Optimization for Data Science June 4, 2018

- 1. (7 POINTS) Describe the gradient method and prove that it converges at a linear rate in the strongly convex case.
- 2. (6 POINTS) Describe in depth the stochastic gradient approaches that exploit variance reduction and explain the reasons why those methods work better than the classic stochastic gradient.
- 3. (7 POINTS) Consider the problem

$$\min_{x \in \Lambda} f(x),$$

with f continuously differentiable and convex function and

$$\Delta = \{ x \in \mathbb{R}^n : e^{\top} x = 1, \ x \ge 0 \}.$$

Calculate the maximum stepsize that can be taken at a point x_k along the away-step direction (i.e., d_k^{AS}) and the pairwise Frank Wolfe direction (i.e., $d_k^{PWFW} = d_k^{FW} + d_k^{AS}$).

4. (8 POINTS) Consider the mean-risk problem:

$$\min_{x \in \Delta} \quad \gamma \sqrt{x^{\top} M x} - c^{\top} x$$

where $M \in \mathbb{R}^{n \times n}$ is a symmetric positive definite matrix, $c \in \mathbb{R}^n$, $\gamma > 0$ is the risk-aversion parameter and

$$\Delta = \{ x \in \mathbb{R}^n : e^{\top} x = 1, \ x \ge 0 \}.$$

Analyze in depth its properties. Then describe a method for finding an optimal solution and properly justify the choice.

5. (8 POINTS) Consider the problem

$$\min_{x \in \mathbb{R}^n} f(x) = \frac{1}{2} x^{\top} Q x + c^{\top} x,$$

with $Q \in \mathbb{R}^{n \times n}$ symmetric positive definite matrix and $c \in \mathbb{R}^n$. Let $\gamma_1, \ldots, \gamma_n$ be the eigenvalues of the matrix Q. Prove that the gradient method defined as follows:

$$x_{k+1} = x_k - \frac{1}{\gamma_k} \nabla f(x_k),$$

with $k \geq 1$, converges in at most n iterations to the solution of the problem.