### Tutorial 1

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This file contains properties and tricks regarding:

- Convex Vs Closed Sets
- Convex functions
- Properties of Lipchitz Gradients
- Properties of Strong convexity.

### 1 Convex sets

- (a) Closed sets and convex sets.
  - i. A polyhedron  $\{x \in \mathbb{R}^n : Ax \leq b\}$ , for some  $A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$ , is both convex and closed.
- ii. Show that if  $S_i \subseteq \mathbb{R}^n$ ,  $i \in I$  is a collection of convex sets, then their intersection  $\cap_{i \in I} S_i$  is also convex. Show that the same statement holds if we replace "convex" with "closed".
- iii. Given an example of a closed set in  $\mathbb{R}^2$  whose convex hull is not closed.
- iv. Let  $A \in \mathbb{R}^{m \times n}$ . Show that if  $S \subseteq \mathbb{R}^m$  is convex then so is  $A^{-1}(S) = \{x \in \mathbb{R}^n : Ax \in S\}$ , which is called the preimage of S under the map  $A : \mathbb{R}^n \to \mathbb{R}^m$ . Show that the same statement holds if we replace "convex" with "closed".
- v. Let  $A \in \mathbb{R}^{m \times n}$ . Show that if  $S \subseteq \mathbb{R}^n$  is convex then so is  $A(S) = \{Ax : x \in S\}$ , called the image of S under A.
- vi. Give an example of a matrix  $A \in \mathbb{R}^{m \times n}$  and a set  $S \subseteq \mathbb{R}^n$  that is closed and convex but such that A(S) is not closed.

#### (b, 4 pts) Polyhedra.

i. Show that if  $P \subseteq \mathbb{R}^n$  is a polyhedron, and  $A \in \mathbb{R}^{m \times n}$ , then A(P) is a polyhedron. Hint: you may use the fact that

 $P \subseteq \mathbb{R}^{m+n}$  is a polyhedron  $\Rightarrow \{x \in \mathbb{R}^n : (x,y) \in P \text{ for some } y \in \mathbb{R}^m\}$  is a polyhedron.

ii. Show that if  $Q \subseteq \mathbb{R}^m$  is a polyhedron, and  $A \in \mathbb{R}^{m \times n}$ , then  $A^{-1}(Q)$  is a polyhedron.

## 2 Convex functions (14 points)

(a) Let f be twice differentiable, with dom(f) convex. Prove that:

$$f$$
 is convex  $\iff (\nabla f(x) - \nabla f(y))^T (x - y) \ge 0$ , for all  $x, y$ .

- (b) A function  $f: \mathbb{R}^n \to \mathbb{R}$  is said to be *coercive* provided that  $f(x) \to \infty$  as  $||x||_2 \to \infty$ . A key fact about coercive functions is that they attain their infimums. Prove that a twice differentiable, strongly convex function is coercive and hence attains its infimum. Hint: use Q3 part (b.iv).
- (b) Prove that the maximum of a convex function over a bounded polyhedron must occur at one of the vertices.

### 3 Lipschitz gradients

Let f be convex and twice continuously differentiable. We will show that the following statements are equivalent.

- i.  $\nabla f$  is Lipschitz with constant L;
- ii.  $(\nabla f(x) \nabla f(y))^T (x y) \le L ||x y||_2^2$  for all x, y;
- iii.  $\nabla^2 f(x) \leq LI$  for all x;
- iv.  $f(y) \le f(x) + \nabla f(x)^T (y x) + \frac{L}{2} ||y x||_2^2$  for all x, y.

# 4 Strong convexity

Let f be convex and twice continuously differentiable. We will show that the following statements are equivalent.

- i. f is strongly convex with constant m;
- ii.  $(\nabla f(x) \nabla f(y))^T (x y) \ge m ||x y||_2^2$  for all x, y;
- iii.  $\nabla^2 f(x) \succeq mI$  for all x;
- iv.  $f(y) \ge f(x) + \nabla f(x)^T (y x) + \frac{m}{2} ||y x||_2^2$  for all x, y.