T_s(\bar{x}) := \left\{ d \in \mathbb{R}^n \mid \exists \{x^k \in S\} \rightarrow \bar{x}, \{t_k\} \downarrow 0 \text{ s.t. } \frac{x^k - \bar{x}}{t_k} \rightarrow d \right\}$$

is called the *tangent cone of S at \bar{x}* .

→ **Proposition 3.1:** Let $S \subset \mathbb{R}^n, x \in S$. Then $T_S(x)$ is a closed cone.

→ **Theorem 3.1** (Basic First-Order Optimality Conditions): Let \bar{x} be a local minimizer of (\dagger) .

Then,

1. $\nabla f(\bar{x})^T d \geq 0$ for all $d \in T_S(\bar{x})$;
2. if S is convex, then $\nabla f(\bar{x})^T (x - \bar{x}) \geq 0$ for all $x \in S$.

PROOF.

- Let $d \in T_S(\bar{x})$. By definition, there exists $\{x^k\} \subset S$ and $\{t_k\} \downarrow 0$ for which $\frac{x^k - \bar{x}}{t_k} \rightarrow d$. As x^k feasible and \bar{x} a local minimizer of f over S ,

$$f(x^k) - f(\bar{x}) \geq 0$$

for all k sufficiently large. By the mean value theorem, there is for each k sufficiently large a θ_k on the line between x^k and \bar{x} for which

$$f(x^k) - f(\bar{x}) = \nabla f(\theta_k)^T (x^k - \bar{x}),$$

so

$$0 \leq \frac{f(x^k) - f(\bar{x})}{t_k} = \frac{\nabla f(\theta_k)^T (x^k - \bar{x})}{t_k} \xrightarrow{k} \nabla f(\bar{x})^T d.$$

- Suppose not. Then, there exists a $\hat{x} \in S$ such that $\nabla f(\bar{x})^T (\hat{x} - \bar{x}) < 0$. By convexity, $\bar{x} + \lambda(\hat{x} - \bar{x}) \in S$ for $\lambda \in (0, 1)$. By mean value theorem, for every such λ there exists a θ_λ on the line between $\bar{x} + \lambda(\hat{x} - \bar{x})$ and \bar{x} for which

$$f(\bar{x} + \lambda(\hat{x} - \bar{x})) - f(\bar{x}) = \lambda \nabla f(\theta_\lambda)^T (\hat{x} - \bar{x}).$$

By supposition, for λ sufficiently close to 0, the right-hand side will remain negative (since $\nabla f(\theta_\lambda) \xrightarrow{\lambda \rightarrow 0} \nabla f(\bar{x})$), so for sufficiently small λ ,

$$f(\bar{x} + \lambda(\hat{x} - \bar{x})) < f(\bar{x}),$$

and since $\bar{x} + \lambda(\hat{x} - \bar{x})$ remains feasible for all λ by convexity, this contradicts minimality. ■

Remark 3.2: Computationally, this isn't very helpful - in practice, i.e. in trying to compute local minimizers, we'd need to compute $\nabla f(\bar{x})^T d$ for every d in the tangent cone of a given S at a given point \bar{x} . In general, we don't know what this set looks like, and even if we did, this isn't a feasible condition to check for every such point, since it isn't easy to interpret computationally.

You can never tell the computer what the fucking set looks like

— Tim H

III.1.2 Farkas' Lemma

→ **Definition 3.3** (Projection): Let $S \subset \mathbb{R}^n$ be nonempty, $x \in \mathbb{R}^n$. The *projection* of x onto S is given by

$$P_S(x) := \operatorname{argmin}_{y \in S} \frac{1}{2} \|x - y\|^2.$$

Remark 3.3: This is, in general, a set-valued function; it could even be empty (for instance, if $S = [0, 1]$ and $x = 2$.)

→ **Proposition 3.2:** Let $x \in \mathbb{R}^n$, $S \subset \mathbb{R}^n$ nonempty, closed and convex. Then,

1. $P_S(x)$ has exactly one element, so P_S can be viewed $\mathbb{R}^n \rightarrow S$;
2. $P_S(x) = x \Leftrightarrow x \in S$;
3. (The Projection Theorem) $(P_S(x) - x)^T(y - P_S(x)) \geq 0$ for all $y \in S$.

PROOF.

1. This follows from the fact that $S \ni y \mapsto \|x - y\|_2^2$ a strongly convex function.
2. Clear.
3. Take $f(y) = \frac{1}{2}\|x - y\|^2$ in the last theorem.

■

→ **Lemma 3.1:** Let $B \in \mathbb{R}^{\ell \times n}$. Then, $\{Bx \mid x \in \mathbb{R}_+^n\}$ is a nonempty, closed, convex cone.

PROOF. Convexity and cone properties are clear. Closed? ■

→ **Theorem 3.2 (Farkas' Lemma):** Let $B \in \mathbb{R}^{\ell \times n}$, $h \in \mathbb{R}^n$. Then, the following are equivalent:

1. The system

$$B^T x = h, x \geq 0$$

has a solution.

2. $h^T d \geq 0$ for all d such that $Bd \geq 0$.

Remark 3.4: $x \geq 0$ should be understood component-wise, i.e. each component of x is nonnegative.

PROOF. (1. \Rightarrow 2.) Let $x \geq 0$ such that $B^T x = h$. Then, if d such that $Bd \geq 0$,

$$h^T d = (B^T x)^T d = x^T Bd \geq 0.$$

(2. \Rightarrow 1.) Suppose 1. doesn't hold, i.e.

$$h \notin K = \{B^T x \mid x \geq 0\},$$

where K a closed, convex cone as the previous lemma. Set $\bar{s} = P_K(h) \in K$, which is well-defined since K closed and convex. Set $\bar{d} = \bar{s} - h \neq 0$. Thus, by the rojection theorem,

$$\bar{d}^T(s - \bar{s}) \geq 0$$

for all $s \in K$.

By taking $s = 2\bar{s} \in K$, we see then that $\bar{d}^T \bar{s} \geq 0$. Also, taking $\bar{s} = 0$, this implies $-\bar{d}^T \bar{s} \geq 0$, by which we must have $\bar{d}^T \bar{s} = 0$ and thus $\bar{d}^T s \geq 0$ for all $s \in K$. By definition of K , $(B\bar{d})^T x = \bar{d}^T B^T x \geq 0$ for all $x \geq 0$. This implies $B\bar{d} \geq 0$, by taking x to be each standard unit vector e_i .

OTOH,

$$h^T \bar{d} = (\bar{s} - \bar{d})^T \bar{d} = \underbrace{\bar{s}^T \bar{d}}_{=0} - \|\bar{d}\|^2 < 0,$$

since $\bar{d} \neq 0$. This contradicts 2. ■

III.1.3 Karush-Kuhn-Tucker Conditions

→ **Definition 3.4** (KKT Conditions): Consider the standard nonlinear program

$$\begin{aligned} \min f(x) \text{ s.t. } & g_i(x) \leq 0 \forall i = 1, \dots, m, \\ & h_j(x) = 0 \forall j = 1, \dots, p \end{aligned} \quad (*)$$

1. The function $L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$ defined by

$$\begin{aligned} L(x, \lambda, \mu) &= f(x) + \sum_{i=1}^m \lambda_i g_i(x) + \sum_{j=1}^p \mu_j h_j(x) \\ &= f(x) + \lambda^T g(x) + \mu^T h(x), \end{aligned}$$

where $\lambda := (\lambda_1, \dots, \lambda_m)$, $g = (g_1, \dots, g_m)$, $\mu = (\mu_1, \dots, \mu_p)$, $h = (h_1, \dots, h_p)$, is called the *Lagrangian* of the problem $(*)$.

