Problem Sheet 8

Problems in Part A will be discussed in class. Problems in Part B come with solutions and should be tried at home.

Part A

(8.1) Consider the general convex optimization problem

minimize
$$f(x)$$
 subject to $f(x) \le 0$, $Ax = b$.

The central path consists of the set of solutions x(t), t > 0, of the barrier problem

minimize
$$tf(x) + \varphi(x)$$
 subject to $Ax = b$,

where $\varphi(x) = -\sum_{i=1}^m \log(-f_i(x))$ is the logarithmic barrier function. Show that a point x is equal to a point $x^*(t)$ on the central path if and only if there exist dual multipliers λ^* and μ^* such that the following conditions are satisfied:

$$egin{aligned} oldsymbol{f}(oldsymbol{x}^*) &\leq oldsymbol{0} \ oldsymbol{A}oldsymbol{x}^* &= oldsymbol{b} \ oldsymbol{\lambda}^* &\geq oldsymbol{0} \ -\lambda_i^* f_i(oldsymbol{x}^*) &= rac{1}{t}, \ 1 \leq i \leq m \end{aligned}$$
 $abla_{oldsymbol{x}} f(oldsymbol{x}^*) + \sum_{i=1}^m \lambda_i^*
abla_{oldsymbol{x}} f_i(oldsymbol{x}^*) + oldsymbol{A}^{ op} oldsymbol{\mu}^* &= oldsymbol{0}, \end{aligned}$

(8.2) Let $\{x_1, \ldots, x_n\}$ be a series of data points with $x_i \in \mathbb{R}^p$ for $1 \le i \le n$, and associated labels $\{y_1, \ldots, y_n\}$ with $y_i \in \{-1, 1\}$. Consider the following version of the Support Vector Machine optimization problem that allows for few mistakes:

$$\begin{aligned} & \text{minimize} & & \frac{1}{2} \| \boldsymbol{w} \|^2 + \mu \sum_{j=1}^n s_j \\ & \text{subject to} & & y_i(\boldsymbol{w}^\top \boldsymbol{x}_i + b) - 1 + s_i \geq 0, \quad 1 \leq i \leq n \\ & & s_i \geq 0, \quad 1 \leq i \leq n, \end{aligned}$$

Formulate the Lagrange dual and the KKT conditions for this problem. Show that the Lagrange dual does only depend on the inner products $\langle x_i, x_j \rangle$ of the data points.

(**8.3**) A matrix

$$oldsymbol{A} = egin{pmatrix} oldsymbol{B} & oldsymbol{v} \ oldsymbol{v}^{ op} & b \end{pmatrix},$$

is positive definite if and only if $b - v^{\top} B^{-1} v \ge 0$. Use this, and the fact that a symmetric matrix factors as $A = M^{\top} M$ for some M, to show that the QCQP from Problem Sheet 7 can be formulated as a semidefinite programming problem.

Part B

- (8.4) Given a symmetric matrix A, formulate the problem of computing the largest eigenvalue $\lambda_{\max}(A)$ as a semidefinite programming problem.
- **(8.5)** In many applications one is interested in finding a matrix of low rank that satisfies certain constraints. For example, one could have a covariance matrix, or a matrix containing user ratings of products, or a matrix whose entries are the squared distances between objects, but where only some entries are known. A common heuristic is to replace the rank of a symmetric matrix with the sum of the eigenvalues
 - (a) Show that for a symmetric matrix A, the sum of the eigenvalues $\lambda_1 + \cdots + \lambda_n$ equals the trace tr(A). We can therefore write

$$\lambda_1 + \cdots + \lambda_n = \operatorname{tr}(\boldsymbol{A}) = \boldsymbol{I} \bullet \boldsymbol{A}.$$

(b) Formulate the problem of minimizing the trace of a symmetric positive semidefinite matrix X subject to constraints of the form

$$x_{ij} = a_{ij}$$

for some subset of indices $(i,j) \in \Omega \subseteq \{1,\ldots,n\}^2$. The problem is that of finding the matrix of smallest trace with some predetermined entries. Determine the dual of this problem.

- (c) Using CVXPY in Python or CVX in MATLAB, perform the following experiment:
 - Generate a random matrix $X_0 \in SYM_{100}$ of rank 10.
 - For an increasing subcollection of "known" entries from X_0 , solve the trace minimization problem and determine if the solution of this optimization problem coincides with the matrix X_0 , thus effectively recovering it from only limited information.