

Any questions? Do not hesitate to contact us!

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## Exercise 4.1: (Conjugate gradient (CG) method)

Let  $A \in \mathbb{R}^{n \times n}$  be a symmetric positive definite matrix, and let  $\bar{x}$  be the solution to

$$A\bar{x} = b.$$

We say that  $u$  and  $v$  are conjugate if

$$(u, v)_A := (u, Av) = 0.$$

A corresponding norm is defined as  $\|\cdot\|_A := (u, u)_A$ .

a) Let  $u, v \in \mathbb{R}^n \setminus \{0\}$ . Prove that if  $(u, v)_A = 0$ , then  $u$  and  $v$  are linearly independent.

**Answer.** Suppose  $\alpha_1 u + \alpha_2 v = 0$  for some  $\alpha_1, \alpha_2 \in \mathbb{R}$ . Then

$$\begin{aligned} (\alpha_1 u + \alpha_2 v, u)_A &= (0, u)_A \\ \alpha_1 (u, u)_A + \alpha_2 (v, u)_A &= (0, u)_A \\ \alpha_1 (u, Au) + \alpha_2 \cancel{(v, u)_A} &= 0 \\ \alpha_1 (u, Au) &= 0 \end{aligned}$$

Then  $\alpha_1$  should be 0. And

$$\begin{aligned} (\alpha_1 u + \alpha_2 v, v)_A &= (0, v)_A \\ \alpha_1 (u, v)_A + \alpha_2 (v, v)_A &= (0, v)_A \\ \alpha_1 \cancel{(u, v)_A} + \alpha_2 (v, Av) &= 0 \\ \alpha_2 (v, Av) &= 0 \end{aligned}$$

Then  $\alpha_2$  should be 0. So we can conclude that  $u, v$  are L.I.

b) Let  $U_k = \text{span}\{p_0, \dots, p_k\}$  with pairwise conjugate vectors  $p_k$ . Show that

$$x_{k+1} = \underset{x \in U_k}{\operatorname{argmin}} \|x - \bar{x}\|_A$$

is equivalent to

$$x_{k+1} = \sum_{j=0}^k \frac{(p_j, b)}{(p_j, p_j)_A} p_j.$$

**Answer.** First we will show that  $\operatorname{argmin}_{x \in U_k} \|x - \bar{x}\|_A = \operatorname{argmin}_{x \in U_k} F(x)$

$$\begin{aligned}
\|x - \bar{x}\|_A &= (x - \bar{x}, Ax - A\bar{x}) \\
&= (x - \bar{x}, Ax - b) \\
&= (x, Ax) - (x, b) - (\bar{x}, Ax) + (\bar{x}, b) \\
&= (x, Ax) - (x, b) - (A\bar{x}, x) + (\bar{x}, b) \longrightarrow \text{Symmetry of } A \\
&= (x, Ax) - 2(x, b) + (\bar{x}, b)
\end{aligned}$$

Then we can reformulate our problem as

$$\begin{aligned}
\operatorname{argmin}_{x \in U_k} \|x - \bar{x}\|_A &= \operatorname{argmin}_{x \in U_k} [(x, Ax) - 2(x, b) + (\bar{x}, b)] \\
&= \operatorname{argmin}_{x \in U_k} \left[ \frac{1}{2}(x, Ax) - (x, b) \right] = \operatorname{argmin}_{x \in U_k} F(x)
\end{aligned}$$

Now is enough to proof that  $\operatorname{argmin}_{x \in U_k} F(x) = \sum_{j=0}^k \frac{(p_j, b)}{(p_j, p_j)_A} p_j$ .

Notice that for all  $x \in U_k$ :  $x = (\alpha_0 p_0 + \dots + \alpha_k p_k)$  with  $\alpha_i \in \mathbb{R}$  for  $i = 1, \dots, k$  and

$$\begin{aligned}
F(x) &= \frac{1}{2} x^T A x - x^T b \\
&= \frac{1}{2} (\alpha_0 p_0 + \dots + \alpha_k p_k)^T A (\alpha_0 p_0 + \dots + \alpha_k p_k) - (\alpha_0 p_0 + \dots + \alpha_k p_k)^T b \\
&= \sum_{j=0}^k \frac{1}{2} (\alpha_j p_j)^T A (\alpha_j p_j) - \sum_{j=0}^k (\alpha_j p_j)^T b = \sum_{j=0}^k F(\alpha_j p_j)
\end{aligned}$$

