

Optimization

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Abstract:

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Introduction

0.1. Definitions

0.2. Useful lemmas and Theorems.

Lemma 0.1.

Let $(x_n)_{n \in \mathbb{N}}$ be a bounded sequence in a Hilbert Space H . Then $(x_n)_{n \in \mathbb{N}}$ possesses a weakly convergent subsequence.

Lemma 0.2.

Let $(x_n)_{n \in \mathbb{N}}$ be a sequence in a Hilbert Space H . Then $(x_n)_{n \in \mathbb{N}}$ converges if and only if it is bounded and possesses at most one weak sequential cluster point.

Theorem 0.1.

Let $f : H \rightarrow (\infty, \infty]$ be a convex functional on a Hilbert space. Then the following are equivalent:

- (i) f is weakly sequentially lower semicontinuous.
- (ii) f is sequentially lower semicontinuous.
- (iii) f is lower semicontinuous.
- (iv) f is weakly lower semicontinuous.

Lemma 0.3.

A convex set is closed if and only if it is weakly closed.

Lemma 0.4.

Every bounded linear operator over a Banach Space is weakly continuous.

Lemma 0.5 (Parallelogram law).

$$\|x + y\|^2 + \|x - y\|^2 = 2\|x\|^2 + 2\|y\|^2$$

1. Lecture 1

Fact 1.1.

Let $x \in H$, let U be a neighborhood of x , let G be a real Banach space, let $T : U \rightarrow G$, let V be a neighborhood of Tx , and let $R : V \rightarrow K$. Suppose that T is Frchet differentiable at x and that R is Gateaux differentiable at Tx . Then $R \circ T$ is Gateaux differentiable at x and $D(R \circ T)(x) = (DR(Tx)) \circ DT(x)$. If R is Fréchet differentiable at x , then so is $R \circ T$.

Fact 1.2.

Let $x \in H$, let U be a neighborhood of x , let K be a real Banach space, and let $T : U \rightarrow K$. Suppose that T is twice Fréchet differentiable at x . Then $\forall (y, z) \in H \times H$, $(D^2T(x)y)z = (D^2T(x)z)y$.

Definition 1.1.

Let $x \in H$, let $C \in \mathcal{V}(x)$, and let $T : C \rightarrow K$. Then T is Fréchet differentiable at x if there exists an operator $DT(x) \in B(H, K)$, called the Frchet derivative of T at x , such that

$$\lim_{0 \neq \|y\| \rightarrow 0} \frac{\|T(x+y) - Tx - DT(x)y\|}{\|y\|} = 0$$

2. Lecture 2

2.1. Convexity

Definition 2.1.

Let U be linear space. A functional $J : U \rightarrow \overline{\mathbb{R}}$ is called convex, if for $t \in [0, 1]$ and $u_1, u_2 \in U$.

$$J(tu_1 + (1-t)u_2) \leq tJ(u_1) + (1-t)J(u_2) \quad (1)$$

holds such that the right hand side is well defined.

- J is strictly convex if (1) holds strictly for $\forall u_1, u_2 \in U$, $u_1 \neq u_2$ and $t \in (0, 1)$ with $J(u_1) < \infty$ and $J(u_2) < \infty$.
- An optimization problem,

$$\min_{u \in C} J(u)$$

is called convex if both C and J are convex.

Lemma 2.1.

If C and V are convex in U , then

- $\alpha V = \{w = \alpha v, v \in C\}$ is convex.
- $C + V$ is convex.

Proof.

□

Lemma 2.2.

Let V be a collection of convex sets in U , then $C = \bigcap_{K \in V} K$ is convex.

Proof. If $C = \emptyset$, then C the statement is vacuously true. Consider $C \neq \emptyset$ and $u_1, u_2 \in C$ then $u_1, u_2 \in K$ for all $K \in V$

$$\implies tu_1 + (1-t)u_2 \in K, \quad \forall K \in V \implies tu_1 + (1-t)u_2 \in \bigcap_{K \in V} K$$

□

Lemma 2.3.

Let $C \in U$ convex and $J : C \rightarrow \mathbb{R}$. Define $\alpha = \inf_{u \in C} J(u)$. Then the set $\Psi = \{u \mid J(u) = \alpha\}$ is convex, i.e. the solution of

$$\min_{u \in C} J(u)$$

is a convex set.