2. The set of conditions

$$\begin{aligned} \nabla L_x(x, \lambda, \mu) &= 0, \\ h(x) &= 0, \\ \lambda &\geq 0, g(x) \leq 0, \lambda^T g(x) = 0 \end{aligned}$$

are called the *KKT Condition* of $(*)$.

3. A triple $(\bar{x}, \bar{\lambda}, \bar{\mu})$ that satisfies the KKT conditions is called a *KKT point* of $(*)$.
4. Given \bar{x} feasible for $(*)$, define

$$M(\bar{x}) = \{(\lambda, \mu) \mid (\bar{x}, \lambda, \mu) \text{ is a KKT point of } (*)\}.$$

→ **Definition 3.5** (Linearized Cone): Let X be the feasible set of $(*)$ and $\bar{x} \in X$. The *linearized cone* (of X) at \bar{x} is given by the set

$$\mathcal{L}_X(\bar{x}) := \left\{ d \mid \begin{array}{l} \nabla g_i(\bar{x})^T d \leq 0 \forall i \in I(\bar{x}) \\ \nabla h_j(\bar{x})^T d = 0 \forall j \in J \end{array} \right\}.$$

→ **Definition 3.6** (Abadie Constraint Qualification): Let $\bar{x} \in X$. We say that the *Abadie constraint qualification (ACQ)* holds at \bar{x} if $T_X(\bar{x}) = \mathcal{L}_X(\bar{x})$.

Remark 3.5: We may represent the constraints that lead to X in different ways. These different representations may lead to different linearized cones $\mathcal{L}_X(\bar{x})$, but will NOT change $T_X(\bar{x})$. So, the ACQ may hold/not hold depending on how we represent X for a fixed problem.

→ **Theorem 3.3** (KKT Conditions Under ACQ): Let \bar{x} be a local minimizer of (\star) such that ACQ holds at \bar{x} . Then, there exist $(\bar{\lambda}, \bar{\mu}) \in \mathbb{R}^m \times \mathbb{R}^p$ such that $(\bar{x}, \bar{\lambda}, \bar{\mu})$ a KKT point.

PROOF. \bar{x} a local minimizer implies by the basic first-order optimality conditions for (\star) that $\nabla f(\bar{x})^T d \geq 0$ for all $d \in T_X(\bar{x})$. Set

$$B = \begin{pmatrix} -\nabla g_i(x)^T & (i \in I(\bar{x})) \\ -\nabla h_j(x)^T & (j \in J) \\ \nabla h_j(x)^T & (j \in J) \end{pmatrix} \in \mathbb{R}^{(|I(\bar{x})|+2p) \times n}.$$

Note that $d \in \mathcal{L}_X(\bar{x})$ iff $Bd \geq 0$. By the ACQ, $\nabla f(\bar{x})^T d \geq 0$ for all $d \in \mathcal{L}_X(\bar{x})$, hence $\nabla f(\bar{x})^T d \geq 0$ for all d such that $Bd \geq 0$. By Farkas' Lemma (taking B as defined, $h = \nabla f(\bar{x})$), there exists a $y = (y^1, y^2, y^3) \in \mathbb{R}^{|I(\bar{x})|} \times \mathbb{R}^p \times \mathbb{R}^p$ such that $B^T y = \nabla f(\bar{x})$ and $y \geq 0$. Define

$$\bar{\lambda} := \begin{cases} y_i^1 & i \in I(\bar{x}), \\ 0 & \text{else} \end{cases}, \quad \bar{\mu} := y^2 - y^3.$$

Then, $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is a KKT point. ■

⊕ **Example 3.1:** Consider

$$\min x_1^2 + x_2^2 \quad \text{s.t. } x_1, x_2 \geq 0, x_1 x_2 = 0,$$

with $X = \{x \in \mathbb{R}^2 \mid x_1, x_2 \geq 0, x_1 x_2 = 0\}$. Let $\bar{x} = (0, 0)^T \in X$. We find that

$$T_X(\bar{x}) = X, \quad \mathcal{L}_X(\bar{x}) = \mathbb{R}_+^2.$$

So, ACQ does not hold. However, with $\bar{\lambda} = 0$ and $\bar{\mu} = 1$, we find $\nabla f(\bar{x}) + \bar{\lambda}_1 \nabla g_1(\bar{x}) + \bar{\lambda}_2 \nabla g_2(\bar{x}) + \bar{\mu} \nabla h(\bar{x}) = 0$, and we find $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is a KKT point.

III.1.4 Constraint Qualifications

→ **Definition 3.7:** Let \bar{x} be a feasible point of the generic nonlinear program. We say that:

1. the *linear independence constraint qualification (LICQ)* holds at \bar{x} if the vectors

$$\nabla g_i(\bar{x}), i \in I(\bar{x}), \nabla h_j(\bar{x}), j \in J,$$

are linearly independent;

2. the *Mangasarian-Fromovitz CQ (MFCQ)* holds at \bar{x} if the gradients

$$\nabla h_j(\bar{x}), j \in J$$

are linearly independent, and there exists a $d \in \mathbb{R}^n$ such that

$$\nabla g_i(\bar{x})^T d < 0, i \in I(\bar{x}),$$

$$\nabla h_j(\bar{x})^T d = 0, j \in J.$$

→ **Proposition 3.3** ($\text{LICQ} \Rightarrow \text{MFCQ}$): Let \bar{x} be feasible and such that LICQ holds at \bar{x} . Then MFCQ holds at \bar{x} .

PROOF. Left as an exercise. ■

↪ **Theorem 3.4** (Implicit Function Theorem): Let $U \subset \mathbb{R}^p, V \subset \mathbb{R}^m$ open and $F : U \times V \rightarrow \mathbb{R}^b$ continuous differentiable such that for $(\bar{x}, \bar{y}) \in U \times V, F(\bar{y}, \bar{z}) = 0$ and $D_y F(\bar{y}, \bar{z}) \in \mathbb{R}^{p \times b}$ invertible. Then, there exist neighborhoods $\hat{U} \subset U$ and $\hat{V} \subset V$ and $g : \hat{V} \rightarrow \hat{U}$ continuously differentiable such that

$$F(g(z), z) = 0, \forall z \in \hat{V},$$

and

$$Dg(z) = -[D_y F(g(z), z)]^{-1} D_z F(g(z), z),$$

and for all $(y, z) \in \hat{U} \times \hat{V}$ such that $F(y, z) = 0$, then $y = g(z)$.

↪ **Lemma 3.2:** Let \bar{x} be feasible such that $\nabla h_j(\bar{x}), j \in J$ are linearly independent, and there exists d such that $\nabla g_i(\bar{x})^T d < 0$ for $i \in I(\bar{x})$ and $\nabla h_j(\bar{x})^T d = 0$ for $j \in J$. Then, there exists an $\varepsilon > 0$ and a C^1 -curve $x : (-\varepsilon, \varepsilon) \rightarrow \mathbb{R}^n$ such that $x(t)$ feasible for all $t \in [0, \varepsilon]$, $x(0) = \bar{x}$, and $x'(0) = d$.

