

# CONVEX OPTIMIZATION 2025/26

Practical session # 12

January 8, 2025

1. A convex function  $f: \mathbf{R} \rightarrow \mathbf{R}$  is called *self-concordant* if  $|f'''(x)| \leq 2f''(x)^{3/2}$ , for all  $x \in \text{dom}(f)$ .

A general function  $f: \mathbf{R}^n \rightarrow \mathbf{R}$  is self-concordant, if  $t \mapsto f(x+tu)$  is self concordant for all  $x \in \text{dom}(f)$  and  $u \in \mathbf{R}^n$ . Show that the following are self-concordant:

- affine functions
- quadratic functions
- $f(x) = -\log(x)$
- $f(x) = x \log(x) - \log(x)$

2. Show that self-concordant functions are closed under

- sums, scaling with  $\alpha \geq 1$
- precomposition with affine functions

3. Use the above to prove that the objective functions that we get for computing the central path  $x^*(t)$  of a linear program is self-concordant.

4. Let  $x^{(0)}, x^{(1)}, \dots$  be the values computed by Newton descent for minimizing  $f(x)$ . If  $f$  is self-concordant, then we know there are numbers  $\gamma > 0$  and  $0 < \eta \leq 1/4$  such that

- (damped phase) If  $\lambda(x^{(k)}) > \eta$ , then  $f(x^{(k+1)}) - f(x^{(k)}) \leq -\gamma$ ,
- (quadratically convergent phase) If  $\lambda(x^{(k)}) \leq \eta$ , then  $2\lambda(x^{(k+1)}) \leq (2\lambda(x^{(k)}))^2$ .

The main advantage of self-concordance is that we can set the constants to  $\eta = \frac{1-2\alpha}{4}$  and  $\gamma = \alpha\beta\frac{\eta^2}{1+\eta}$ , which do not depend on  $f$ , but only the backtracking parameters  $\alpha, \beta$ .

Using the above inequalities show that we need at most

$$\frac{f(x^{(0)}) - p^*}{\gamma} + \log_2 \log_2(\epsilon^{-1}) = \frac{20 - 8\alpha}{\alpha\beta(1 - 2\alpha)^2} (f(x^{(0)}) - p^*) + \log_2 \log_2(\epsilon^{-1})$$

Newton iterations to reach tolerance  $\epsilon > 0$ . (so, for values  $\alpha = 0.1, \beta = 0.8$  and  $\epsilon = 10^{-10}$ , we get e.g.  $375(f(x^{(0)}) - p^*) + 6$ ).

5. Let us consider one centering step of the log-barrier method.

- (\*) If  $x = x(t)$  and  $x^+ = x(\mu t)$ , then one can prove that

$$\mu t f_0(x) + \phi(x) - \mu t f_0(x^+) - \phi(x^+) \leq m(\mu - 1 - \log \mu)$$

- Use (3), (4) and (\*) to come up with an upper bound of the total number of Newton iterations that is used in solving a linear program using the log-barrier method.
- Try to prove (\*) (Hint: Use that  $\lambda_i^*(t) = -1/(tf_i(x))$ , and  $\log(u) \leq u - 1$ )