Proof. Let $u_1, u_2 \in \Psi$ and $u_t = tu_1 + (1-t)u_2$. Since J is convex, it holds that $J(u_t) \leq tJ(u_1) + (1-t)J(u_2) = \alpha$. Thus $J(u_t) = \alpha, \forall t \in [0, 1]$. Implying $u_t \in \Psi$. Hence Ψ is convex. \square

Lemma 2.4.

Let U be linear normed space, and $C \subset U$ a convex set and $J : U \rightarrow \overline{\mathbb{R}}$ convex functional. Let $\bar{u} \in C$ such that

$$J(\bar{u}) \leq J(u) \quad \forall u \in B_\epsilon(\bar{u}) \cap C,$$

for some ball $B_\epsilon(\bar{u})$ in U with center in \bar{u} . Then $J(\bar{u}) = \inf_{u \in C} J(u)$. In other words, the local minimizer of a convex optimization problem is also a global minimizer.

Proof. Let $B_\epsilon(\bar{u})$ be an open neighborhood of \bar{u} with $J(\bar{u}) \leq J(u)$ for all $u \in B_\epsilon(\bar{u}) \cap C$. Take an arbitrary $u^* \in C$ and consider $u_t = t\bar{u} + (1-t)u^*$. Since C is convex $u_t \in C$.

For some $t \in (0, 1)$, $u_t \in B_\epsilon(\bar{u})$.

Thus,

$$J(\bar{u}) \leq J(u_t) \leq tJ(\bar{u}) + (1-t)J(u^*).$$

We have $\forall t \in [0, 1]$ that $(1-t) \leq 0$, then

$$(1-t)J(\bar{u}) \leq (1-t)J(u^*) \quad \forall u^* \in C$$

Therefore, \bar{u} is a local minimizer for C . \square

Theorem 2.1.

Let U is Banach Space, $C \subset U$ convex and $J : C \rightarrow \mathbb{R}$ Gateaux differentiable. Consider the minimization problem.

$$\min_{u \in C} J(u)$$

1. Let \bar{u} be a local solution. Then $J'(\bar{u}; u - \bar{u}) \geq 0, \forall u \in C$.
2. If J is convex on C , then $J'(\bar{u}; u - \bar{u}) \geq 0, \forall u \in C$ is necessary and sufficient for global optimality of \bar{u}
3. If J is strictly convex on C , then the minimization problem admits at most one solution.
4. If C is closed, and J is convex and continuous with

$$\lim_{\substack{u \in C \\ \|u\| \rightarrow \infty}} J(u) = \infty.$$

Then a global solution $\bar{u} \in C$ exists.

Proof.

1. Let \bar{u} be a local solution $J(\bar{u}) \leq J(u), \forall u \in B_\epsilon(\bar{u}) \cap C$, let $t \in [0, 1]$, $u_t = \bar{u} + t(u - \bar{u})$, then $u_t \in C$, since C is convex.

For small $t > 0$,

$$0 \leq \frac{1}{t} [J(u_t) - J(\bar{u})] \leq \frac{1}{t} [J(\bar{u} + t(u - \bar{u})) - J(\bar{u})] \xrightarrow{t \downarrow 0} J'(\bar{u}; u - \bar{u})$$

2. Since J is convex we have for $u \in C$, $J(\bar{u} + t(u - \bar{u})) \leq J(\bar{u}) + t[J(u) - J(\bar{u})]$, for $t > 0$

$$\implies J(u) - J(\bar{u}) \geq \frac{1}{t} [J(\bar{u} + t(u - \bar{u})) - J(\bar{u})] \xrightarrow{t \downarrow 0} J'(\bar{u}; u - \bar{u}) \geq 0.$$

Therefore \bar{u} is a global minimizer.

3. Assume, that there are two solution for the minimization problem, $\bar{u}, u^* \in C$, such that $\bar{u} \neq u^*$ and $J(\bar{u}) = J(u^*) = \inf_{u \in C} J(u)$. Since J is strictly convex $J(u_t) = J(t\bar{u} + (1-t)u^*) < tJ(\bar{u}) + (1-t)J(u^*) = \alpha$ for all $t \in [0, 1]$. Contradicting our assumption that u^* and \bar{u} are solutions.