PROOF. Define $H : \mathbb{R}^p \times \mathbb{R} \rightarrow \mathbb{R}^p$ by

$$H_j(y, t) := h_j(\bar{x} + td + h'(\bar{x})^T y), \quad j = 1, \dots, p.$$

The equation $H(y, t) = 0$ has as solution $(\bar{y}, \bar{t}) = (0, 0)$, as $h_j(\bar{x}) = 0$ by feasibility. Moreover,

$$D_y H(\bar{y}, \bar{t}) = h'(\bar{x})h'(\bar{x})^T \in \mathbb{R}^{p \times p},$$

with $h'(\bar{x})^T$ having linearly independent columns, hence being invertible, so all of $D_y H(\bar{y}, \bar{t})$ is invertible. By the implicit function theorem, there exists an $\varepsilon > 0$ and a C^1 -curve $y : (-\varepsilon, \varepsilon) \rightarrow \mathbb{R}^p$ for which $y(0) = 0, H(y(t), t) = 0$ for all $t \in (-\varepsilon, \varepsilon)$, and $y'(t) = -[D_y H(y(t), t)]^{-1} D_t H(y(t), t)$ for all $t \in (-\varepsilon, \varepsilon)$. In particular,

$$y'(0) = -[D_y H(0, 0)]^{-1} h'(\bar{x})d = 0,$$

since $h'(\bar{x}) = [\nabla h_j(\bar{x})^T] = 0$ by assumption. Set now $x(t) = \bar{x} + td + h'(\bar{x})^T y(t)$. Making ε smaller if necessary, we see that $x : (-\varepsilon, \varepsilon) \rightarrow \mathbb{R}^n$ has all the desired properties:

- $x \in C^1$ since $y \in C^1$
- $x(0) = \bar{x}$
- $x'(0) = d$
- $x(t)$ is feasible: by construction, for $t \in [0, \varepsilon], h_j(x(t)) = H_j(y(t), t) = 0$; for $i \in I \setminus I(\bar{x})$, then $g_i(\bar{x}) = g_i(x(0)) < 0$, then by continuity $g_i(x(t))$ will remain negative for all sufficiently small t ; for $i \in I(\bar{x}), g_i(\bar{x}) = g_i(x(0)) = 0$, and $\frac{d}{dt} g_i(x(0)) = \nabla g_i(\bar{x})^T d < 0$, which implies $g_i(x(t)) < 0$ for all t sufficiently small.

→ **Proposition 3.4** (MFCQ \Rightarrow ACQ): Let \bar{x} be a feasible point such that MFCQ holds at \bar{x} ; then ACQ holds.

PROOF. We only need to show $\mathcal{L}_X(\bar{x}) \subset T_X(\bar{x})$. Let $d \in \mathcal{L}_X(\bar{x})$. By MFCQ there exists \hat{d} such that $\nabla g_i(\bar{x})^T \hat{d} < 0$ for $i \in I(\bar{x})$ and $\nabla h_j(\bar{x})^T \hat{d} = 0$ for all $j \in J$. Set $d(\delta) = d + \delta \hat{d}$ for all $\delta > 0$. Then,

$$\nabla g_i(\bar{x})^T d(\delta) < 0, \forall i \in I(\bar{x}), \quad \nabla h_j(\bar{x})^T d(\delta) = 0 \forall j \in J.$$

Applying the previous lemma to $d(\delta)$ yields a C^1 -curve $x : (-\varepsilon, \varepsilon) \rightarrow \mathbb{R}^n$ such that $x(0) = \bar{x}$, $x'(0) = d(\delta)$, and $x(t)$ feasible for all $t \in [0, \varepsilon]$. Let $t_k \downarrow 0$ and set $x^k := x(t_k)$, then x^k feasible and $x^k \rightarrow \bar{x}$. We see that

$$d(\delta) = x'(0) = \lim_{k \rightarrow \infty} \frac{x(t_k) - x(0)}{t_k} = \lim_{k \rightarrow \infty} \frac{x^k - \bar{x}}{t_k} \in T_X(\bar{x}),$$

hence for all $\delta > 0$, $d(\delta) \in T_X(\bar{x})$. Letting $\delta \rightarrow 0$, $d(\delta) \rightarrow d$ and thus $d \in T_X(\bar{x})$ as well, since $T_X(\bar{x})$ closed. ■

→ **Corollary 3.1:** Let \bar{x} be a local min of the generic nonlinear program such that MFCQ holds at \bar{x} . Then the following hold:

1. $M(\bar{x}) \neq \emptyset$;
2. $M(\bar{x})$ is bounded.

PROOF. 1. follows from the previous proposition and the related theorem for ACQ. For 2., suppose otherwise, then there exists $\{(\lambda^k, \mu^k)\} \subset M(\bar{x})$ for which $\|(\lambda^k, \mu^k)\| \rightarrow \infty$. Without loss of generality, we may assume $\frac{\lambda^k, \mu^k}{\|(\lambda^k, \mu^k)\|} \rightarrow (\tilde{\lambda}, \tilde{\mu}) \neq 0$. Since $(\bar{x}, \lambda^k, \mu^k)$ is a KKT point, we have

$$0 = \frac{\nabla f(\bar{x}) + \sum_{i \in I(\bar{x})} \lambda_i^k \nabla g_i(\bar{x}) + \sum_{j \in J} \mu_j^k \nabla h_j(\bar{x})}{\|(\lambda^k, \mu^k)\|} \rightarrow \sum_{i \in I(\bar{x})} \tilde{\lambda}_i \nabla g_i(\bar{x}) + \sum_{j \in J} \tilde{\mu}_j \nabla h_j(\bar{x}).$$

If $\tilde{\lambda} = 0$, $\tilde{\mu} \neq 0$ and thus $0 = \sum_j \tilde{\mu}_j \nabla h_j(\bar{x})$ contradicts the linear independence of $\{\nabla h_j(\bar{x})\}$ of MFCQ.

If $\tilde{\lambda} \neq 0$, then there exists $i_0 \in I(\bar{x})$ such that $\tilde{\lambda}_{i_0} > 0$. Multiplying the above expression by d from MFCQ yields

$$0 = \sum_{i \in I(\bar{x})} \underbrace{\tilde{\lambda}_i \nabla g_i(\bar{x})^T d}_{< 0} + \sum_{i \in J} \underbrace{\tilde{\mu}_j \nabla h_j(\bar{x})^T d}_{= 0} \leq \tilde{\lambda}_{i_0} \nabla g_{i_0}(\bar{x})^T d < 0,$$

a contradiction. ■

→ **Corollary 3.2:** Let \bar{x} be a local minimimum of the generic nonlinear program such that LICQ holds. Then, $M(\bar{x})$ is a singleton.

In summary, we have

$$\begin{array}{ccc}
\text{LICQ} \Rightarrow & \text{MFCQ} \Rightarrow & \text{ACQ} \\
\Downarrow & \Downarrow & \Downarrow \\
M(\bar{x}) \text{ is: } & \begin{array}{l} \text{a singleton} \\ \text{nonempty, nonempty} \\ \text{bounded} \end{array} &
\end{array}$$

III.1.5 Affine constraints

→ **Definition 3.8** (Affine CQ): We say that the *affine CQ* holds if all constraints are affine, i.e. there exists $a_i \in \mathbb{R}^n, \alpha_i \in \mathbb{R}$ ($i \in I$), $b_j \in \mathbb{R}^n, \beta_j \in \mathbb{R}$ ($j \in J$) such that

$$g_i(x) = a_i^T x - \alpha_i, \quad h_j(x) = b_j^T - \beta_j.$$

→ **Proposition 3.5:** Let the affine CQ hold. Then, ACQ holds at every feasible point.

PROOF. Let $\bar{x} \in X$. As before, we only need to show $\mathcal{L}_X(\bar{x}) \subset T_X(\bar{x})$, then apply the previous lemma. Pick $d \in \mathcal{L}_X(\bar{x})$, i.e. $a_i^T d \leq 0, b_j^T d = 0$ for $i \in I(\bar{x}), j \in J$. Let now $t_k \downarrow 0$ and $x^k := \bar{x} + t_k d$. Then, $x^k \rightarrow \bar{x}$ as $t_k \rightarrow 0$ and $\frac{x^k - \bar{x}}{t_k} \rightarrow d$. It remains to show that $x^k \in X$ for all k sufficiently large. We check the conditions for x^k to be sufficient.

