

HW 9

1. Since  $\lambda^*$  is an eigenvalue of  $A$ ,

assume  $\underline{v}$  is the eigenvector  $\therefore A\underline{v} = \lambda^* \underline{v}$

$$\begin{aligned}(\lambda^* + r) \underline{v} &= \lambda^* \underline{v} + r \underline{v} \\&= A\underline{v} + r \cdot I \underline{v} \\&= (A + rI) \underline{v}\end{aligned}$$

$\therefore \lambda^* + r$  is an eigenvalue of  $A + rI$ , and  $\underline{v}$  is the eigenvector of both  $A$  and  $A + rI$

$\therefore A$  and  $A + rI$  have the same eigenvectors

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2. Assume  $\underline{v}$  is the eigenvector of  $A$

$$\therefore A\underline{v} = \lambda \underline{v}$$

$$A^{-1} A \underline{v} = A^{-1} \lambda \underline{v}$$

$$\underline{v} = A^{-1} \lambda \underline{v} = \lambda A^{-1} \underline{v}$$

If  $\lambda = 0$ , then  $\underline{v} = 0$ , but eigenvector cannot be 0

$$\therefore \lambda \neq 0$$

$$\therefore A^{-1} \underline{v} = \frac{1}{\lambda} \underline{v}$$

$\therefore \frac{1}{\lambda}$  is an eigenvalue of  $A^{-1}$

Also,  $\underline{v}$  is the eigenvector of  $A^{-1}$  and  $A$

$\therefore$  The eigenvectors of  $A$  are the same as the eigenvectors of  $A^{-1}$

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3. Assume that  $\lambda$  is the eigenvalue of  $P$

Then  $\lambda^2 - \lambda$  is an eigenvalue of  $P^2 - P$

$\therefore P$  is a projection matrix

$$\therefore P^2 = P$$

$\therefore P^2 - P = 0$  and the eigenvalue of  $P^2 - P$  is also 0

$$\therefore \lambda^2 - \lambda = 0$$

$$\therefore \lambda = 0 \text{ or } \lambda = 1$$

The eigenvalues of  $P$  are either 0 or 1

4. (a) proving by contradiction

Assume that  $x_0$  is a local minimum value, Then we assume that there is a point  $x^*$  such that  $f(x^*) < f(x_0)$

Since  $f(x)$  is a convex function, for any  $t \in (0, 1)$

$$f(tx^* + (1-t)x_0) \leq tf(x^*) + (1-t)f(x_0)$$

When  $t \rightarrow 0$ ,  $(tx^* + (1-t)x_0) \rightarrow x_0$  And  $f(tx^* + (1-t)x_0) < f(x_0)$

so  $f(x_0)$  can't be a local minimum value.

So there is a contradiction. Therefore,  $x_0$  is a global minimum value

(b) assume that the set of points equals to minimum value is  $S = \{u \mid f(u) = f(u_0)\}$ , where  $u_0$  is the point that minimize the value

Consider  $u_1, u_2 \in S$ ,  $\lambda \in (0, 1)$

$$u_s = \lambda u_1 + (1-\lambda)u_2$$

$\because u_1, u_2 \in A$ ,  $A$  is convex

$$\therefore f(\lambda u_1 + (1-\lambda)u_2) \leq \lambda f(u_1) + (1-\lambda)f(u_2)$$

$$f(u_s) \leq f(u_0)$$

$\because f(u_s) \geq f(u_0)$  ( $f(u_0)$  is the minimum value)

$$\therefore f(u_s) = f(u_0)$$

$$\therefore u_s \in S$$

$$\therefore \lambda u_1 + (1-\lambda)u_2 \in S$$

$\therefore S$  is convex

(c) There is no such a point

Consider  $V = \mathbb{R}^2$  with  $\|\cdot\|_1$

$$\text{assume } V = \{u \in \mathbb{R}^2 \mid \|u\|_1 \leq 1\} \quad f\left(\frac{1}{2}, \frac{1}{2}\right) = \left|\frac{1}{2} - 1\right| + \left|\frac{1}{2} - 1\right| = 1$$

$$f(1, 0) = 1 \quad \therefore (1, 0) \text{ and } \left(\frac{1}{2}, \frac{1}{2}\right) \text{ are also } u^*$$

$\therefore u^*$  is not unique.

$$J. (a) \underline{V}_1 = P_A \underline{V}_0 = \frac{\langle \underline{V}_0 | \underline{a} \rangle}{\|\underline{a}\|^2} \underline{a} = \frac{50}{\sqrt{5}} \underline{a} = (10, 20)^T$$

$$\underline{V}_2 = P_B \underline{V}_1 = \frac{\langle \underline{V}_1 | \underline{b} \rangle}{\|\underline{b}\|^2} \underline{b} = 10 \underline{b} = (10, 0)^T$$

$$\underline{V}_3 = P_A \underline{V}_2 = \frac{\langle \underline{V}_2 | \underline{a} \rangle}{\|\underline{a}\|^2} \underline{a} = \frac{10}{\sqrt{5}} \underline{a} = (2, 4)^T$$

$$\underline{V}_4 = \frac{\langle \underline{V}_3 | \underline{b} \rangle}{\|\underline{b}\|^2} \underline{b} = 2 \underline{b} = (2, 0)^T$$

(b) when  $n$  is odd, it is a scalar multiple of  $\underline{a}$

when  $n$  is even, it is a scalar multiple of  $\underline{b}$

And the scalar is multiplied by  $\frac{\sqrt{5}}{5}$  when  $n$  increasing 1.