4. $\alpha = \inf_{u \in C} J(u) \in \mathbb{R} \cup \{-\infty\}$, choose a minimizing sequence $(u_k)_k \subset C$ with $J(u_k) \xrightarrow{k \rightarrow \infty} \alpha$

$\implies (u_k)_k$ is bounded, because $J \rightarrow \infty$ as $\|u\| \rightarrow \infty$.

$\implies (u_k)_k$ contains a weakly convergent subsequence $u_{k_e} \xrightarrow{e \rightarrow \infty} \bar{u} \in C$. Since C is closed and convex.

$\implies J$ is weakly-lower semicontinuous because it is convex and continuous.

□

3. Lecture 3

Now consider Hilbert space $(H, \langle \cdot, \cdot \rangle)$ with the norm defined as $\|\cdot\| = \sqrt{\langle \cdot, \cdot \rangle}$.

Let be $J : H \rightarrow \mathbb{R}$ a functional over a Hilbert space H , we define the set,

$$\arg \min_{v \in C \subseteq H} J(x) := \{x \mid x \in C \wedge \forall v \in C : J(x) \leq J(v)\}.$$

By Riesz-Fréchet representation formula, exists a unique vector $\nabla J(x) \in H$ such that,

$$(\forall y \in H) \quad J'(x; y) = \langle y, \nabla J(x) \rangle$$

namely Gateaux gradient of J at x .

Lemma 3.1.

Let H Hilbert space and $C \subset H$ closed and convex. Define $P_C : H \rightarrow C$,

$$P_C(x) = \arg \min_{v \in C} [\|v - x\|].$$

Then,

1. P_C is well defined, i.e. $\exists! u \in H$ such that $P_C(x) = \{u\}$.
2. $\forall u, v \in H$, we have $x = P_C(u) \iff x \in C$ and $\langle u - x, v - x \rangle \leq 0$.
3. $\|P_C(u) - P_C(\bar{u})\| \leq \|u - \bar{u}\| \quad \forall u, \bar{u} \in H$, i.e. The projection P_C is non expansive.
4. $\langle P_C(u) - P_C(\bar{u}), u - \bar{u} \rangle \leq 0, \quad \forall u, \bar{u} \in H$
5. Let be $t > 0$ a real number, then $\forall u \in C$, and $\forall v \in H$, $\phi(t) = \frac{1}{t} \|P_C(u + tv) - u\|$ is non-increasing.

Proof.

1. First we prove existence, let be $(v_k)_k$ a minimizing sequence in C , such that

$$\|x - v_k\| \rightarrow \alpha = \inf_{v \in C} \|x - v\|,$$

By the parallelogram law,

$$\begin{aligned} 2\|v_j - x\|^2 + 2\|v_i - x\|^2 &= \|v_j - v_i\|^2 + \|v_j + v_i - 2x\|^2 \\ 2\|v_j - x\|^2 + 2\|v_i - x\|^2 &= \|v_j - v_i\|^2 + 4\left\|\frac{v_j + v_i}{2} - x\right\|^2 \\ \implies 2\|v_j - x\|^2 + 2\|v_i - x\|^2 - 4\left\|\frac{v_j + v_i}{2} - x\right\|^2 &= \|v_j - v_i\|^2 \end{aligned}$$

Since C is convex $\frac{v_i + v_j}{2} \in C$, then by definition of α ,

$$0 \leq \alpha \leq \left\|\frac{v_j + v_i}{2} - x\right\|$$

Therefore the above equations become in the following inequality,

$$2\|v_j - x\|^2 + 2\|v_i - x\|^2 - 4\alpha^2 \geq \|v_j - v_i\|^2$$

Since $\|v_i - x\| \rightarrow \alpha$ and $\|v_j - x\| \rightarrow \alpha$, we have that $\|v_j - v_i\| \rightarrow 0$, therefore the series is Cauchy and then converges. Since C is closed the series converges to a point $v \in C$.