If $i \notin I(\bar{x})$, $a_i^T \bar{x} < \alpha_i$, so by continuity this strict inequality remains true replacing \bar{x} by x^k for k sufficiently large.

If $i \in I(\bar{x})$, $a_i^T \bar{x} = \alpha_i$ thus

$$a_i^T x^k = a_i^T \bar{x} + t_k a_i^T d \leq \alpha_i.$$

Similar work follows for $j \in J$, i.e. $b_j^T x^k = b_j^T \bar{x} + t_k b_j^T d = \beta_j + 0$. ■

III.1.6 Convex Problems

We consider

$$\begin{array}{ll}
\min f(x) & g_i(x) \leq 0, i \in I \\
\text{s.t.} & b_j^T x = \beta_j, j \in J'
\end{array}$$

where now we assume $f, g_i : \mathbb{R}^n \rightarrow \mathbb{R}$ are C^1 and convex. The feasible set

$$X = \{x \mid g_i(x) \leq 0 (i \in I), b_j^T x = \beta_j (j \in J)\}$$

is then convex (as per a midterm question).

→ **Theorem 3.5** (KKT for Convex NLP): Let \bar{x} be feasible for the convex NLP above and consider the following statements:

1. there exists $(\bar{\lambda}, \bar{\mu}) \in M(\bar{x})$ (i.e., $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is a KKT point);
2. \bar{x} is a (global) minimizer;

then, always 1. \Rightarrow 2., and hence if a constraint qualification holds at \bar{x} , then 1. and 2. are equivalent.

PROOF. Let $(\bar{x}, \bar{\lambda}, \bar{\mu})$ be a KKT point. Then for any $x \in X$,

$$\begin{aligned}
f(x) &\stackrel{\text{convexity}}{\geq} f(\bar{x}) + \nabla f(\bar{x})^T(x - \bar{x}) \\
&\stackrel{\text{KKT}}{\equiv} f(\bar{x}) + \left(- \sum_{i \in I(\bar{x})} \bar{\lambda}_i \nabla g_i(\bar{x}) - \sum_{j \in J} \bar{\mu}_j \nabla h_j(\bar{x}) \right)^T (x - \bar{x}) \\
&= f(\bar{x}) - \sum_{i \in I(\bar{x})} \underbrace{\bar{\lambda}_i \nabla g_i(\bar{x})^T (x - \bar{x})}_{\leq g_i(x) - g_i(\bar{x}) = g_i(x)} - \sum_{j \in J} \underbrace{\bar{\mu}_j \nabla h_j(\bar{x})^T (x - \bar{x})}_{= 0, \text{ feasibility}} \\
&\geq f(\bar{x}) - \underbrace{\sum_{i \in I(\bar{x})} \bar{\lambda}_i g_i(x)}_{\leq 0} \geq f(\bar{x}),
\end{aligned}$$

which gives \bar{x} indeed a local min, so 2. holds. The reverse implication holding under a CQ is the very definition of a CQ. ■

→ **Definition 3.9** (Slater CQ): We say the *Slater CQ* (*SCQ*) holds for the convex NLP if there exists a \hat{x} such that

$$g_i(\hat{x}) < 0, (i \in I), h_j(\hat{x}) = 0 (j \in J).$$

We call such a point a *Slater point*.

→ **Proposition 3.6** (*SCQ* \Rightarrow *ACQ*): Let *SCQ* hold for the convex NLP. Then, *ACQ* holds at every feasible point.

PROOF. Let $\bar{x} \in X$ and set

$$F(\bar{x}) := \{d \mid \nabla g_i(\bar{x})^T d < 0, i \in I, b_j^T d = 0, j \in J\}.$$

Then, $F(\bar{x}) \subset T_X(\bar{x})$ (exercise). As $T_X(\bar{x})$ is closed, it follows that $\overline{F(\bar{x})} \subset T_X(\bar{x})$. We know show that $\mathcal{L}_X(\bar{x}) \subset \overline{F(\bar{x})}$, from whence we'll be done. So, let $d \in \mathcal{L}_X(\bar{x})$ and let \hat{x} be a Slater point. Put $\hat{d} = \hat{x} - \bar{x}$. Then,

$$\nabla g_i(\bar{x})^T \hat{d} \leq g_i(\hat{x}) - g_i(\bar{x}) < 0$$

for $i \in I(\bar{x})$, and moreover, $\nabla h_j(\bar{x})^T \hat{d} = 0$. Define for $\delta > 0$, $d(\delta) := d + \delta \hat{d}$. Then, $d(\delta) \in F(\bar{x})$ for all $\delta > 0$ (CHECK THIS). Let $\delta \rightarrow 0$; then $d(\delta) \rightarrow d \in \overline{F(\bar{x})}$. ■

§III.2 Lagrangian Duality

Consider as before the standard NLP

$$\begin{aligned}
\min f(x) \text{ s.t. } & g_i(x) \leq 0 \forall i = 1, \dots, m, \\
& h_j(x) = 0 \forall j = 1, \dots, p
\end{aligned} \tag{P}$$

with $f, g_i, h_j : \mathbb{R}^n \rightarrow \mathbb{R}$ with $X = \{x \mid g(x) \leq 0, h(x) = 0\} \neq \emptyset$ (we don't make smoothness assumptions just yet). The *Lagrangian* of the problem (P) is given by

$$L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}, \quad L(x, \lambda, \mu) = f(x) + \lambda^T g(x) + \mu^T h(x).$$

III.2.1 The Dual Problem

Observe that

$$\sup_{\lambda, \mu} L(x, \lambda, \mu) = \begin{cases} f(x) & \text{if } x \in X \\ \infty & \text{else} \end{cases}$$

Then, the problem (P) is really equivalent to the problem

$$\min_{x \in \mathbb{R}^n} \sup_{\substack{\lambda \in \mathbb{R}_+^m, \\ \mu \in \mathbb{R}^p}} L(x, \lambda, \mu) = \inf_x p(x),$$

where we call $p(x)$ the *primal objective*. A question of interest is when can we switch the order of the min and the sup?

↪ **Definition 3.10** (Lagrangian Dual): The *(Lagrangian) dual* of (P) is given by

$$\max d(\lambda, \mu) \text{ s.t. } \lambda \geq 0 \quad (D)$$

where

$$d : \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R} \cup \{\infty\}, \quad d(\lambda, \mu) := \inf_x L(x, \lambda, \mu).$$

The latter is called the *dual objective*.

⊗ **Example 3.2** (LP): Consider the standard linear program (LP)

$$\min_x c^T x \mid Ax = b, x \geq 0,$$

with $A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m, c \in \mathbb{R}^n$. The Lagrangian for this problem reads

$$\begin{aligned} L(x, \lambda, \mu) &= c^T x - \lambda^T x + \mu^T (b - Ax) \\ &= (c - \lambda - A^T \mu)^T x + b^T \mu. \end{aligned}$$

We see that $\nabla_x L(x, \lambda, \mu) = c - \lambda - A^T \mu$. Note that the function $x \mapsto L(x, \lambda, \mu)$ is an affine function, which takes its minimum iff $c - \lambda - A^T \mu = 0$, in which case

$$\inf_{x \in \mathbb{R}^n} L(x, \lambda, \mu) = b^T \mu.$$

Otherwise,

$$\inf_{x \in \mathbb{R}^n} L(x, \lambda, \mu) = -\infty.$$

Thus, the dual objective in this case just reads

$$d(\lambda, \mu) = \begin{cases} b^T \mu & \text{if } c = \lambda A^T \mu \\ -\infty & \text{else} \end{cases}$$

Maximizing this function is thusly equivalent to

$$\max_x b^T \mu \text{ s.t. } A^T \mu + \lambda = c, \lambda \geq 0.$$

We can incorporate λ directly into the first constraint, and get the one-variable problem

$$\max_\mu b^T \mu \text{ s.t. } A^T \mu \leq c.$$

III.2.2 Weak and Strong Duality

→ **Theorem 3.6** (Weak Duality): Let \hat{x} be feasible for (P) and $(\hat{\lambda}, \hat{\mu})$ be feasible for (D) . Then, $p(\hat{x}) \geq d(\hat{\lambda}, \hat{\mu})$.

