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## Math221: Matrix Computations Homework \#9 Solutions

- Problems 5.1, 5.2, 5.4, 5.5, 5.6, 5.7, 5.18.
- Problem 5.4 Solution: We will only consider the second bullet. The first is a special case of the second with $n=m+1$. Let $\mathbf{R}^{j}$ be any $j$ dimensional subspace of $\mathcal{R}^{m}$, let

$$
\widehat{\mathbf{R}}^{j}=\left\{\binom{\mathbf{x}}{\mathbf{0}_{n-m}}, \quad \text { where } \quad \mathbf{x} \in \mathbf{R}^{j} .\right\}
$$

In other words, $\widehat{\mathbf{R}}^{j}$ is the set of vectors obtained by padding zeros to the vectors in $\mathbf{R}^{j}$. It is easy to show that $\widehat{\mathbf{R}}^{j}$ is a $j$ dimensional subspace of $\mathcal{R}^{n}$. For any non-zero vector $u \in \mathbf{R}^{j}$, let $\widehat{u}$ be the corresponding vector in $\widehat{\mathbf{R}}^{j}$. We can easily verify that

$$
\frac{u^{T} H u}{u^{T} u}=\frac{\widehat{u}^{T} A \widehat{u}}{\widehat{u}^{T} \widehat{u}} .
$$

In other words, $\rho(u, H)=\rho(\widehat{u}, A)$. Let $\widetilde{\mathbf{R}}^{j}$ be any $j$ dimensional subspace of $\mathcal{R}^{n}$. Since

$$
\min _{0 \neq u \in \mathbf{R}^{j}} \rho(u, H)=\min _{0 \neq \widehat{u} \in \widehat{\mathbf{R}}^{j}} \rho(\widehat{u}, A) \leq \max _{\widetilde{\mathbf{R}}^{j}} \min _{0 \neq \widetilde{u} \in \widetilde{\mathbf{R}}^{j}} \rho(\widetilde{u}, A)=\alpha_{j}
$$

by the Courant-Fischer minimax theorem, it follows by the same theorem that

$$
\theta_{j}=\max _{\mathbf{R}^{j}} \min _{0 \neq u \in \mathbf{R}^{j}} \rho(u, H) \leq \alpha_{j} .
$$

Similarly, let $\mathbf{S}^{j}$ be a $j$ dimensional subspace of $\mathcal{R}^{m}$, let $\widehat{\mathbf{S}}^{j}$ bet the set of vectors obtained by padding zeros to the vectors in $\mathbf{S}^{j}$. It is again easy to show that $\widehat{\mathbf{S}}^{j}$ is a $j$ dimensional subspace of $\mathcal{R}^{n}$. For any non-zero vector $u \in \mathbf{S}^{j}$, again let $\widehat{u}$ be the corresponding vector in $\widehat{\mathbf{S}}^{j}$. We have
by the Courant-Fischer minimax theorem, it follows by the same theorem that

$$
\theta_{j}=\min _{\mathbf{S}^{m-j+1}} \max _{0 \neq u \in \mathbf{S}^{m-j+1}} \rho(u, H) \geq \alpha_{j+n-m}
$$

- Problem 5.5 Solution: First of all, for any non-zero vector $u \in \mathbf{R}^{n}$, we have

$$
\theta_{n} \leq \frac{u^{T} H u}{u^{T} u} \leq \theta_{1}
$$

It follows that

$$
\frac{u^{T} A u}{u^{T} u}+\theta_{n} \leq \frac{u^{T}(A+H) u}{u^{T} u} \leq \frac{u^{T} A u}{u^{T} u}+\theta_{1}
$$

for any non-zero vector $u \in \mathbf{R}^{n}$. By the Courant-Fischer minimax theorem, we have

$$
\lambda_{j}=\min _{\mathbf{S}^{n-j+1}} \max _{0 \neq u \in \mathbf{S}^{n-j+1}} \frac{u^{T}(A+H) u}{u^{T} u} \leq \min _{\mathbf{S}^{n-j+1}} \max _{0 \neq u \in \mathbf{S}^{n-j+1}}\left(\frac{u^{T} A u}{u^{T} u}+\theta_{1}\right)=\alpha_{j}+\theta_{1} .
$$

Similarly,

$$
\lambda_{j}=\min _{\mathbf{S}^{n-j+1}} \max _{0 \neq u \in \mathbf{S}^{n-j+1}} \frac{u^{T}(A+H) u}{u^{T} u} \geq \min _{\mathbf{S}^{n-j+1}} \max _{0 \neq u \in \mathbf{S}^{n-j+1}}\left(\frac{u^{T} A u}{u^{T} u}+\theta_{n}\right)=\alpha_{j}+\theta_{n} .
$$

- Problem 5.6 Solution: Let

$$
\mathcal{A}=\left(\begin{array}{cc}
0 & A \\
A^{T} & 0
\end{array}\right)=\left(\begin{array}{ccc}
0 & A_{1} & A_{2} \\
A_{1}^{T} & 0 & 0 \\
A_{2}^{T} & 0 & 0
\end{array}\right)
$$

and let

$$
\mathcal{A}_{1}=\left(\begin{array}{cc}
0 & A_{1} \\
A_{1}^{T} & 0
\end{array}\right) .
$$

Then $\tau_{j}$ and $\sigma_{j}$ are the $j$-th largest eigenvalues of $\mathcal{A}_{1}$ and $\mathcal{A}$, respectively. Since $\mathcal{A}_{1} \in$ $\mathbf{R}^{(n+m) \times(n+m)}$ is a leading principle submatrix of $\mathcal{A} \in \mathbf{R}^{(2 n) \times(2 n)}$, it follows from Problem 5.4 that

$$
\sigma_{j} \geq \tau_{j} \geq \sigma_{j+n-m}
$$

- Problem 5.7 Solution: We only consider the case where $d \neq 0$. Let $q_{d}=d /\|d\|_{2}$. Since $d$ is orthogonal to $q$, there must exist a matrix $\widehat{Q}$ such that $Q \stackrel{\text { def }}{=}\left(q q_{d} \widehat{Q}\right) \in \mathbf{R}^{n \times n}$ is an orthogonal matrix. It follows that

$$
(q+d) q^{T}-I=Q\left(\begin{array}{c}
1 \\
\|d\|_{2} \\
0
\end{array}\right)\left(\begin{array}{lll}
1 & 0 & 0
\end{array}\right) Q^{T}-Q Q^{T}=Q\left(\begin{array}{ccc}
0 & 0 & 0 \\
\|d\|_{2} & -1 & \\
0 & 0 & -I
\end{array}\right) Q^{T} .
$$

Hence

$$
\left\|(q+d) q^{T}-I\right\|_{2}=\left\|\left(\begin{array}{ccc}
0 & 0 & 0 \\
\|d\|_{2} & -1 & \\
0 & 0 & -I
\end{array}\right)\right\|_{2}=\sqrt{1+\|d\|_{2}^{2}}=\|q+d\|_{2} .
$$