Second we prove uniqueness, we proceed by contradiction, take $v, v' \in C$ such $v \neq v'$, and both of them minimizing the distant with respect the point x , i.e.

$$\|x - v\| = \|x - v'\| = \alpha = \min_{u \in C} \|u - x\|$$

By the parallelogram law,

$$2\|x - v\|^2 + 2\|x - v'\|^2 = \|2x - v - v'\|^2 + \|v - v'\|^2$$

Since C is convex, $\left\|\frac{v+v'}{2} - x\right\| \geq \alpha$

$$\begin{aligned} \|v - v'\|^2 &= 2\|x - v\|^2 + 2\|x - v'\|^2 - \|2x - v - v'\|^2 \\ \|v - v'\|^2 &= 2\|x - v\|^2 + 2\|x - v'\|^2 - 4\left\|x - \frac{v+v'}{2}\right\|^2 \\ \|v - v'\|^2 &= 2\alpha^2 + 2\alpha^2 - 4\left\|x - \frac{v+v'}{2}\right\|^2 \leq 0 \end{aligned}$$

Therefore $\|v - v'\| = 0$, and $v = v'$.

By the uniqueness and existence $\arg \min_{u \in C} [\|u - x\|]$ is not empty set and has only one element for each $x \in H$.

Thus, P_C is well defined. □

Theorem 3.1.

Let H be Hilbert space, $C \subset H$ closed and convex, $J : C \rightarrow \mathbb{R}$, Gateaux differentiable at the local solution \bar{u} of $\min_{u \in C} J(u)$. Thus, $J'(\bar{u}; u - \bar{u}) \geq 0$, $\forall u \in C$ and it is equivalent to $\bar{u} = P_C(\bar{u} - \delta \nabla J(\bar{u}))$, $\forall \delta > 0$.

Proof. Since every Hilbert Space is a Banach space, and C is closed and Convex subset of H , and \bar{u} is a solution of minimization problem; we can apply 2.1.

Thus $J'(\bar{u}; u - \bar{u}) \geq 0 \iff \langle u - \bar{u}, \nabla J(\bar{u}) \rangle \geq 0 \forall u \in C$.

For all $\delta > 0$, we multiply the Gateaux gradient $(-\delta)$ and we have,

$$\langle u - \bar{u}, -\delta \nabla J(\bar{u}) \rangle \leq 0 \forall u \in C,$$

adding zero to the gradient, $\langle u - \bar{u}, \bar{u} - \delta \nabla J(\bar{u}) - \bar{u} \rangle \leq 0$. Then we set $w \in H$ as $w := \bar{u} - \delta \nabla J(\bar{u})$, and applying lemma 3.1 we have,

$$\bar{u} = P_C(w) \iff \langle u - \bar{u}, w - \bar{u} \rangle$$

Thus,

$$\bar{u} = P_C(\bar{u} - \delta \nabla J(\bar{u}))$$

□

3.1. Application

Consider U, Y, Z Hilbert spaces. Let be $J : Y \times U \rightarrow \mathbb{R}$ a functional. Consider the minimization problem,

$$\begin{cases} \bar{u} = \min_{y,u} J(y, u) \\ Ay = Bu \quad u \in U_{ad} \subset U \end{cases}$$

For some set U_{ad} closed, convex and bounded. And $A \in \mathcal{L}(Y, Z)$ bounded and invertible with $A^{-1} \in \mathcal{L}(Z, Y)$ and $B \in \mathcal{L}(U, Z)$.

Then we can write $y \in Y$ as a function of $u \in U$,

$$y = y(u) = A^{-1}Bu$$

Consider the reduced cost functional $F(u) := J(y(u), u)$, then our problem is equivalent to

$$\bar{u}_{ad} = \min_{u \in U_{ad}} F(u)$$

Let $(u_k)_k \in U_{ad}$ denote a minimizing sequence, i.e. $F(u_k) \rightarrow \inf_{u \in U_{ad}} F(u)$, since $u_k \in U_{ad}$ the sequence is bounded. Therefore we can find a convergent subsequence $u_{k_l} \xrightarrow{l \rightarrow \infty} \bar{u}$, moreover since U_{ad} is closed and convex U_{ad} is weakly closed, implying $\bar{u} \in U_{ad}$

Proposition 3.1.

