

Variational Methods for Computer Vision: Solution Sheet 3

Exercise: November 14, 2017

Part I: Theory

1. (a) Suppose x^* is a local but not a global minimizer. Then there exists a $z \in \mathbb{R}^n$ with $f(z) < f(x^*)$. Consider the line segment

$$x_\lambda = \lambda z + (1 - \lambda)x^*, \lambda \in (0, 1).$$

By convexity we have:

$$f(x_\lambda) = f(\lambda z + (1 - \lambda)x^*) \leq \lambda f(z) + (1 - \lambda)f(x^*) < \lambda f(x^*) + (1 - \lambda)f(x^*) = f(x^*).$$

\Rightarrow Any neighbourhood of x^* contains a point x_λ with $f(x_\lambda) < f(x^*)$, which is a contradiction to the assumption.

- (b) Assume that x^* is a stationary point but not a global minimizer. Then there is a $z \in \mathbb{R}^n$ with $f(z) < f(x^*)$, and

$$\begin{aligned} \langle \nabla f(x^*), z - x^* \rangle &= \lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} (f(x^* + \epsilon(z - x^*)) - f(x^*)) \\ &\leq \lim_{\epsilon \rightarrow 0} \frac{1}{\epsilon} (\epsilon f(z) + (1 - \epsilon)f(x^*) - f(x^*)) \\ &= f(z) - f(x^*) < 0. \end{aligned}$$

Thus $\langle \nabla f(x^*), z - x^* \rangle \neq 0 \Rightarrow \nabla f(x^*) \neq 0 \Rightarrow x^*$ is not a stationary point.

2. f convex \Rightarrow (epi f) convex:

Take arbitrary $(u, a), (v, b) \in \text{epi } f$. Then

$$f(\lambda u + (1 - \lambda)v) \leq \lambda f(u) + (1 - \lambda)f(v) \leq \lambda a + (1 - \lambda)b.$$

Thus $(\lambda u + (1 - \lambda)v, \lambda a + (1 - \lambda)b) = \lambda(u, a) + (1 - \lambda)(v, b) \in \text{epi } f$.

(epi f) convex $\Rightarrow f$ convex:

Take arbitrary $x, y \in \mathbb{R}^n$ and let $a := f(x), b := f(y)$. Then $(x, a), (y, b) \in \text{epi } f$. Since epi f is convex:

$$(\lambda x + (1 - \lambda)y, \lambda a + (1 - \lambda)b) \in \text{epi } f, \quad \text{i.e.}$$

$$f(\lambda x + (1 - \lambda)y) \leq \lambda a + (1 - \lambda)b = \lambda f(x) + (1 - \lambda)f(y).$$

This is exactly the definition of convexity of f .

3. (a) A direct calculation shows:

$$\begin{aligned} h(\lambda x + (1 - \lambda)y) &= \alpha f(\lambda x + (1 - \lambda)y) + \beta g(\lambda x + (1 - \lambda)y) \\ &\leq \alpha \lambda f(x) + \alpha(1 - \lambda)f(y) + \beta \lambda g(x) + \beta(1 - \lambda)g(y) \\ &= \lambda(\alpha f(x) + \beta g(x)) + (1 - \lambda)(\alpha f(y) + \beta g(y)) \\ &= \lambda h(x) + (1 - \lambda)h(y). \end{aligned}$$

(b) Since $h = \max(f, g)$, we have for each x that $h(x) \geq f(x)$ and $h(x) \geq g(x)$. Thus,

$$\begin{aligned} \lambda h(x) + (1 - \lambda)h(y) &\geq \lambda f(x) + (1 - \lambda)f(y) \geq f(\lambda x + (1 - \lambda)y) \quad \text{and} \\ \lambda h(x) + (1 - \lambda)h(y) &\geq \lambda g(x) + (1 - \lambda)g(y) \geq g(\lambda x + (1 - \lambda)y) , \end{aligned}$$

where the second “ \geq ” sign is due to convexity of f and g , respectively. Now, since both of these relations hold, we have that

$$\lambda h(x) + (1 - \lambda)h(y) \geq \max(f(\lambda x + (1 - \lambda)y), g(\lambda x + (1 - \lambda)y)) = h(\lambda x + (1 - \lambda)y).$$

This is exactly the definition of convexity of h .

Alternative: We see that

$$\begin{aligned} \text{epi } f \cap \text{epi } g &= \{(x, a) \mid f(x) \leq a\} \cap \{(x, a) \mid g(x) \leq a\} \\ &= \{(x, a) \mid \max\{f(x), g(x)\} \leq a\} = \text{epi } h \end{aligned}$$

Since the intersection of two convex sets is always convex, $\text{epi } h$ is a convex set. This implies by Ex. 2 that h is also a convex function.

Now we need to prove that the intersection of two convex sets is convex (always $\lambda \in (0, 1)$):

S_1, S_2 convex

$$\begin{aligned} &\Rightarrow (\forall x, y \in S_1: \lambda x + (1 - \lambda)y \in S_1) \wedge (\forall x, y \in S_2: \lambda x + (1 - \lambda)y \in S_2) \\ &\Rightarrow (x, y \in S_1 \wedge x, y \in S_2 \Rightarrow \lambda x + (1 - \lambda)y \in S_1 \wedge \lambda x + (1 - \lambda)y \in S_2) \\ &\Rightarrow \forall x, y \in S_1 \cap S_2: \lambda x + (1 - \lambda)y \in S_1 \cap S_2 \\ &\Rightarrow S_1 \cap S_2 \text{ convex.} \end{aligned}$$

(c) Counterexample: $h(x) = \min\{(x - 1)^2, (x + 1)^2\}$ is clearly not convex: take e.g. $x = 1$, $y = -1$ and $\lambda = \frac{1}{2}$, then

$$h(\lambda x + (1 - \lambda)y) = h(0) = 1 > 0 = \lambda h(x) + (1 - \lambda)h(y).$$

4.

$$\begin{aligned} h''(x) &= f(g(x))'' = (f'(g(x))g'(x))' \\ &= \underbrace{f''(g(x))}_{\geq 0} \underbrace{g'(x)g'(x)}_{\geq 0} + f'(g(x)) \underbrace{g''(x)}_{\geq 0} \end{aligned}$$

Thus $h''(x) \geq 0$ if $f'(g(x)) \geq 0$, so f being a convex non-decreasing function is a sufficient condition for the convexity of h .

Part II: Practical Exercises

1. From the lecture, we have the following condition on u :

$$\begin{aligned}\frac{dE_\lambda}{du_l} &= (u_l - f_l) + \lambda \sum_{\substack{l,j \\ \text{neighbours}}} (u_l - u_j) = 0 \\ \Rightarrow (1 + \lambda n_l)u_l - \lambda \sum_{\substack{l,j \\ \text{neighbours}}} u_j &= f_l,\end{aligned}$$

with n_i being the number of neighbours of pixel i . Thus the Gauss-Seidel update step becomes

$$u_i^{(k+1)} = \frac{1}{1 + \lambda n_i} \left(f_i + \lambda \sum_{\substack{j \in \mathcal{N}(i) \\ j < i}} u_j^{(k+1)} + \lambda \sum_{\substack{j \in \mathcal{N}(i) \\ j > i}} u_j^{(k)} \right)$$

for the given energy.