PROOF. We have

$$\begin{aligned} p(\hat{x}) &= f(\hat{x}) \\ &\geq f(\hat{x}) + \underbrace{\hat{\lambda}^T g(\hat{x})}_{\leq 0} + \underbrace{\mu^T h(\hat{x})}_{=0} \\ &= L(\hat{x}, \hat{\lambda}, \hat{\mu}) \geq \inf_{x \in \mathbb{R}^n} L(x, \hat{\lambda}, \hat{\mu}) = d(\hat{\lambda}, \hat{\mu}). \end{aligned}$$

■

From weak duality, $\bar{p} := \inf_{x \in X} p(x) \geq \sup_{\lambda \geq 0} d(\lambda, \mu) =: \bar{d}$, we have the *duality gap* $\bar{p} - \bar{d} \geq 0$ (taking by convention $+\infty - \infty := +\infty$.)

⊕ **Example 3.3** (Nonzero Duality Gap): Consider

$$\min f(x) := \begin{cases} x^2 - 2x & x \geq 0, \\ x & \text{else} \end{cases}$$

such that $g(x) := -x \leq 0$. The Lagrangian reads

$$L(x, \lambda) := \begin{cases} x^2 - (2 + \lambda)x & x \geq 0, \\ (1 - \lambda)x & \text{else} \end{cases}$$

A short computation gives

$$d(\lambda) = \begin{cases} -\frac{(2+\lambda)^2}{4} & \lambda \geq 1, \\ -\infty & \text{else} \end{cases}$$

and thus $\bar{d} = d(1) = -\frac{9}{4}$. On the other hand, the optimal value of the primal is $f(1) = -1$.

→ **Theorem 3.7** (Strong Duality): Consider the convex NLP

$$\min f(x) \text{ s.t. } g_i(x) \leq 0 \forall_{i=1}^m, h_j(x) = 0 \forall_{j=1}^p,$$

with $f, g_i : \mathbb{R}^n \rightarrow \mathbb{R}$ convex and $h_j : \mathbb{R}^n \rightarrow \mathbb{R}$ affine. If Slater CQ holds, then $\bar{p} = \bar{d}$.

PROOF. This one's TOO hard :-(. ■

III.2.3 The Saddle Point Theorem

→ **Definition 3.11** (Saddle Point of a Lagrangian): Let $L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$ be the Lagrangian of (P) . Then, $(\bar{x}, \bar{\lambda}, \bar{\mu})$ is called a *saddle-point* of L if the following inequalities hold:

$$L(\bar{x}, \lambda, \mu) \leq L(\bar{x}, \bar{\lambda}, \bar{\mu}) \leq L(x, \bar{\lambda}, \bar{\mu}), \quad \forall (x, \lambda, \mu) \in \mathbb{R}^n \times \mathbb{R}_+^m \times \mathbb{R}^p.$$

→ **Theorem 3.8** (Saddle Point Theorem): Let $(\bar{x}, \bar{\lambda}, \bar{\mu}) \in \mathbb{R}^n \times \mathbb{R}_+^m \times \mathbb{R}^p$. TFAE:

1. $(\bar{x}, \bar{\lambda}, \bar{\mu})$ a saddle point of L for (P) ;
2. \bar{x} solves (P) , $(\bar{\lambda}, \bar{\mu})$ solves (D) and $f(\bar{x}) = d(\bar{\lambda}, \bar{\mu})$, i.e. the duality gap is zero.

PROOF. (1. \Rightarrow 2.) We see that

$$\begin{aligned}
L(\bar{x}, \bar{\lambda}, \bar{\mu}) &= \underbrace{\inf_{x \in \mathbb{R}^n} L(x, \bar{\lambda}, \bar{\mu})}_{=d(\bar{\lambda}, \bar{\mu})} \leq \sup_{\substack{\lambda \in \mathbb{R}_+^m \\ \mu \in \mathbb{R}^p}} \inf_{x \in \mathbb{R}^n} L(x, \bar{\lambda}, \bar{\mu}) \\
&\leq \inf_{x \in \mathbb{R}^n} \sup_{\substack{\lambda \in \mathbb{R}_+^m \\ \mu \in \mathbb{R}^p}} L(x, \lambda, \mu) \\
&\leq \underbrace{\sup_{\substack{\lambda \in \mathbb{R}_+^m \\ \mu \in \mathbb{R}^p}} L(\bar{x}, \lambda, \mu)}_{=p(\bar{x})} = L(\bar{x}, \bar{\lambda}, \bar{\mu}),
\end{aligned}$$

using the saddle point properties in the first, last equalities. Thus equality must hold throughout, so in particular, $d(\bar{\lambda}, \bar{\mu}) = p(\bar{x})$; moreover $p(\bar{x}) < \infty$ by the same chain of equalities so \bar{x} feasible for (P) . By definition $(\bar{\lambda} \geq 0)$ too, $(\bar{\lambda}, \bar{\mu})$ feasible for (D) . Moreover, by weak duality, \bar{x} solves (P) and $(\bar{\lambda}, \bar{\mu})$ solves (D) .

(2. \Rightarrow 1.) Observe

$$\begin{aligned}
L(\bar{x}, \bar{\lambda}, \bar{\mu}) &\leq f(\bar{x}) (= d(\bar{\lambda}, \bar{\mu})) \\
&= p(\bar{x}) \\
&= \overbrace{\sup_{\lambda \geq 0, \mu} L(\bar{x}, \lambda, \mu)}^{(c)} \\
&= d(\bar{\lambda}, \bar{\mu}) = \underbrace{\inf_x L(x, \bar{\lambda}, \bar{\mu})}_{(b)} \leq \overbrace{L(\bar{x}, \bar{\lambda}, \bar{\mu})}^{(d)}.
\end{aligned}$$

The inequalities $(b) \leq (d) = (a) \leq (c)$ gives the desired result. ■

§III.3 Penalty Methods

Consider

$$\min f(x) \text{ s.t. } x \in X \quad (1).$$

Replace (1) with a sequence of unconstrained problems

$$\min f(x) + \alpha_k r(x), \quad \forall k \in \mathbb{N},$$

where $\alpha_k > 0$ a *penalty parameter*, $r(x) : \mathbb{R}^n \rightarrow \mathbb{R}$ such that $r(x) \geq 0$ and $r(x) = 0 \Leftrightarrow x \in X$. The sum $f + \alpha_k r$ is called the *penalty function*.

III.3.1 The Quadratic Penalty Function

Consider a special instance of (1) given by

$$\min f(x) \text{ s.t. } h_j(x) = 0 \forall_{j=1}^p,$$

for $f, h_j : \mathbb{R}^n \rightarrow \mathbb{R}$ at least continuous. The *quadratic penalty function* for the problem is given by

$$P_\alpha(x) = f(x) + \frac{\alpha}{2} \|h(x)\|^2.$$

This readily gives rise to the (abstract) algorithm Algorithm 3.11.

Quadratic Penalty Method
S0. Choose $\alpha_0 > 0$, set $k = 0$
S1. Determine $x^k \in \mathbb{R}^n$ as a solution of $\min P_{\alpha_k}(x)$
S2. If $h(x^k) = 0$, STOP
S3. Choose $\alpha_{k+1} > \alpha_k$, increment k and go to S.