(c) when  $n$  is even,  $n+1$  is odd,  $\underline{V}_n = \alpha_n \underline{b}$

$$\underline{V}_{n+1} = P_A \underline{V}_n = \frac{\underline{a} \underline{a}^T}{\|\underline{a}\|^2} \alpha_n \underline{b} = \alpha_n \frac{\underline{a}^T \underline{b}}{\|\underline{a}\|^2} \underline{a} = \alpha_{n+1} \underline{a}$$

when  $n$  is odd,  $n+1$  is even,  $\underline{V}_n = \alpha_n \underline{a}$

$$\underline{V}_{n+1} = P_B \underline{V}_n = \alpha_n \frac{\underline{b} \underline{b}^T}{\|\underline{b}\|^2} \underline{a} = \alpha_n \frac{\underline{b}^T \underline{a}}{\|\underline{b}\|^2} \underline{b} = \alpha_{n+1} \underline{b}$$

$$\therefore \alpha_{n+1} = \alpha_n$$

$$\therefore \underline{a}^T \underline{b} = \underline{b}^T \underline{a} = 4$$

$$\|\underline{a}\| = \|\underline{b}\| = \sqrt{5}$$

$$\therefore \alpha_{n+1} = \frac{4}{5} \alpha_n$$

$$(d) P_C = \tilde{C} \tilde{C}^T \quad P_A = [\tilde{C} \tilde{A}] [\tilde{C} \tilde{A}]^T = \tilde{C} \tilde{C}^T + \tilde{A} \tilde{A}^T = P_C + \tilde{A} \tilde{A}^T$$

$$P_B = [\tilde{C} \tilde{B}] [\tilde{C} \tilde{B}]^T = \tilde{C} \tilde{C}^T + \tilde{B} \tilde{B}^T = P_C + \tilde{B} \tilde{B}^T$$

$$P_A P_B = (P_C + \tilde{A} \tilde{A}^T) (P_C + \tilde{B} \tilde{B}^T) = P_C + \tilde{A} \tilde{A}^T \tilde{B} \tilde{B}^T$$

$$\text{For } n \text{ odd, } \underline{V}_n = P_C \underline{V}_0 + \tilde{A} \underline{z}$$

$$\underline{V}_{n+1} = P_B \underline{V}_n = P_C \underline{V}_0 + \tilde{B} (\tilde{B}^T \tilde{A} \underline{z}) = P_C \underline{V}_0 + \tilde{B} \underline{z}$$

$$\text{for } \underline{z} = \tilde{B}^T \tilde{A} \underline{z}, \quad \gamma \triangleq \max_{\underline{z} \neq 0} \frac{\|\tilde{B}^T \tilde{A} \underline{z}\|}{\|\underline{z}\|} = \max_{\underline{z} \in \mathbb{R}^n} \|\tilde{B}^T \tilde{A} \underline{z}\| = \|\tilde{B}^T \tilde{A}\|$$

Similarly, when  $n$  is even, the decay rate equals to  $\tilde{A}^T \tilde{B}$

Thus,  $\gamma$  equals the largest singular value of  $\tilde{B}^T \tilde{A}$  and  $\|\underline{V}_n - P_C \underline{V}_0\| \leq \gamma^{n+1} \|\underline{V}_0 - P_C \underline{V}_0\|$

6. (a) Since  $G$  is positive definite, we can write  $G = U^T \Lambda U$  where  $U$  is orthogonal and  $\Lambda$  is a positive diagonal matrix

$$\underline{v}^T G \underline{v} = \underline{v}^T U^T \Lambda^{\frac{1}{2}} \Lambda^{\frac{1}{2}} U \underline{v} = (\underline{v}^T U^T \Lambda^{\frac{1}{2}}) (\Lambda^{\frac{1}{2}} U \underline{v}) = \|\Lambda^{\frac{1}{2}} U \underline{v}\|^2$$

(b) We can use the triangle inequality

$$(\alpha \underline{u} + (1-\alpha) \underline{v})^T G (\alpha \underline{u} + (1-\alpha) \underline{v}) + \underline{c}^T (\alpha \underline{u} + (1-\alpha) \underline{v})$$

$$= \|A(\alpha \underline{u} + (1-\alpha) \underline{v})\|^2 + \alpha \underline{c}^T \underline{u} + (1-\alpha) \underline{c}^T \underline{v}$$

$$\leq \alpha \|A \underline{u}\|^2 + (1-\alpha) \|A \underline{v}\|^2 + \alpha \underline{c}^T \underline{u} + (1-\alpha) \underline{c}^T \underline{v}$$

$$= \alpha (\underline{u}^T G \underline{u} + \underline{c}^T \underline{u}) + (1-\alpha) (\underline{v}^T G \underline{v} + \underline{c}^T \underline{v})$$

$$(c) \quad \underline{v}^T G \underline{v} + \underline{c}^T \underline{v} = (\underline{v} - \underline{v}_0)^T G (\underline{v} - \underline{v}_0) + d$$

$$\underline{v}^T G \underline{v} + \underline{c}^T \underline{v} = \underline{v}^T G \underline{v} - \underline{v}_0^T G \underline{v}_0 + d$$

$$d = \underline{v}_0^T G \underline{v}_0 \quad \underline{v}_0 = G^{-1} \underline{c}$$

$G$  is invertible  $\because$  it is positive definite

the minimum value  $d = \underline{v}_0^T G \underline{v}_0$  where  $\underline{v}_0 = G^{-1} \underline{c}$