

Metarules

APPM 5630 Spring 2023

Advanced Convex Optimization

Caveat: most of these rules implicitly assume that the minimizers exist. All mistakes due to Stephen Becker.

1.
 - $\min_{x \in C} f(x) = -\max_{x \in C} -f(x)$
 - $\operatorname{argmin}_{x \in C} f(x) = \operatorname{argmax}_{x \in C} -f(x)$
 - $\operatorname{argmin}_{x \in C} f(x) = \operatorname{argmin}_{x \in C} \varphi(f(x))$ if φ is a monotonic increasing function on the range of f .
 - What can you say if φ is simply monotonic non-decreasing? e.g., take $\varphi(\beta) \equiv 0$.
 - Example: $\operatorname{argmin}_x \|Ax - b\| = \operatorname{argmin}_x \frac{1}{2} \|Ax - b\|^2$
2. $\min_{x \in C} f(x) \leq \min_{x \in D} f(x)$ if $D \subset C$
 - Caveat: existence. e.g., take $f(x) = x$ and $D = (0, 1)$ and $C = [0, 1]$, then $\min_{x \in D} x$ does not exist but $\min_{x \in C} x$ does. Or vice-versa: take $C = (0, 1)$ and $D = \{0.5\}$.
3. $\min_x [f(x) + g(x)] \neq [\min_x f(x)] + [\min_y g(y)]$
 - In fact, you can say the following: $\min_x [f(x) + g(x)] \geq [\min_x f(x)] + [\min_y g(y)]$
4. $\min_x \min_y f(x, y) = \min_y \min_x f(x, y)$ (hence $\min_{x,y} f(x, y)$ is well-defined). [Caveat: minima need to exist, e.g., $\min_{x \geq 0} \min_y x \cdot e^{-y}$, where the joint minimum value is 0 (e.g., at $(0, 2)$) but for an arbitrary $x \neq 0$ the problem $\min_y x \cdot e^{-y}$ is ill-defined since there is no minimizer]
 - *Proof* Let $f(x^*, y^*) = \min_x \min_y f(x, y) \equiv A$, and let $B \equiv \min_y \min_x f(x, y)$. Then

$$B = \min_y \min_x f(x, y) \leq \min_x f(x, y^*) \leq f(x^*, y^*) = A$$
 hence $B \leq A$, and similarly you could show $A \leq B$, hence $A = B$.
 - A similar statement (probably?) holds with $\inf - \inf$ (and of course with $\max - \max$ and $\sup - \sup$ too).
 - On the other hand, if you have a **mixed** min/max or inf/sup, now it is not always true, and you need to satisfy the conditions of a saddle point theorem. What is always true is an **inequality**,

$$\sup_y \inf_x f(x, y) \leq \inf_x \sup_y f(x, y).$$

Myths

See Harvey Greenberg's nice document from about 2010. I only point out a few here:

1. Myth: $\min_{x,y} g(x) + h(y) : y = g(x)$ is equivalent to $\min_y y + h(x)$ (via direct substitution)
 - This is true sometimes (e.g., under some conditions), but in general, it is not true, and you need to do a proper Lagrange multiplier treatment. Here's a counter-example. Take $\min_{x,y} x^2 + (y-5)^2$ subject to $16y = x^2$. So substitute in the x^2 and get $\min_y 16y + (y-5)^2$, which is unconstrained and has just one critical point at $y = -3$, but at this point, there is no real value of x , so we don't have a solution to the original problem! The issue is we needed to divide into cases of whether $x \geq 0$ or $x < 0$. The true minimum is at $(x, y) = (0, 0)$.