→ **Theorem 3.9:** Suppose f, h continuous such that the feasible set $X \neq \emptyset$. Let $\alpha_k \uparrow \infty$ and $\{x^k\}$ generated by Algorithm 3.11. Then, the following hold:

1. $\{P_{\alpha_k}(x^k)\}$ is monotonically increasing;
2. $\{\|h(x^k)\|\}$ is monotonically decreasing;
3. $\{f(x^k)\}$ is monotonically increasing;
4. $\lim_k h(x^k) = 0$;
5. Every cluster point of $\{x^k\}$ is a solution of the constrained optimization problem.

PROOF.

1. $P_{\alpha_k}(x^k) \leq P_{\alpha_k}(x^{k+1})$ since x^k minimizes P_{α_k} , and $P_{\alpha_k}(x^{k+1}) \leq P_{\alpha_{k+1}}(x^{k+1})$ since $\alpha_{k+1} > \alpha_k$.
2. We have similarly that $P_{\alpha_k}(x^k) \leq P_{\alpha_k}(x^{k+1})$ and $P_{\alpha_{k+1}}(x^{k+1}) \leq P_{\alpha_{k+1}}(x^k)$, so adding these gives us

$$P_{\alpha_k}(x^k) + P_{\alpha_{k+1}}(x^{k+1}) \leq P_{\alpha_k}(x^{k+1}) + P_{\alpha_{k+1}}(x^k).$$

Both sides of this inequality contain $f(x^k) + f(x^{k+1})$; cancelling these and multiplying by 2, we get

$$\alpha_k \|h(x^k)\|^2 + \alpha_{k+1} \|h(x^{k+1})\|^2 \leq \alpha_k \|h(x^{k+1})\|^2 + \alpha_{k+1} \|h(x^k)\|^2.$$

Rearranging, we get

$$(\alpha_k - \alpha_{k+1}) (\|h(x^k)\|^2 - \|h(x^{k+1})\|^2) \leq 0.$$

Since $\alpha_k - \alpha_{k+1} < 0$, we get the result.

3. From $P_{\alpha_k}(x^k) \leq P_{\alpha_k}(x^{k+1})$, we get

$$f(x^k) + \frac{\alpha_k}{2} \|h(x^k)\|^2 \leq f(x^{k+1}) + \frac{\alpha_k}{2} \|h(x^{k+1})\|^2.$$

Using $\|h(x^{k+1})\|^2 \leq \|h(x^k)\|^2$ (from 2.) and cancelling gives $f(x^k) \leq f(x^{k+1})$, as needed.

4. Observe that $P_{\alpha_k}(x^k) = \inf_{x \in \mathbb{R}^n} P_{\alpha_k}(x) \leq \inf_{x \in X} P_{\alpha_k}(x)$

You can't get worse from picking from a bigger set; that's what the Quebec government doesn't understand.

But if $x \in X$, $P_{\alpha_k}(x) = f(x)$ so further $P_{\alpha_k}(x^k) \leq \inf_X f(x) < \infty$ (since $X \neq \emptyset$). Thus, we have that

$$f(x^0) + \frac{\alpha_k}{2} \|h(x^k)\|^2 \leq P_{\alpha_k}(x^k) < \infty.$$

Letting $k \rightarrow \infty$, $\alpha_k \rightarrow \infty$; but the whole sequence must be bounded, and thus $\|h(x^k)\|^2$ must go to zero (so in particular $h(x^k) \rightarrow 0$).

5. Let \bar{x} a cluster point of x^k , supposing it converges along the whole sequence wlog.

Thus, $h(\bar{x}) = 0$ by continuity and 4., so in particular $\bar{x} \in X$. Moreover, $f(\bar{x}) = \lim_k f(x^k) \leq \lim_k P_{\alpha_k}(x^k) \leq \inf_X f$ (using the bound we used in 4.). Thus, \bar{x} indeed a solution of the corresponding optimization problem. ■

Remark 3.6:

1. We used often the fact $f(x^k) \leq P_{\alpha_k}(x^k) \leq \inf_X f$; in particular if $x^k \in X$, then x^k solves the problem (hence why our stopping criterion is appropriate).
2. Algorithm 3.11, and the corresponding theorem, also apply to the more general problem $\min f$ with both $h(x) = 0$ and $g(x) \leq 0$ (with the components of h, g continuous) because this problem is equivalent to the equality-constraint problem

$$\min f(x) \text{ s.t. } h_j(x) = 0, \max\{g_i(x), 0\} = 0.$$

The corresponding (quadratic) penalty function would then be

$$P_\alpha(x) = f(x) + \frac{\alpha}{2} \|h(x)\|^2 + \frac{\alpha}{2} \sum_{i=1}^p \max\{g_i(x), 0\}^2.$$

Then, P_α remains continuous. In fact, if $f, g_i, h_j \in C^1$, so is P_α ; the only stick point is in whether the function $\tau \mapsto \max\{\tau, 0\}^2$ is C^1 (indeed, without the square this is not true).

Our goal now is, assuming $f, h_j \in C^1$ and given $\{x^k\}$ generated by Algorithm 3.11, to find $\{\mu^k\}$ such that $\{(x^k, \mu^k)\}$ converges to a KKT point.

Observe that $x^k \in \operatorname{argmin}_X P_\alpha \Rightarrow 0 = \nabla P_{\alpha_k}(x^k) = \nabla f(x^k) + \sum_{j=1}^p \alpha_j h_j(x^k) \nabla h_j(x^k)$. Put $\mu_j^k := \alpha_j h_j(x^k)$; these needn't be a KKT point, since we don't know if x^k feasible hence we don't know if $h_j(x^k) = 0$. But it seems like μ_j^k seems like a good choice.

↪ **Theorem 3.10:** With the hypotheses of the previous remarks, let $\{x^k\}$ be generated by Algorithm 3.11 and assume $x^k \rightarrow \bar{x}$, and that LICQ holds at \bar{x} . For $\mu_j^k = \alpha_j h_j(x^k)$, we have μ^k converges to some $\bar{\mu}$ and $\bar{\mu} \in M(\bar{x})$.

PROOF. Define $A_k = h'(x^k) \in \mathbb{R}^{p \times n}$. We see that $A_k \rightarrow h'(\bar{x}) =: \bar{A}$ by continuity. By LICQ, $\bar{A} \cdot \bar{A}^T \in \mathbb{R}^{p \times p}$ is invertible. Thus, $A_k \cdot A_k^T$ is also invertible for k sufficiently large, so $(A_k \cdot A_k^T)^{-1} \rightarrow (\bar{A} \cdot \bar{A}^T)^{-1}$ as well. Thus,

$$\nabla f(x^k) + \sum_{j=1}^p \mu_j^k \nabla h_j(x^k) = 0 \Leftrightarrow A_k^T \mu_k = -\nabla f(x^k),$$

and thus

$$\mu_k = -\left(A_k A_k^T\right)^{-1} A_k \nabla f(x^k) \rightarrow -\left(\overline{A} \overline{A}^T\right)^{-1} \overline{A} \nabla f(\bar{x}) =: \bar{\mu}.$$

This completes the proof, since \bar{x} feasible as well. ■

III.3.2 Exact Penalty Functions

Consider a penalty function $P_\alpha^r = f + \alpha r, \alpha > 0$ where $r \geq 0$ and $r(x) = 0 \Leftrightarrow x \in X$.

→ **Definition 3.12** (Exactness): The penalty function P_α^r is called *exact* at a local minimum if there exists an $\bar{\alpha} > 0$ such that \bar{x} also a local minimum of P_α^r for any $\alpha > \bar{\alpha}$.

