



1 **Saad, Exercise 5.3** We first consider the system $Ax = b$ with $\mathcal{L} = A\mathcal{K}$. Let

$$\mathcal{K} = \text{span}\{v_1, \dots, v_m\},$$

$$V_m = [v_1 \mid \dots \mid v_m] \in \mathbb{R}^{n \times m}.$$

In the first case, the approximate solution $\tilde{x}$ to $Ax = b$ must satisfy

$$\tilde{x} - x_0 \in \mathcal{K},$$

$$(AV_m)^T(b - A\tilde{x}) = 0.$$

Next, we consider the system $A^T Ax = A^T b$ with $\mathcal{L} = \mathcal{K}$ (*orthogonal* projection). The approximate solution must now satisfy

$$\tilde{x} - x_0 \in \mathcal{K},$$

$$V_m^T(A^T b - A^T A\tilde{x}) = 0$$

$$\Downarrow$$

$$(AV_m)^T(b - A\tilde{x}) = 0.$$

Hence, we get the same system $(AV_m)^T A\tilde{x} = (AV_m)^T b$ or $(AV_m)^T A\delta = (AV_m)^T r_0$, where $\tilde{x} = x_0 + \delta$. This shows that the two methods are equivalent.

2 We use $N = 100$, $v = e_1$, and $m = 10, 20, 30, 40, 50$, as suggested. The results for both **a)** and **b)** are reported in Table 1, where we report the errors $\|V_m^T AV_m - H_m\|_\infty$ and $\|V_m^T V_m - I_m\|_\infty$ after $m = 10, 20, 30, 40, 50$ iterations for Gram–Schmidt (GS) orthogonalization and modified Gram–Schmidt (MGS) orthogonalization. From the table we conclude that MGS performs slightly better than GS in this case.

m	GS		MGS	
	$\ V_m^T AV_m - H_m\ _\infty$	$\ V_m^T V_m - I_m\ _\infty$	$\ V_m^T AV_m - H_m\ _\infty$	$\ V_m^T V_m - I_m\ _\infty$
10	$2.90 \cdot 10^{-13}$	$3.91 \cdot 10^{-14}$	$9.69 \cdot 10^{-14}$	$1.92 \cdot 10^{-14}$
20	$1.33 \cdot 10^{-11}$	$1.72 \cdot 10^{-12}$	$3.89 \cdot 10^{-12}$	$7.73 \cdot 10^{-13}$
30	$2.04 \cdot 10^{-8}$	$2.64 \cdot 10^{-9}$	$5.98 \cdot 10^{-9}$	$1.19 \cdot 10^{-9}$
40	$3.55 \cdot 10^{-3}$	$4.61 \cdot 10^{-4}$	$1.04 \cdot 10^{-3}$	$2.07 \cdot 10^{-4}$
50	80.4	8.04	19.2	2.41

Table 1: MGS is a little bit better than GS.

3 a) Since A is SPD, it follows from Exercise 2, Problem 1c), that A^{-1} is also SPD. Thus, it can be used to define the A^{-1} -norm in the same way as the SPD matrix A defines the A -norm.

b) We are given the system $Ax = b$, where A is SPD. Then, for all $\tilde{x} \in \mathbb{R}^n$,

$$\begin{aligned}\|x - \tilde{x}\|_A^2 &= (x - \tilde{x})^T A (x - \tilde{x}) \\ &= (x - \tilde{x})^T A A^{-1} A (x - \tilde{x}) \\ &= (Ax - A\tilde{x})^T A^{-1} (Ax - A\tilde{x}) \\ &= (b - A\tilde{x})^T A^{-1} (b - A\tilde{x}) \\ &= \tilde{r}^T A^{-1} \tilde{r} \\ &= \|\tilde{r}\|_{A^{-1}}^2.\end{aligned}$$

Hence,

$$x_m = \operatorname{argmin}_{\tilde{x} \in \mathcal{K}_m} \|x - \tilde{x}\|_A^2 = \operatorname{argmin}_{\tilde{x} \in \mathcal{K}_m} \|\tilde{r}\|_{A^{-1}}^2.$$

c) The functional $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is given by $f(w) = \frac{1}{2} w^T A w - w^T b$. This functional attains a minimum since A is SPD. Starting at x_j and minimizing f along the search direction p_j gives

$$\begin{aligned}f(x_j + \alpha p_j) &= \frac{1}{2} (x_j + \alpha p_j)^T A (x_j + \alpha p_j) - (x_j + \alpha p_j)^T b, \\ &= \frac{1}{2} x_j^T A x_j + \alpha x_j^T A p_j + \frac{1}{2} \alpha^2 p_j^T A p_j - x_j^T b - \alpha p_j^T b.\end{aligned}$$

At the minimum,

$$\begin{aligned}0 &= \frac{df}{d\alpha} = x_j^T A p_j + \alpha p_j^T A p_j - p_j^T b \\ &= -p_j^T r_j + \alpha p_j^T A p_j \\ &\Downarrow \\ \alpha &= \frac{(p_j, r_j)}{(A p_j, p_j)}.\end{aligned}$$

But

$$\begin{aligned}p_j &= r_j + \beta_{j-1} p_{j-1} \\ &= r_j + \beta_{j-1} (r_{j-1} + \beta_{j-2} p_{j-2}) \\ &\vdots \\ &= r_j + \sum_{i=0}^{j-1} c_i r_i,\end{aligned}$$

where c_i are constants. Hence, due to the orthogonality of the residuals r_i , we get that $(p_j, r_j) = (r_j, r_j)$, which in turn gives us the result

$$\alpha = \frac{(r_j, r_j)}{(A p_j, p_j)}.$$