If J is continuous and weakly lower semicontinuous, then $\bar{u} = \arg \min_{u \in U_{ad}} [F(u)]$.

Proof. If J is weakly lower semicontinuous

$$J(y(\bar{u}), \bar{u}) \leq \liminf_{l \rightarrow \infty} J(y(u_k), u_k)$$

That is,

$$F(\bar{u}) \leq \liminf_{l \rightarrow \infty} F(u_k) = \alpha$$

Since $u_{k_l} \xrightarrow{l \rightarrow \infty} \bar{u}$, $\implies y(u_k) \rightharpoonup y(\bar{u})$ and $A^{-1}Bu_k \rightharpoonup A^{-1}B\bar{u}$

□

J is Gateaux differentiable, applying the chain rule to F and valuating in u we have

$$F_u(u; h) = J_y(y; \alpha(u; h), u) + J_u(y, u; h)$$

$$\begin{aligned} 0 &\leq \langle u - \bar{u}, \nabla_u F(\bar{u}) \rangle \quad \forall u \in U_{ad} \\ &= \langle A^{-1}B(u - \bar{u}), \nabla_y J(\bar{y}, \bar{u}) \rangle_{Y^*Y} + \langle u - \bar{u}, \nabla_u J(\bar{y}, \bar{u}) \rangle_{U^*U} \\ &= \langle A^{-1}B(u - \bar{u}), \nabla_y J(\bar{y}, \bar{u}) \rangle_{Y^*Y} + \langle u - \bar{u}, \nabla_u J(\bar{y}, \bar{u}) \rangle_{U^*U} \\ &= \langle u - \bar{u}, (A^{-1}B)^* \nabla_y J(\bar{y}, \bar{u}) \rangle_{U^*U} + \langle u - \bar{u}, \nabla_u J(\bar{y}, \bar{u}) \rangle_{U^*U} \\ &= \langle u - \bar{u}, (A^{-1}B)^* \nabla_y J(\bar{y}, \bar{u}) + \nabla_u J(\bar{y}, \bar{u}) \rangle_{U^*U} \end{aligned}$$

Setting $p^* = (A^{-1}B)^* \nabla_y J(\bar{y}, \bar{u})$. We have that $\bar{u} = P_{U_{ad}}(\bar{u} - \delta(p^* + \nabla_u J(\bar{y}, \bar{u})))$

4. Lecture 4

Lemma 4.1.

Let U be linear space and $J : U \rightarrow \bar{\mathbb{R}}$. Then

1. If J is convex, then the effective domain $\text{dom}(J) = \{u \in U \mid J(u) < \infty\}$ is convex.
2. J is convex $\iff \text{epi}(J) = \{(u, \alpha) \in U \times \mathbb{R} \mid J(u) \leq \alpha\}$ is convex.

Proof. Since U and \mathbb{R} are linear spaces, is easy to see that scalar multiplications and sums are well defined over $U \times \mathbb{R}$ and so over $\text{epi}(J)$.

1. Assume J convex. If $u_1 \in \text{dom}(J)$ and u_2 are elements of $\text{dom}(J)$. Therefore, $J(u_1) < \infty$, and $J(u_2) < \infty$, therefore for $t \in [0, 1]$, we have $tJ(u_1) < \infty$ and $(1-t)J(u_2) < \infty$. Since J is convex,

$$J(tu_1 + (1-t)u_2) \leq tJ(u_1) + (1-t)J(u_2) < \infty$$

,

Therefore, $tu_1 + (1-t)u_2 \in \text{dom}(J)$. Hence $\text{dom } J$ is convex.