Then  $\operatorname{argmin}_{x \in U_k} F(x) = \operatorname{argmin}_{\alpha_j p_j \in U_k} \sum_{j=0}^k F(\alpha_j p_j) = \sum_{j=0}^k \operatorname{argmin}_{\alpha_j \in \mathbb{R}} F(\alpha_j p_j)$

For all  $j = 1, \dots, k$  we can compute  $F(\alpha_j p_j) = \alpha_j \left[ \frac{1}{2} \alpha_j p_j^T A p_j - p_j^T b \right]$  and

$$\frac{\partial F(\alpha_j p_j)}{\partial \alpha_j} = \alpha_j p_j^T A p_j - p_j^T b$$

then

$$\frac{\partial F(\alpha_j p_j)}{\partial \alpha_j} = 0 \iff \alpha_j = \frac{(p_j, b)}{(p_j, p_j)_A} := \bar{\alpha}_j$$

In conclusion

$$\begin{aligned}
\operatorname{argmin}_{x \in U_k} \|x - \bar{x}\|_A &= \sum_{j=0}^k \operatorname{argmin}_{\alpha_j \in U_k} F(\alpha_j p_j) \\
&= \bar{\alpha}_j p_j = \frac{(p_j, b)}{(p_j, p_j)_A} p_j
\end{aligned}$$

c) Prove that the CG method yields the exact solution after at most  $n$  steps.

**Answer.** The step number  $n$  of CG is

$$x_n = \sum_{j=0}^{n-1} \frac{(p_j, b)}{(p_j, p_j)_A} p_j$$

then for all  $\ell = 0, \dots, n-1$  we have

$$\begin{aligned} p_\ell^T A x_n &= \sum_{j=0}^{n-1} \frac{(p_j, b)}{(p_j, p_j)_A} p_\ell^T A p_j \\ &= \frac{(p_\ell, b)}{(p_\ell, p_\ell)_A} p_\ell^T A p_\ell \longrightarrow \text{def. Conjugate (??)} \\ &= (p_\ell, b) \end{aligned}$$

In conclusion  $[P] A x_n = [P] b$  where  $[P]$  is the matrix with all the vectors  $p_\ell$  and this implies that  $A x_n = b$ .

## Exercise 4.2

a) Consider the following linear system:

$$\begin{pmatrix} 1 & 2 \\ 2 & 5 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 3 \\ 7 \end{pmatrix}$$

and the starting point  $x^{(0)} = (2, 2)^T$ .

1) Is it possible to apply the CG method to solve this linear system?

**Answer.** Yes, because  $A = A^t$  and  $\det(A - \lambda I) = (1 - \lambda)(5 - \lambda) - 4 = 0 \rightarrow \lambda_1 = 5.83$  and  $\lambda_2 = 0.17$ , i.e  $A$  is positive definite.

2) Find the quadratic functional (to minimize) associated to this system.

**Answer.**

$$\begin{aligned} F(x) &= \frac{1}{2} \begin{pmatrix} x \\ y \end{pmatrix}^t \begin{pmatrix} 1 & 2 \\ 2 & 5 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} x \\ y \end{pmatrix}^t \begin{pmatrix} 3 \\ 7 \end{pmatrix} \\ &= \frac{1}{2} x^2 + 2xy + \frac{5}{2} y^2 - 3x - 7y \end{aligned}$$

3) Find the solution of this problem using the CG method.

**Answer.**

$$r_0 = b - Ax = \begin{pmatrix} -3 \\ -7 \end{pmatrix}$$

$$p_0 = r_0$$

$$\alpha_0 = \frac{r_0^t r_0}{p_0^t A p_0} = 0.1716$$

$$x_1 = \begin{pmatrix} 1.48 \\ 0.79 \end{pmatrix}$$

$$r_1 = \begin{pmatrix} -0.0828 \\ 0.0355 \end{pmatrix}$$

$$\beta_1 = 1.4005 \times 10^{-4}$$

$$p_1 = \begin{pmatrix} -0.0833 \\ 0.0345 \end{pmatrix}$$

$$\alpha_1 = 5.8272$$

$$x_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$r_2 = \begin{pmatrix} -0.26 \\ 0.71 \end{pmatrix} \times 10^{-14}$$

$$\beta_2 = 7.08 \times 10^{-27}$$

$$p_2 = \begin{pmatrix} 0.2665 \\ 0.7105 \end{pmatrix} \times 10^{-14}$$

The solution is  $x_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$ .

b) Figure 1 is a contour plot of  $F(X)$  for

$$\begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 3 \\ 4 \end{pmatrix}$$

Start at  $x^{(0)} = (-2, 4)^T$  and sketch a few steps of the steepest descent method.