Consider now the standard NLP

$$\begin{aligned} \min f(x) \text{ s.t. } g_i(x) \leq 0 \forall i = 1, \dots, m, \\ h_j(x) = 0 \forall j = 1, \dots, p. \end{aligned}$$

A whole class of penalty functions in the above form for the above problem is defined via

$$r_q(x) = \|(\max(g(x), 0), h(x))\|_q,$$

where for $y \in \mathbb{R}^m$, $\max(y, 0) = [\max\{y_i, 0\}]_{i=1}^m$, i.e. component-wise maxima, $\|\cdot\|_q$ the usual q -norm, and we're writing $(x, y) \in \mathbb{R}^{m \times p}$ for shorthand. We focus on $q = 1$, which gives rise to the penalty function

$$P_\alpha^1(x) = f(x) + \alpha \sum_{j=1}^p |h_j(x)| + \alpha \sum_{i=1}^m \max\{g_i(x), 0\}.$$

→ **Theorem 3.11:** Let $(\bar{x}, \bar{\lambda}, \bar{\mu})$ be a KKT point for the typical convex NLP, where f, g_i convex and h_j affine. Then, $\bar{x} \in \operatorname{argmin}_X P_\alpha^1(x)$ for any $\alpha \geq \|(\bar{\lambda}, \bar{\mu})\|_\infty$. In particular, P_α^1 is exact if a constraint qualification holds at \bar{x} . **might need to add some constraint**

PROOF. By the KKT theorem for convex problems, \bar{x} is a (global) minimizer. Therefore, by the saddle-point theorem, \bar{x} is a global minimizer of $L(\cdot, \bar{\lambda}, \bar{\mu})$. Thus, for all $x \in \mathbb{R}^n, \alpha \geq \|(\bar{\lambda}, \bar{\mu})\|_\infty$,

$$\begin{aligned}
P_\alpha^1(\bar{x}) &= f(\bar{x}) + \alpha \underbrace{\sum_j |h_j(\bar{x})|}_{=0} + \alpha \sum_j \underbrace{\max(g_i(x), 0)}_{=0} \\
&= f(\bar{x}) \\
&= f(\bar{x}) + \bar{\lambda}^T g(\bar{x}) + \bar{\mu}^T h(\bar{x}) \\
&= L(\bar{x}, \bar{\lambda}, \bar{\mu}) \\
&\leq L(x, \bar{\lambda}, \bar{\mu}) \\
&= f(x) + \sum_{i=1}^m \bar{\lambda}_i g_i(x) + \sum_{j=1}^p \bar{\mu}_j h_j(x) \\
&\leq f(x) + \sum_{i=1}^m \bar{\lambda}_i \max(g_i(x), 0) + \sum_{j=1}^p |\bar{\mu}_j| |h_j(x)| \\
&\leq f(x) + \|(\bar{\lambda}, \bar{\mu})\|_\infty \left(\sum_{i=1}^m \max(g_i(x), 0) + \sum_{j=1}^p |h_j(x)| \right) \\
&\leq f(x) + \alpha \left(\sum_{i=1}^m \max(g_i(x), 0) + \sum_{j=1}^p |h_j(x)| \right) \\
&= P_\alpha^1(x).
\end{aligned}$$

■

→ **Theorem 3.12:** Let \bar{x} be an isolated minimum such that MFCQ holds at \bar{x} . Then for all $q \in [1, \infty)$, there exists an $\alpha_q > 0$ such that for any $\alpha \geq \alpha_q$, then the point \bar{x} is a local minimimum of P_α^q , i.e. P_α^q is exact at \bar{x} .

θ convex and increasing, $g : \mathbb{R}^n \rightarrow \mathbb{R}$ convex implies $\theta(g)$ convex.

$g(\lambda x + (1 - \lambda)y) \leq \lambda g(x) + (1 - \lambda)g(y)$. θ increasing thus

$$\theta(g(\lambda x + (1 - \lambda)y)) \leq \theta(\lambda g(x) + (1 - \lambda)g(y)),$$

then we just apply convexity to $\lambda \cdot g(x), (1 - \lambda) \cdot g(y)$.

III.4 SQP Methods

III.4.1 The Lagrange-Newton Method

Consider

$$\min f(x) \text{ s.t. } h_j(x) = 0, \forall_{j=1}^p,$$

with $f, h_j : \mathbb{R}^n \rightarrow \mathbb{R}$ in C^2 . Define

$$\Phi : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^n \times \mathbb{R}^p, \quad \Phi(x, \mu) = \begin{pmatrix} \nabla_x L(x, \mu) \\ h(x) \end{pmatrix},$$

where L the Lagrangian of the problem. Then, (x, μ) a KKT point iff $\Phi(x, \mu) = 0$. So, we can just throw Newton methods at Φ to find KKT points (note that we couldn't work with inequality

constraints, since this would result in max's showing up in Φ , which aren't differentiable). This leads to the following algorithm, which is just Newton's specialized to Φ .

Lagrange-Newton
S0. Choose $(x^0, \mu^0) \in \mathbb{R}^n \times \mathbb{R}^p$, set $k := 0$
S1. If $\Phi(x^k, \mu^k) = 0$, STOP
S2. Determine $\begin{pmatrix} \Delta x^k \\ \Delta \mu^k \end{pmatrix}$ as a solution
$\Phi'(x^k, \mu^k)(\Delta x, \Delta \mu) = -\Phi(x^k, \mu^k)$
S3. Set $(x^{k+1}, \mu^{k+1}) = (x^k, \mu^k) + (\Delta x^k, \Delta \mu^k)$, increment k and go to S1.

Recall that the crucial condition for the convergence of the Newton's algorithm we discussed was invertibility of the Jacobian at the critical point.

↪ **Theorem 3.13:** Let $(\bar{x}, \bar{\mu}) \in \mathbb{R}^n \times \mathbb{R}^p$ be a KKT point, such that

1. LICQ holds ($\nabla h_j(\bar{x})$ are linearly independent), and
2. we have $d^T \nabla_{xx}^2 L(\bar{x}, \bar{\mu})d > 0$ for all $d \neq 0$ such that $\nabla h_j(\bar{x})^T d = 0, j \in J$

Then, $\Phi'(\bar{x}, \bar{\mu})$ is invertible.

PROOF. Observe that

$$\Phi'(x, \mu) = \begin{pmatrix} \nabla_{xx}^2 L(x, \mu) & h'(x)^T \\ h'(x) & 0 \end{pmatrix}.$$

Let (q, r) s.t. $\Phi'(\bar{x}, \bar{\mu}) \begin{pmatrix} q \\ r \end{pmatrix} = 0$. Then,

$$\nabla_{xx}^2 L(\bar{x}, \bar{\mu})q + h'(\bar{x})^T r = 0,$$

$$h'(\bar{x})q = 0.$$

Thus,

$$0 = q^T \nabla_{xx}^2 L(\bar{x}, \bar{\mu})q + \underbrace{q^T h'(\bar{x})^T r}_{=(h'(\bar{x}q))^T = 0} = q^T \nabla_{xx}^2 L(\bar{x}, \bar{\mu})q.$$

Moreover, we see that $\nabla h_j(\bar{x})^T q = 0$ for all $j \in J$. Thus, by our second assumption, it must be that, if q nonzero, $q^T \nabla_{xx}^2 L(\bar{x}, \bar{\mu})q > 0$; this isn't the case thus it must be $q = 0$. This implies $h'(\bar{x})^T r = 0$, but by MFCQ, $h'(\bar{x})^T$ has linearly independent columns (the gradients of h_j), thus a trivial kernel so $r = 0$. So, $\begin{pmatrix} q \\ r \end{pmatrix} = 0$, and thus $\Phi'(\bar{x}, \bar{\mu})$ has trivial kernel so invertible. ■

