1. Let $f: \mathbb{R}^{d} \rightarrow \mathbb{R}$. Assume that for any $x$ there exists $g_{x} \in \mathbb{R}^{d}$ such that for all $y$ one has $f(x)-f(y) \leq g_{x} \cdot(x-y)$. Show that $f$ is convex. Furthermore if $f$ is differentiable, show that one can take $g_{x}=\nabla f(x)$.
2. Prove that $X \mapsto-\log \operatorname{det}(X)$ is convex on the set of positive definite matrices. Hint: to exhibit a subgradient at $x=X$, consider some other point $y=X+Y$ and write it as $X^{1 / 2}\left(I+X^{-1 / 2} Y X^{-1 / 2}\right) X^{1 / 2}$ (recall also the AM-GM inequality).
3. For a convex set $K \subset \mathbb{R}^{d}$ we define the normal cone of $K$ at $x \in K$ by $N_{K}(x)=\{\theta \in$ $\left.\mathbb{R}^{d}: \forall y \in K, \theta \cdot(y-x) \leq 0\right\}$. What are the normal cones of the Euclidean ball? Draw a picture for a 2 -dimensional polytope.
4. Show that for a convex function one has $x=\operatorname{argmin}_{x^{\prime} \in K} f\left(x^{\prime}\right) \Leftrightarrow \nabla f(x)+\lambda=0$ for some $\lambda \in N_{K}(x)$.
5. Let $x \in \mathbb{R}^{d}$ and $y$ be its Euclidean projection on $K$. Show that for any $z$ in $K$, one has $\|y-z\| \leq\|x-z\|$.
6. Consider a polytope written as $K=\left\{x: a_{j} \cdot x \leq b_{j} \forall j \in[m]\right\}$. Show that $N_{K}(x)=$ $\left\{\sum_{j: a_{j} \cdot x=b_{j}} \lambda_{j} a_{j}, \lambda_{j} \geq 0\right\}$.
7. Show that the algorithm $x_{t+1}=\operatorname{argmin}_{x \in \operatorname{span}\left(\nabla f\left(x_{0}\right), \ldots, \nabla f\left(x_{t}\right)\right)} f(x)$ always terminate in at most $d$ steps.
8. Consider a quadratic function $f(x)=\frac{1}{2} x^{\top} A x+b^{\top} x$. Derive a simple formula for the update of the above algorithm (Hint: you may want to work with the inner product $\langle x, y\rangle_{A}=x^{\top} A y$, and first note that the updates $x_{t+1}-x_{t}$ form an orthogonal basis for that inner product).
9. Prove that for a smooth function $f$, with a noisy oracle such that $\mathbb{E}\left[\|g-\nabla f(x)\|^{2}\right] \leq \sigma^{2}$ one has that the rate of gradient descent is of order $\frac{\beta}{t}+\frac{\sigma}{\sqrt{t}}$.
10. How can the above result be used in a machine learning setting? Think about doing mini-batches (to leverage parallel processing).