**MATLAB CODE!!!**

### Exercise 4.3 (Matlab)

- a) Suppose that an object can be at any one of  $n + 1$  equally spaced points  $x_0, x_1, \dots, x_n$ . When an object is at location  $x_i$ , it is equally likely to move to either  $x_{i-1}$  or  $x_{i+1}$  and cannot directly move to any other location. Consider the probabilities  $\{P_i\}_{i=0}^n$  that an object starting at location  $x_i$  will reach the left endpoint  $x_0$  before reaching the right endpoint  $x_n$ . Clearly,  $P_0 = 1$  and  $P_n = 0$ . Since the object can move to  $x_i$  only from  $x_{i-1}$  or  $x_{i+1}$  and does so with probability  $\frac{1}{2}$  for each of these locations.

$$P_i = \frac{1}{2}P_{i-1} + \frac{1}{2}P_{i+1} \quad \text{for each } i = 1, 2, \dots, n-1.$$

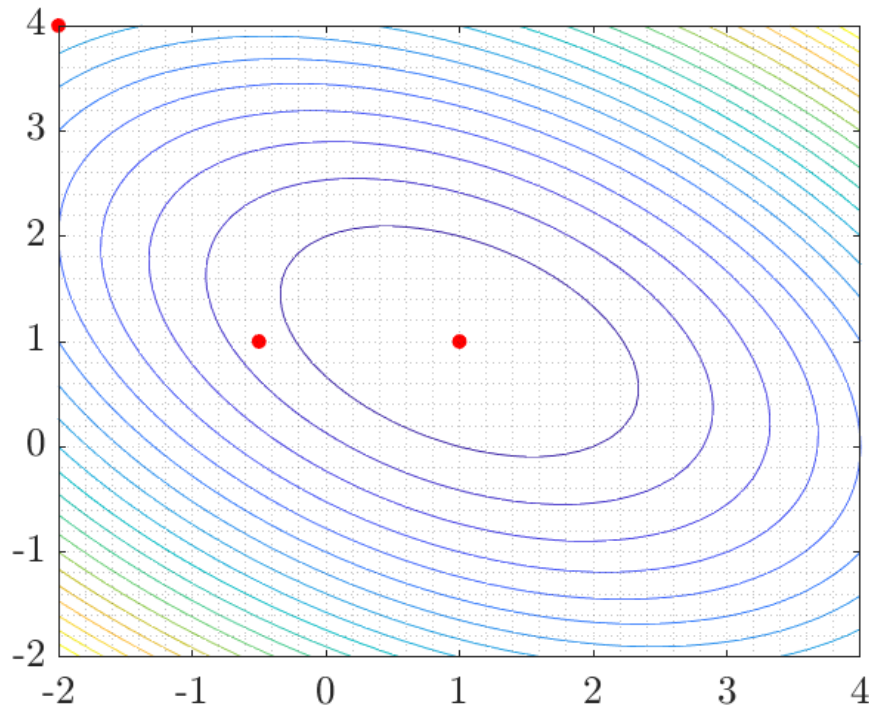


Figure 1: **Answer.** Exercise 4.2

(i) Show that

$$\begin{pmatrix} 1 & -\frac{1}{2} & & & & \\ -\frac{1}{2} & 1 & -\frac{1}{2} & & & \\ & -\frac{1}{2} & 1 & -\frac{1}{2} & & \\ & & & \dots & & \\ & & & & -\frac{1}{2} & 1 & -\frac{1}{2} \\ & & & & -\frac{1}{2} & 1 \end{pmatrix} \begin{pmatrix} P_1 \\ P_2 \\ \vdots \\ P_{n-1} \end{pmatrix} = \begin{pmatrix} \frac{1}{2} \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

- b) Write a Matlab code to solve this system using conjugate gradient method. Test your code with  $n = 10, 50, 100$ .
- c) Compare your results against a Monte Carlo simulation for this case.

*Monte Carlo method is a class of numerical methods that relies on random sampling.*

- First, the input random variables are sampled.
- Second, for each sample, a calculation is performed to obtain the outputs. Due to the randomness in the inputs, the outputs are also random variables.
- Finally, the statistics of the output random variables are computed, which estimates the output.

**MATLAB CODE!!!**