2. First consider J a convex functional, then we have for all $u_1, u_2 \in U$,

$$J(tu_1 + (1-t)u_2) \leq tJ(u_1) + (1-t)J(u_2) \quad \forall t \in [0, 1]$$

Let $(u_1, \alpha_1), (u_2, \alpha_2)$ elements of $\text{epi}(J)$, then $J(u_1) < \alpha_1$ and $J(u_2) < \alpha_2$. Since J is convex.

$$J(tu_1 + (1-t)u_2) \leq t\alpha_1 + (1-t)\alpha_2$$

Then $(tu_1 + (1-t)u_2, t\alpha_1 + (1-t)\alpha_2) \in \text{epi}(J)$. Therefore, if J is convex, and $(u_1, \alpha_1), (u_2, \alpha_2)$ are elements of $\text{epi}(J)$ then,

$$t(u_1, \alpha_1) + (1-t)(u_2, \alpha_2) = (tu_1 + (1-t)u_2, t\alpha_1 + (1-t)\alpha_2) \in \text{epi}(J)$$

Hence $\text{epi}(J)$ is convex.

Now assume $\text{epi}(J)$ convex. Let $(u_1, \alpha_1), (u_2, \alpha_2)$ elements of $\text{epi}(J)$ then $(tu_1 + (1-t)u_2, t\alpha_1 + (1-t)\alpha_2)$, then

$$J(tu_1 + (1-t)u_2) \leq t\alpha_1 + (1-t)\alpha_2 \quad \forall t \in [0, 1]$$

By definition of $\text{epi}(J)$, if $u_1, u_2 \in \text{dom } J$, then $(u_1, J(u_1))$ and $(u_2, J(u_2))$, are elements of $\text{epi}(J)$, therefore

$$J(tu_1 + (1-t)u_2) \leq tJ(u_1) + (1-t)J(u_2) \quad \forall t \in [0, 1]$$

Implying that J is convex.

□

Definition 4.1.

5. Lecture 5

6. Lecture 6

7. Lecture 7

Remark 7.1.

Some elementary properties of conjugate functions

- **Young inequality** $J(u) + J^*(p^*) \geq p^*(u) \quad \forall u \in U, \forall p^* \in U^*$
- $J^*(0) = \sup_{u \in U} ((0, u) - J(u)) = \sup_{u \in U} (-J(u)) = \inf_{u \in U} J(u)$

In many applications in optimization, is used the equivalent formulation,

$$\inf_{u \in U} J(u) = -J^*(0).$$

$$J \leq F \implies J^* \geq F^*$$

Theorem 7.1.

Let U a Banach space and $J^* : U^* \rightarrow \overline{\mathbb{R}}$ be the conjugate of the $J : U \rightarrow \overline{\mathbb{R}}$. Then for all $u \in U$.

$$p^* \in \partial J(u) \iff J(u) + J^*(p^*) = p^*(u)$$

.

Proof. content...

□

Corollary 7.1.

It follows from previous theorem that $\partial J(u) = \{p^* \in U^* | J(u) + J^*(p^*) = (p^*, u)\}$.

Theorem 7.2.

Let U be a Banach space and $J : U \rightarrow \mathbb{R}$ be proper function. If $p^* \in \partial J(u)$ then $u \in \partial J^*(p^*)$

Proof. Let $p^* \in \partial J(u)$. For any $g^* \in U^*$, it follows

$$J^*(g^*) = \sup_{v \in U} (g^*(v) - J(v)) \geq g^*(u) - J(u) \geq g^*(u) - J(u)$$

From theorem 7.1

$$J^*(g^*) \leq g^*(u) - p^*(u) + J^*(p^*) = (g^* - p^*)(u) + J^*(p^*) \implies u \in \partial J^*(p^*).$$

□

By iteration the definition, we obtain the bipolar function $(J^*)^* = J^{**} : U^{**} \rightarrow \overline{\mathbb{R}}$,

$$J^{**}(u) = \sup_{p^* \in U^*} \{p^*(u) - J^*(p^*)\}$$

Theorem 7.3.

Let U be a reflexive Banach space. The J^{**} is the maximum convex functional below J (also called convex envelope), i.e. $J^{**}(u) \leq J(u)$, $\forall u \in U$ and $F(u) \leq J^{**}(u)$, $\forall u \in U$ if F is also convex and $F(u) \leq J(u)$, $\forall u$. In particular $J^{**} = J$ if and only if J is convex.

