1. Let  $A \in \mathbb{R}^{p \times n}$  and  $b \in \mathbb{R}^p$ . Consider the following primal problem with variable  $x \in \mathbb{R}^n$ :

$$\begin{array}{ll}
\text{minimize} & x^T x \\
\text{subject to} & Ax = b.
\end{array}$$

- (a) In the case of n=2, show that  $f(x)=x_1^2+x_2^2$  for  $x=(x_1,x_2)\in\mathbb{R}^2$  is **strictly** convex. (10%)
- (b) What is the corresponding dual problem with dual variable  $\nu \in \mathbb{R}^p$ ? (10%)
- (c) What are the KKT conditions for  $x^*$  and  $\nu^*$  being optimal? What is the KKT system? (10%)
- 2. Show that  $f(x,y) = -\log y \log(\log y x)$  on  $\{(x,y) : e^x < y\}$  is self-concordant. (Recall that for a convex function  $g: \mathbb{R} \to \mathbb{R}$  with  $\operatorname{dom} g = \mathbb{R}_{++}$  and  $|g'''(x)| \leq 3\frac{g''(x)}{x}$  for all x > 0,  $f(x) = -\log(-g(x)) - \log x$  is self-concordant on  $\{x|x>0, g(x)<0\}$ .) (20%)
- 3. Consider the function  $f(x) = x_1^2 + x_2^2$  with dom  $f = \mathbb{R}^2$ . Suppose we are using the following method.

given an initial point  $x \in \text{dom } f$ .

repeat 1.  $\Delta x = -\nabla f(x)$ .

- 2. Line search. Choose step size t via exact line search.
- 3. Update.  $x := x + t\Delta x$ .

**until**  $||\nabla f(x)||_2 \le 0.005$ .

- (a) Suppose the initial point is  $x^{(0)} = (2,3)$ . What is the initial descent direction  $\Delta x$ ? (5%)
- (b) In exact line search, the step size t is determined by

$$\arg\min_{s>0} f(x+s\Delta x).$$

What is the step size t at the first iteration? (10%)

- (c) What is  $p^* = \inf_x f(x)$ ? How many iterations are required? (10%)
- 4. Consider the following equality-constrained optimization problem:

minimize 
$$f(x)$$

subject to 
$$Ax = b$$
.

subject to Ax = b. The Newton step  $\Delta x_{\rm nt}$  of f at feasible x is given by the **solution** v of  $\begin{bmatrix} \nabla^2 f(x) & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} v \\ w \end{bmatrix} = \begin{bmatrix} -\nabla f(x) \\ 0 \end{bmatrix}$ . Suppose  $Q \succeq 0$ . The following modified problem

minimize 
$$f(x) + (Ax - b)^T (Ax - b)$$

subject to 
$$Ax = b$$
.

is equivalent to the original problem. Is the Newton step for this problem the same as the Newton step for the original problem? Prove or disprove it. (15%)

5. Consider the following inequality-constrained optimization problem with variable  $x \in \mathbb{R}^2_+$ :

minimize 
$$\frac{1}{2}x_1^2 + \frac{1}{2}x_2^2$$
  
subject to 
$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \succeq \begin{bmatrix} 3 \\ 2 \end{bmatrix}$$

subject to 
$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \succeq \begin{bmatrix} 3 \\ 2 \end{bmatrix}$$

- (a) Consider the generalized logarithm  $\psi(x) = \log x_1 + \log x_2$  for  $\mathbb{R}^2_+$ . Show that there exists  $\theta > 0$ such that for s > 0,  $y >_{\mathbb{R}^2} 0$ ,  $\psi(sy) = \psi(y) + \theta \log s$ . (5%)
- (b) What is the corresponding centering problem if the generalized logarithm  $\psi$  is used? (5%)
- (c) What is the centrality condition? (5%)
- (d) Suppose in the centering problem t = 1 and  $x^{(0)} = (1, 2)$ . What is the initial Newton step? (15%)