

## Recitation 20

*Tuesday November 22, 2022*

### 1 Recap

#### 1.1 Unconstrained Quadratic Programming

Any quadratic function  $f(x_1, \dots, x_n)$  can be expressed as  $x^\top Ax + b^\top x$  where  $A$  is a symmetric matrix  $\in \mathbb{R}^{n \times n}$  and  $b \in \mathbb{R}^n$  are coefficient matrices, and  $x = [x_1 \dots x_n]^\top$  represents a vector of  $n$  variables.

Our goal is to find  $x^*$  that minimizes the objective function  $f$ . In other words, we want to find

$$x^* = \operatorname{argmin}_{x \in \mathbb{R}^n} x^\top Ax + b^\top x$$

We might also want to the minimum value of  $f$  attained by  $x^*$  which is  $f(x^*)$ .

##### 1.1.1 Simplifying via Eigendecomposition

Using the fact that  $A$  is symmetric, we express  $A = UDU^\top$ , where  $U$  is orthogonal ( $UU^\top = I$ ) and  $D$  is diagonal of  $A$ 's eigenvalues. Now, our minimization problem looks like

$$\begin{aligned} \min_{x \in \mathbb{R}^n} x^\top Ax + b^\top x \\ &= \min_{x \in \mathbb{R}^n} (x^\top U) D (U^\top x) + b^\top U (U^\top x) \\ &= \min_{z \in \mathbb{R}^n} z^\top D z + \hat{b}^\top z \end{aligned}$$

where  $z = U^\top x$  and  $\hat{b}^\top = b^\top U$ .

The expression is equivalent to

$$\min_{z \in \mathbb{R}^n} \left( \sum_{i=1}^n \lambda_i z_i^2 + \hat{b}_i z_i \right) = \sum_{i=1}^n \min_{z_i} \left( \lambda_i z_i^2 + \hat{b}_i z_i \right)$$

For each term of the summation,

- If  $\lambda_i > 0$ , then the minimum value is  $-\hat{b}_i^2 / (4\lambda_i)$  attained by  $z_i = -\hat{b}_i / (2\lambda_i)$ .
- If  $\lambda_i = 0$ , we can find a minimum only if  $\hat{b}_i = 0$ , which yields the minimum value 0 attained by any  $z_i \in \mathbb{R}$ .
- If  $\lambda_i < 0$ , then we cannot find a minimum since  $\lambda_i z_i^2 + \hat{b}_i z_i \rightarrow -\infty$  when  $|z_i| \rightarrow +\infty$ .

When  $A$  is symmetric:

- if all of  $A$ 's eigenvalues are strictly positive, we say  $A$  is *positive definite (pd)*
- if all of  $A$ 's eigenvalues are non-negative, we say  $A$  is *positive semidefinite (psd)*

Altogether, we can find a solution if matrix  $A$  is either 1) pd, or 2) psd with additional conditions that  $\hat{b} = 0$  whenever  $\lambda_i = 0$ .

Finally, if the minimum value (w.r.t  $z_i$ 's) is attainable by  $z^*$ , then we can retrieve  $x^* = (UU^\top)x^* = U(U^\top x^*) = Uz^*$ .

## 1.2 Equality Constrained QP

We are interested in solving a quadratic program (QP) for which the set of *feasible points* is no longer the whole space  $\mathbb{R}^n$ , but is restricted to some subspace. In particular, we are interested in constraints of the form  $\{x \in \mathbb{R}^n \mid Ax = b\}$  for a given  $m \times n$  matrix  $A$  and  $m$ -dimensional vector  $b$ . In particular, we can state our problem as:

$$\min_{x \in \mathbb{R}^n \text{ s.t. } Ax=b} \frac{1}{2}x^\top Px + q^\top x =: f(x) \quad (1)$$

where  $P$  is an  $n \times n$  symmetric matrix, and  $q$  is an  $n$ -dimensional vector.

## 2 Exercises

1. The formal definition of positive semidefinite (psd) matrix is given as follows. A matrix  $A \in \mathbb{R}^{n \times n}$  is said to be *positive semidefinite* iff any  $x \in \mathbb{R}^n$  satisfies  $x^\top A x \geq 0$ . Show that if  $A$  is symmetric, then  $A$  is psd if and only if all of its eigenvalue is non-negative.

*Remarks: a similiar analogy applies for positive definite matrices; however, the condition must have become  $x^\top A x > 0$ .*

2. True/False: explain or give a counter example. It might be easier to think within the framework of symmetric matrices.
  - (a) A non-negative matrix is always positive semidefinite.
  - (b) A positive semidefinite matrix is always non-negative.
  - (c) A positive definite matrix is always invertible.
3.
  - (a) The sum of two positive semidefinite matrices is also positive semidefinite.
  - (b) Show that  $A^\top A$  is positive semidefinite for any matrix  $A$  of any dimensions.
  - (c) Let  $A \in \mathbb{R}^{n \times n}$  be a positive semidefinite matrix and  $B \in \mathbb{R}^{n \times n}$  be another matrix. Show that  $B^\top A B$  is also positive semidefinite.

*Hint: an alternative defitiontion of psd from Question 1 could be helpful.*

4.

$$\min_{x,y,z} \frac{5}{2}x^2 - 2xy - xz + 2y^2 + 3yz + \frac{5}{2}z^2 + 2x - 35y - 47z$$

- (a) Write the equation above in matrix-vector form  $\mathbf{x}^\top A \mathbf{x} + b^\top \mathbf{x}$ .
- (b) Does it have a unique solution? If so, find the solution. If no, explain why not.