Proof.

$$J^{**}(u) = \sup_{p^* \in U^*} \{p^*(u) - J^*(p^*)\} \tag{2}$$

$$= \sup_{p^* \in U^*} \left\{ p^*(u) - \sup_{v \in U} \{p^*(v) - J(v)\} \right\} \tag{3}$$

$$= \sup_{p^* \in U^*} \left\{ p^*(u) + \inf_{v \in U} \{p^*(v) - J(v)\} \right\} \tag{4}$$

$$\tag{5}$$

Since for any $p^* \in U^*$,

$$\inf_{v \in U} \{p^*(u - v) + J(v)\} \leq p^*(u - u) + J(u)$$

We have that $J^{**}(u) \leq J(u)$.

Now we assume that F is a convex functional and $g^* \in \partial F(u)$ for $u \in U$.

$$\implies F(v) \geq F(v) + g^*(v - u) \tag{6}$$

$$F^{**}(u) = \sup_{p^* \in U^*} \inf_{v \in U} \{p^*(u - v) + F(v)\} \tag{7}$$

$$\geq \sup_{p^* \in U^*} \inf_{v \in U} \{(p^* - g^*)(u - v) + F(u)\} \tag{8}$$

$$\geq \inf_{v \in U} \{(g^* - q^*)(u - v) + F(u)\} \tag{9}$$

$$= F(u) \tag{10}$$

If F is convex,

$$\implies F(u) \leq F^{**}(u) \leq F(u) \implies F(u) = F^{**}(u), \tag{11}$$

$$F(u) = F^{**}(u) = \sup_{p^* \in U^*} \inf_{v \in U} \{p^*(u - v) + F(v)\} \leq J^{**}(u) \tag{12}$$

□

8. Lecture 8

Definition 8.1.

Let U and Y Banach spaces and $J : U \rightarrow \overline{\mathbb{R}}$ is a proper function. We consider an optimization problem (P) called primal problem

$$\inf_{u \in U} J(u) \quad (\text{P})$$

Then the problem is said to be nontrivial if there is $\bar{u} \in U$ such that $J(\bar{u}) < \infty$. A function $\Phi : U \times Y \rightarrow \overline{\mathbb{R}}$ is said to be a perturbation function of J ,

$$\inf_{u \in U} \Phi(u, p) \quad (\text{Pp})$$

if $\Phi(u, 0) = J(u)$ for all $u \in U$. For each $p \in Y$, the minimization problem (Pp) is called a perturbation problem. The variable p is called perturbation parameter. If we denote by Φ^* the convex conjugate function of Φ , the *dual problem*, with respect to Φ is defined by

$$\sup_{p^* \in Y^*} -\Phi^*(0, p^*) \quad (\text{P}^*)$$

where $\Phi^* : (U \times Y)^* \cong U^* \times Y^* \rightarrow \overline{\mathbb{R}}$, a function defined as follows.

$$\Phi^*(u^*, p^*) = \sup_{\substack{u \in U \\ p \in Y}} ((u^*, u)_{U^*U} + (p^*, p)_{Y^*Y} - \Phi(u, p))$$

Remark 8.1.

For $p = 0$, $(\text{P}^*) \equiv (\text{Pp})$. We denote the infimum for problem (P) by $\inf(\text{P})$ and the supremum for problem (P^*) by $\sup(\text{P}^*)$

Lemma 8.1 (Weak duality).

For the problem (P) and (P^*) it holds that

$$-\infty \leq \sup(\text{P}^*) \leq \inf(\text{P}) \leq \infty.$$

Proof. Let $p^* \in Y^*$. It follows

$$-\Phi^*(0, p^*) = - \sup_{\substack{u \in U \\ p \in Y}} ((0, u) + (p^*, p) - \Phi(u, p)) \quad (13)$$

$$= \inf_{\substack{u \in U \\ p \in Y}} (\Phi(u, p) - (p^*, p)) \quad (14)$$

$$\leq (\Phi(u, 0) - (p^*, 0)) \quad \forall u \in U, p^* \in Y^* \quad (15)$$

$$\implies \sup_{p^* \in Y^*} (-\Phi^*(0, p^*)) \leq \inf_{u \in U} \Phi(u, 0) = \inf(\text{P}) \quad (16)$$

□

By iteration we can define, a bidual problem

$$- \sup_{u \in U} (-\Phi^*(u, 0)) = \inf_{u \in U} \Phi^*(u, 0) \quad (\text{P}^{**})$$

In case the space U is reflexive then $U^{**} = U$.

