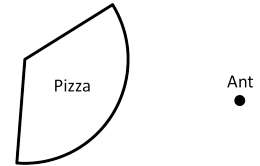


## ME 598/494 Exam 1 - September 14, 2017

### Problem 1 (20 Points)

Check if the following statements are true or not. Explain.

- (a) If  $x_*$  is a stationary point of a continuous and differentiable function  $f$ , then  $x_*$  is a local minimum of  $f$ .
- (b) The union of two convex sets is also convex. If true, please explain; if not, please provide a counter example.
- (c) The problem  $\min_x \frac{1}{x} + x$  for  $x \geq 0$  has a minimizer.
- (d) An ant is planning a move to the pizza (see figure). There is a unique shortest path from this ant to this piece of pizza.



### Solutions

- (a) False. Could be saddle or local maximum.
- (b) False. Counter example: draw two circles with some overlap.
- (c) True. Set derivative to zero to find  $x^* = 1$ . Also Hessian (second order derivative) is positive.
- (d) True. The pizza is convex. The distance function on  $\mathbb{R}^2$  is a convex function. Therefore finding a shortest distance within the pizza is a convex problem and has one unique solution.

### Problem 2 (25 Points)

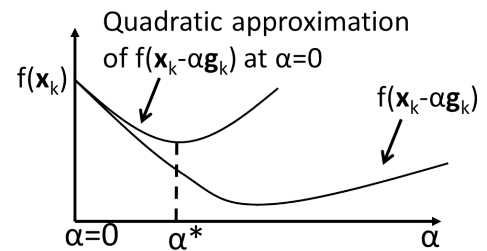
- (a) *Derive* the iteration formula for solving  $n$ -dimensional unconstrained problems with the gradient descent method without line search. (5 Points)
- (b) *Derive* the iteration formula for solving  $n$ -dimensional unconstrained problems with Newton's method without line search. (5 Points)
- (c) Explain why line search is needed for gradient descent and Newton's method. Propose a line search algorithm (can be an existing one). (5 Points)
- (d) Discuss briefly advantages and disadvantages of using Newton's method in solving optimization problems. (10 Points)

## Solutions

See notes.

### Problem 3 (10 Points)

For an unconstrained function  $f$  in  $\mathbb{R}$  that is continuous and differentiable, perform the following line search at the current point  $\mathbf{x}_k$  with gradient  $\mathbf{g}_k$  and Hessian  $\mathbf{H}_k$ : (1) Consider the one-dimensional function  $f(\mathbf{x}_k - \alpha \mathbf{g}_k)$  with respect to  $\alpha$ . Derive its second order approximation at  $\alpha = 0$ . (2) Minimize this approximation to find the optimal step  $\alpha^*$ . What could go wrong with this line search method? (Hint: see figure)



## Solutions

See notes.

### Problem 4 (10 Points)

- (a) Consider the linear programming problem  $\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x}$ , where  $\mathbf{c}$  is a constant vector. Does this problem have a solution? (2 Points)
- (b) Consider the linear programming problem  $\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x}$ , subject to  $\mathbf{A}\mathbf{x} \leq \mathbf{b}$ , where  $\mathbf{c}$  is a  $p$ -by-1 constant vector,  $\mathbf{b}$  is an  $n$ -by-1 constant vector, and  $\mathbf{A}$  is an  $n$ -by- $p$  constant matrix. If this problem has solutions (local minima), how many solutions do you expect to have? Please explain. (8 Points) Hint: An optimization problem is convex if the objective is a convex function, and the feasible domain is a convex set. The problem is strictly convex when the objective is strictly convex.

## Solutions

- (a) No. Let  $\mathbf{x} = -t\mathbf{c}$ , where  $t > 0$ . Then the objective is  $-t\|\mathbf{c}\|^2 < 0$ . This value can go to  $-\infty$  as  $t \rightarrow \infty$ .
- (b) Notice that the objective is a convex function, and the feasible domain of  $\mathbf{x}$  is a convex set, the problem has a global solution, but this solution is not necessarily unique. See <http://ftp.cs.wisc.edu/pub/techreports/1978/TR316.pdf> the uniqueness proof. **Note:** You get full points if you show convexity of the objective and the constraints.

## Problem 5 (10 Points)

Consider a triangle with three sides  $a$ ,  $b$  and  $c$ . Fix  $a = 1$ , and  $b + c = 2$ . How does the triangle look like when it has the largest area (by changing  $b$  and  $c$ ). (Hint: The Heron's formula for triangle area is  $A = \sqrt{s(s-a)(s-b)(s-c)}$ , where  $s = (a + b + c)/2$ . The optimal solution for a positive function  $f(x)$  is also optimal for  $f(x)^2$ .)

## Solutions

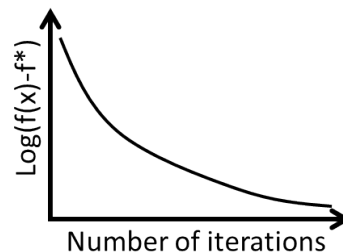
The objective is proportional to the negative squared area:  $f(b, c) = -(1 + b)(1 + c)$ , with the constraint  $b + c = 2$ . Convert this to an unconstrained problem:  $\bar{f}(b) = -(1 + b)(3 - b)$ . The derivative is  $df/db = (3 - b) - (1 + b) = 0$ . Thus  $b^* = 1$  and  $c^* = 1$ . The second-order derivative is  $d^2f/db^2 = 2 > 0$ . Therefore the stationary point is a global minimizer.

## Problem 6 (25 Points)

Consider a linear system of equations  $\mathbf{Ax} = \mathbf{b}$ , where  $\mathbf{A}$  is a  $n$ -by- $n$  matrix,  $\mathbf{x}$  is  $n$ -by-1, and  $\mathbf{b}$  is  $n$ -by-1. We can find the solution  $\mathbf{x}$  by solving

$$\min_{\mathbf{x}} 0.5(\mathbf{Ax} - \mathbf{b})^T(\mathbf{Ax} - \mathbf{b}). \quad (1)$$

- (a) Is this problem convex? Please explain. (5 Points)
- (b) In what cases is this problem strictly convex? (5 Points, optional for MAE494)
- (c) The figure to the right shows the convergence of gradient descent on this problem. Do you trust this result? Please explain. (5 Points)
- (d) Consider solving the problem using Newton's method starting at  $\mathbf{x}_0$ . How many steps will you take to reach the solution? Please explain. (5 Points)
- (e) Please explain in what cases you will not be able to use Newton's method, and how you will resolve this issue. (5 Points, optional for MAE494)



## Solutions

- (a) The Hessian  $\mathbf{A}^T\mathbf{A}$  is psd. To show this, let  $\mathbf{x}$  be an arbitrary non-zero vector. Then  $\mathbf{x}^T\mathbf{A}^T\mathbf{Ax} = \|\mathbf{Ax}\|^2 \geq 0$ . Therefore the problem is convex.

- (b) It is strictly convex when all eigenvalues of  $\mathbf{A}^T \mathbf{A}$  are positive, or equivalently  $\mathbf{A}$  is non-singular.
- (c) No. Since this is a convex problem, the convergence should be linear.
- (d) One step. The problem is quadratic and convex.
- (e) When  $\mathbf{A}$  is singular. We can use a modified Hessian  $\mathbf{A}^T \mathbf{A} + \lambda \mathbf{I}$  with  $\lambda > 0$  to ensure the convergence.