Remark 3.7: As in the proof above, we see that the update in S2. is equivalent to the equation (putting $H_k := \nabla_{xx}^2 L(x^k, \mu^k)$)

$$H_k \Delta x + h'(x^k)^T \Delta \mu = -\nabla_x L(x^k, \mu^k),$$

$$h'(x^k)^T \Delta x = -h(x^k)$$

In particular, if we put $\mu^+ := \mu^k + \Delta \mu$, then since $\nabla_x L(x, \mu) = \nabla f(x) + h'(x)^T \mu$, equivalently

$$H_k \Delta x + h'(x^k)^T \mu^+ = -\nabla f(x^k),$$

$$\nabla h_j(x^k)^T \Delta x = -h_j(x^k), \quad j \in J.$$

Also, consider the following (quadratic objective, affine constraint) problem:

$$\min_{\Delta x} \frac{1}{2} (\Delta x)^T H_k \Delta x + \nabla f(x^k)^T \Delta x \quad \text{s.t.} \quad \nabla h_j(x^k)^T \Delta x + h_j(x^k) = 0, j \in J.$$

The KKT conditions in this case read,

$$H_k \Delta x + \nabla f(x^k) + h'(x^k)^T \mu = 0,$$

$$\nabla h_j(x^k)^T \Delta x + h_j(x^k) = 0, j \in J,$$

which are precisely the conditions we wrote out above, with μ (here) equal to μ^+ (above).

We want to consider the general NLPs, i.e. with inequality constraints; we'll assume our objective and constraints are C^2 ;

$$(\dagger) \quad \min f(x) \quad \text{s.t.} \quad g_i(x) \leq 0, i \in I, \quad h_j(x) = 0, j \in J.$$

Given (x^k, λ^k, μ^k) , consider

$$\min \frac{1}{2} (\Delta x)^T H_k \Delta x + \nabla f(x^k)^T \Delta x \quad \text{s.t.} \quad \nabla g_i(x^k)^T \Delta x + g_i(x^k) \leq 0, i \in I, \quad \nabla h_j(x^k)^T \Delta x + h_j(x^k) = 0, j \in J.$$

This leads to the following:

Local SQP Method
S0. Choose $(x^0, \lambda^0, \mu^0) \in \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p$, set $k := 0$, and choose $H_0 \in \mathbb{R}^{n \times n}$ symmetric
S1. If (x^k, λ^k, μ^k) a KKT point of the underlying NLP (\dagger) , STOP
S2. Determine $(x^{k+1}, \lambda^{k+1}, \mu^{k+1})$ of the quadratic program
$\min_{x \in \mathbb{R}^n} \frac{1}{2} (x - x^k)^T H_k (x - x^k) + \nabla f(x^k)^T (x - x^k),$ s.t. $\nabla g_i(x^k)^T (x - x^k) + g_i(x^k) \leq 0, i \in I, \quad \nabla h_j(x^k)^T (x - x^k) + h_j(x^k) = 0, j \in J.$
S3. Choose $H_{k+1} \in \mathbb{R}^{n \times n}$ symmetric, increment k , and go to S1.

Remark 3.8: Instead of the exact choice $H_k = \nabla_{xx}^2 L(x^k, \lambda^k, \mu^k)$, as in our derivation, one can update H_k using some (modified) Newton techniques.

↪**Theorem 3.14** (Convergence of Algorithm 3.13): Let $(\bar{x}, \bar{\lambda}, \bar{\mu})$ be a KKT point of (†) such that

- i. (strict complementarity) $g_i(\bar{x}) = 0 \Rightarrow \bar{\lambda}_i > 0$, for all $i \in I$,
- ii. (LICQ) $\nabla g_i(\bar{x}), i \in I(\bar{x}), \nabla h_j(\bar{x}), j \in J$ are linearly independent, and
- iii. (2nd order sufficient conditions) $d^T \nabla_{xx}^2 L(\bar{x}, \bar{\lambda}, \bar{\mu}) d > 0, \forall d \in \mathcal{L}_X(\bar{x}) \setminus \{0\}$.

Then, there exists $\varepsilon > 0$ such that for all $(x^0, \lambda^0, \mu^0) \in B_\varepsilon(\bar{x}, \bar{\lambda}, \bar{\mu})$ such that the following hold for any sequence $\{x^k, \lambda^k, \mu^k\}$ generated by Algorithm 3.13 with update $H_k := \nabla_{xx}^2 L(x^k, \lambda^k, \mu^k)$ and such that in S2., one choose the KKT point closest to the previous iterate (x^k, λ^k, μ^k) :

1. $\{(x^k, \lambda^k, \mu^k)\}$ well-defined and converges to $(\bar{x}, \bar{\lambda}, \bar{\mu})$ superlinearly, and
2. if $\nabla^2 f, \nabla^2 g_i, \nabla^2 h_j$ are locally Lipschitz, then the rate is quadratic.

The natural next generalization is globalizing this method, as we globalized Newton's method.

III.4.2 A Globalized SQP Method

Recall that globalization of the Newton's method involving introducing a step-size based on the Armijo rule. For SQP, we will introduce a step-size based on the (exact) ℓ_1 -penalty function

$$P_\alpha^1(x) = f(x) + \alpha \sum_{j=1}^p |h_j(x)| + \alpha \sum_{i=1}^m \max\{g_i(x), 0\}.$$

Note P_α^1 is not generally differentiable, hence we use the directional derivative to detect descent directions.

↪**Theorem 3.15** (Chain Rule for Directional Derivatives): Let $H : \mathbb{R}^n \rightarrow \mathbb{R}^m$, $G : \mathbb{R}^m \rightarrow \mathbb{R}^p$, and set $F := G \circ H$. Assume that for $x \in \mathbb{R}^m$,

1. H is directionally differentiable at x ,
2. G is directionally differentiable at $H(x)$, and
3. G is locally Lipschitz at $H(x)$.

Then, F is directionally differentiable at x , and

$$F'(x; d) = G'(H(x); H'(x; d)),$$

for all $d \in \mathbb{R}^n$.

PROOF. Let $d \in \mathbb{R}^n$ and let $L > 0$ be the (local) Lipschitz constant of G around $H(x)$.

For $t > 0$ sufficiently small, we have

$$\begin{aligned} & \left\| \frac{F(x + td) - F(x)}{t} - \frac{G(H(x) + tH'(x; d)) - G(H(x))}{t} \right\| \\ &= \left\| \frac{G(H(x + td)) - G(H(x) + tH'(x; d))}{t} \right\| \\ &\leq L \left\| \frac{H(x + td) - H(x)}{t} - H'(x; d) \right\| \rightarrow 0. \end{aligned}$$

Since the term on the RHS of the first line converges to $G'(H(x); H'(x; d))$, we're done. ■

↪**Corollary 3.3** (Directional derivative of ℓ_1 -penalty): For any $\alpha > 0$, the ℓ_1 -penalty function is directionally differentiable, with

$$\begin{aligned} (P_\alpha^1)'(x; d) = & \nabla f(x)^T d \\ & + \alpha \sum_{j:h_j(x)>0} \nabla h_j(x)^T d - \alpha \sum_{j:h_j(x)<0} \nabla h_j(x)^T d + \alpha \sum_{j:h_j(x)=0} |\nabla h_j(x)^T d| \\ & + \alpha \sum_{i:g_i(x)>0} \nabla g_i(x)^T d + \alpha \sum_{i:g_i(x)=0} \max\{\nabla g_i(x)^T d, 0\}. \end{aligned}$$