Lecture 1 for EE127 (Fall 2018): Optimization Models in Engineering

Scribes: Nilesh Tripuraneni *(Change This To Your Names)*

01/01/01 *(Change This to Lecture Date)*

1 Scribing

This document provides a scribing template. Try to organize the sections/subsections for your lecture in a coherent way. Also please read the directions detailed in the *instructions.pdf* file contained in the Github (`https://github.com/nileshtrip/EE127Notes`)

1.1 What a scribe should do

Definition 1.1 (Good Scribe)**.** A good scribe should follow the scribing instructions.

2 Convex functions

We care a lot about convex functions.

Theorem 2.1 (The name of the theorem)**.** *Although this class is not proof-oriented if the lectures contain any theorems put them in a theorem environment.*

Proof of Theorem 2.1. A clear, well-written proof (or reference to a proof in one of the course texts) about convexity might go here. ■

2.1 Examples relating to the aforementioned theorem

- You will learn to love linear spaces $\{x \in \mathbb{R}^n \mid Ax = 0\}$ and halfspaces $\{x \in \mathbb{R}^n \mid \langle a, x \rangle \geqslant 0\}$.
- You will also encounter the cone of positive semidefinite matrices, denotes, $S_+^n = \{A \in \mathbb{R}^{n \times n} \mid A \succeq 0\}$ later in this course. Here we write $A \succeq 0$ to indicate that $x^\top Ax \geqslant 0$ for all $x \in \mathbb{R}^n$.

- See [BV04] for lots of other examples. This is how you should cite a reference. If the reference is not contained in the *notes.bib* file you should add the bibtex (Google Scholar is a good place to get these bibtex blurbs).

Fact 2.2. *A fun fact about convexity or linear algebra.*

A nice, multi-line equation about convexity,

$$f(1-\gamma)x + \gamma y) \leqslant (1-\gamma)f(x) + \gamma f(y) \tag{1}$$
$$f(1-\gamma)x + \gamma y) \leqslant (1-\gamma)f(x) + \gamma f(y) \tag{2}$$

An in-line equation $f(x) \leqslant f(y)$.

An equation without a label,

$$f(y) \geqslant f(x) + g^\top (y-x)\,.$$

2.2 An important characterization perhaps

Proposition 2.3. *Something important about differentiability and convexity.*

$$f(y) = f(x) + \nabla f(x)^\top (y-x) + \int_0^1 (1-\gamma) \frac{\partial^2 f(x+\gamma(y-x))}{\partial \gamma^2}\,\mathrm{d}\gamma$$

Proof. A nice proof. ■

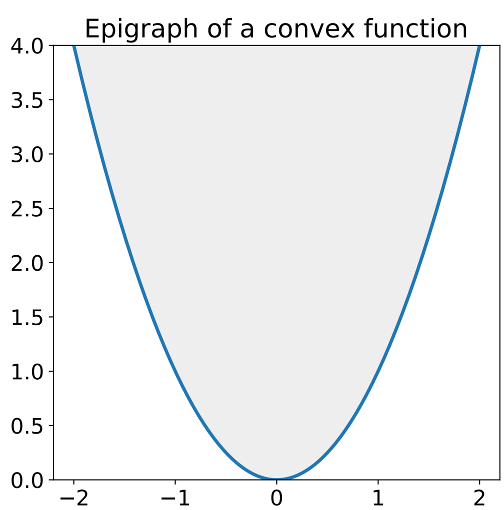

Figure 1: A fun figure about epigraphs completely unrelated to Proposition 2.3.

3 Convex optimization

We care a lot about $f \colon \Omega \to \mathbb{R}$ over a convex domain Ω :

$$\min_{x \in \Omega} \quad f(x)$$

Remark 3.1 (Subgradients)**.** subgradients *are great!*

$$f(y) \geqslant f(x) + g^\top (y - x) \,.$$

Maybe we need to reference Theorem 2.1 here.

Subgradients are useful for optimizing convex functions.

References

[BV04] Stephen Boyd and Lieven Vandenberghe. *Convex optimization*. Cambridge university press, 2004.