If the perturbation function $\Phi(u, p)$ is proper, convex and weakly lower semicontinuous. Then $\Phi^{**} = \Phi$. In this case $\Phi(u, 0) = \Phi^{**}(u, 0)$ i.e $(\text{P}) \equiv (\text{P}^{**})$

Definition 8.2.

Consider the infimal value function

$$h(p^*) = \inf (\mathbf{P}_p) = \inf_{u \in U} \Phi(u, p)$$

The problem (\mathbf{P}) is called stable if $h(0)$ is finite and its sub-differentiable in zero is not empty.

Theorem 8.1.

The primal problem (\mathbf{P}) is stable if and only if the following conditions are simultaneously satisfied:

- The dual problem (\mathbf{P}^*) has a solution.
- There is no duality gap, i.e.

$$\inf (\mathbf{P}) = \sup (\mathbf{P}^*) \leq \infty$$

Theorem 8.2 (Extremal relation).

Let $\Phi : U \times Y \rightarrow \overline{\mathbb{R}}$, be convex the the following statements are equivalent:

1. (\mathbf{P}) and (\mathbf{P}_p) have solutions \bar{u} and \bar{p}^* and $\inf(P) = \sup(P^*)$
2. $\Phi(\bar{u}, 0) + \Phi^*(0, \bar{p}^*) = 0$
3. $(0, \bar{p}^*) \in \partial\Phi(u, 0)$ and $(\bar{u}, 0) \in \partial\Phi^*(0, p^*)$

Proof. We proceed by parts:

1. $(1) \implies (2)$: \bar{u} solution of $\inf(\mathbf{P})$ and \bar{p}^* solution of $\sup(\mathbf{P}^*)$ and $\inf(\mathbf{P}) = \sup(\mathbf{P}^*)$. This properties implies, $\Phi(\bar{u}, 0) = \inf(\mathbf{P}) = \sup(\mathbf{P}^*) = -\Phi^*(0, \bar{p}^*) \implies \Phi(\bar{u}, 0) + \Phi^*(0, \bar{p}^*) = 0$.
2. $(2) \implies (1)$: $-\Phi^*(0, \bar{p}^*) = \sup(\mathbf{P}^*) \leq \inf(\mathbf{P}) = \Phi(\bar{u}, 0) = -\Phi^*(0, \bar{p}^*) \implies \sup(\mathbf{P}^*) = \inf(\mathbf{P})$
3. $(2) \iff (3)$: $\Phi(\bar{u}, 0) + \Phi^*(0, \bar{p}^*) = 0 = (0, \bar{u}) + (\bar{p}^*, 0) = ((0, \bar{p}^*), (\bar{u}, 0)) \iff (0, \bar{p}^*) \in \partial\Phi(\bar{u}, 0) \forall u \in U, \forall p^* \in \partial J(u) \iff J(u) + J^*(p^*) = (p^*, u)$

□

Fenchel duality.

Consider the functional $J : U \rightarrow \overline{\mathbb{R}}$,

$$J(u) = F(u) + G(Au)$$

with $F : U \rightarrow \overline{\mathbb{R}}$, G convex function $G : V \rightarrow \overline{\mathbb{R}}$ and $A : U \rightarrow V$ bounded and linear.

We introduce the perturbation $\Phi(u, p) = F(u) + G(Au - p)$. The dual problem is obtained with,

$$\Phi^*(0, p^*) = \sup_{\substack{u \in U \\ p \in V}} ((p^*, p) - F(u) - G(Au - p))$$

For fixed u we set $q : Au - p$.

$$\begin{aligned}
\Phi^*(0, p^*) &= \sup_{u \in U} \sup_{p \in V} ((p^*, Au - q) - F(u) - G(q)) \\
&= \sup_{u \in U} \sup_{p \in V} ((A^* p^*, u) - (p^*, q) - F(u) - G(q)) \\
&= \sup_{u \in U} ((p^*, Au) - F(u)) + \sup_{p \in V} ((-p^*, q) - G(q)) \\
&= F^*(A^* p^*) + G^*(-p^*)
\end{aligned}$$

References
