Indian Statistical Institute, Bangalore

B. Math. Second Year

First Semester - Optimization

Duration : 3 hours

Semester Exam

Total marks: 50

Date : November 22, 2017

Section I: Answer any four and each question carries 6 marks.

1. Prove QR-decomposition for full column rank matrices and prove the decomposition is unique if R is required to have positive entries on the diagonal.

Solution: Let A be an $m \times n$ matrix with $m \ge n$ and rank of A is n. Let a_i be the *i*th column of A. Then $\{a_1, ..., a_n\}$ is a linearly independent set in \mathbb{R}^m . Let

$$u_1 = a_1, u_2 = \frac{\langle u_1, a_2 \rangle}{||u_1||^2} u_1, \tag{1}$$

$$u_i = a_i - \sum_{k=1}^{i-1} \frac{\langle u_k, a_i \rangle}{||u_k||^2} u_k.$$
(2)

Let $\bar{e}_i = \frac{u_i}{||u_i||}$ for all $i \leq i \leq n$. Then $\{\bar{e}_1, ..., \bar{e}_n\}$ is an orthonormal set, such that span $\{\bar{e}_1, ..., \bar{e}_n\} = \text{span}\{a_1, ..., a_n\}$. Let $Q = [\bar{e}_1 \bar{e}_n]$. Then Q is an $m \times n$ orthogonal matrix.

Let
$$R = \begin{pmatrix} \langle \bar{e_1}, a_1 \rangle & \langle \bar{e_1}, a_2 \rangle & \dots & \bar{e_1}, a_n \rangle \\ 0 & \langle \bar{e_2}, a_2 \rangle & \dots & \langle \bar{e_2}, a_n \rangle \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \langle \bar{e_n}, a_n \rangle \end{pmatrix}$$

Then A = QR.

Now we show that the QR-decomposition is unique if R is required to have positive entries on the diagonal. Let

$$A = Q_1 R_1 = Q_2 R_2.$$

Now

$$R_1^t R_1 = R_1^t Q_1^t Q_1 R_1 = (Q_1 R_1)^t Q_1 R_1 = A^t A.$$

Similarly, $R_2^t R_2 = A^t A$. Now

$$R_2 R_1^{-1} = (R_2^t)^{-1} R_1^t = ((R_2 R_1^{-1})^t)^{-1}.$$

 $R_2 R_1^{-1}$ is upper triangular and $((R_2 R_1^{-1})^t)^{-1}$ is lower triangular. Hence $R_2 R_1^{-1} = D$, where D is a diagonal matrix. But again $D = (D^t)^{-1} = D^{-1}$, which implies that D is the identity matrix. Hence $R_1 = R_2$ and consequently $Q_1 = Q_2$.

2. If $A = UDV^t$ is the singular value decomposition, prove that Ax = b has a solution if and only if $b \perp U_i$ for all i > k where k is the rank of A.

Solution: Let $\sigma_1, \sigma_2, \ldots, \sigma_k$ be the singular values of A. Then the non-zero entries of the diagonal matrix D are $\sigma_1, \sigma_2, \ldots, \sigma_k$ respectively.

Now

$$Ax = b \Leftrightarrow UDV^t x = b \Leftrightarrow DV^t x = U^t b.$$

As D is a diagonal matrix with first k entries being non-zero and

$$U^{t}b = \begin{pmatrix} < U_{1}, b > \\ < U_{2}, b > \\ \vdots \\ < U_{m}, b > \end{pmatrix},$$

it follows that Ax = b has a solution if and only if $b \perp U_i$ for all i > k.

3. Prove that Spr(A) has algebraic multiplicity one for a nonnegative irreducible matrix A.

Solution: Let r = Spr(A) and $\phi(\lambda) = det(\lambda I - A)$, where I is the identity matrix. it is enough to show that $\phi'(r) \neq 0$. Let $(\lambda I - A)_{kl}$ be the matrix obtained from $(\lambda I - A)$ by deleting kth row and lth column. Let

$$c_{ij}(\lambda) = (-1)^{i+j} det[(\lambda I - A)_{ij}] \forall i, j.$$

Let $c(\lambda) = (c_{ij}(\lambda))$. Then

$$[(\lambda I - A)c(\lambda)] = \phi(\lambda)I = c(\lambda)(\lambda I - A).$$

Differentiating with respect to λ , we get

$$c'(\lambda)(\lambda I - A) + c(\lambda) = \phi'(\lambda)I.$$

Putting $\lambda = r$, we get

$$c'(r)(rI - A) + c(r) = \phi'(r)I.$$

Let $T = \begin{pmatrix} A_1 & O_{n-1\times 1} \\ O_{1\times n-1} & 0 \end{pmatrix}$, where A_1 is obtained from A by deleting the nth row and nth column. Then $T \ge 0$ and $A \ge T$. Moreover T is not irreducible. Hence $T \ne A$. Since $A \ge T$, $r = \operatorname{Spr}(A) \ge \operatorname{Spr}(T)$ and (rI - T) is one-one. Therefore, $c(r) \ne 0$. Let $u \in C_A \cap B$ such that A(u) = ru. Now

$$c'(r)(rI - A)(u) + c(r)u = \phi'(r)I(u)$$

$$\Rightarrow c(r)(u) = \phi'(r)(u)$$

$$\Rightarrow \sum c(r)_{nj}u_j = \phi'(r)u_n.$$

We have $u \in C_A \cap B$ and A(u) = ru, which implies that

$$(rI - A)c(r) = \phi(r)I = O_{n \times n}$$

Hence $(rI - A)c_j = 0$, where c_j is the *j*th column of c(r). So, $A(c_j) = rc_j$ for all *j*. Therefore, all column vectors of c(r) are eigenvectors of *A* corresponding to the eigenvalue *r*. Since the eigenvalue *r* has geometric multiplicity 1, it follows that each column of c(r) is a multiple of *u*.

Now A^t is also non-negative and irreducible and $\operatorname{Spr}(A) = \operatorname{Spr}(A^t) = r$. There exists $v \in B$ such that $A^t(v) = rv$ and $v_i > 0$ for all *i*. It follos as above that all rows of c(r) are constant multiples of *v*. Therefore, $c(r)_n^t$ is a non-zero vector with all components having same sign. Hence

$$\sum_{j=1}^{n} c_{nj}(r) u_j \neq 0 \ (u_j \neq 0).$$

Then it follows that $(c(r)u)_n \neq 0$. So, $\phi'(r)u = c(r)u \neq 0$, which implies that $\phi'(r) \neq 0$.

4. Solve by simplex method

Maximize
$$9x_1 + 10x_2$$

subj
$$x_1 + 2x_2 \le 8$$

$$5x_1 + 2x_2 \le 16$$

$$x > 0.$$

Solution: Starring with the initial simplex tableau and applying simplex method, we get

x_1	x_2	x_3	x_4	z	
	2				
5	2	0	1	0	16
-9	-10	0	0	1	0

Applying the operation $\frac{1}{2}R_1$ we get

Then applying $R_2 - 2R_1$ and $R_3 + 10R_1$, we get

Again $\frac{1}{4}R_2$ gives

Then applying $R_1 - \frac{1}{2}R_2$ and $R_3 + 4R_2$, we get

Hence the optimal solution is $x_1 = 2$, $x_2 = 3$ and the maximum value is 48.

5. Solve the following game: Ruby conceals either a Rs. 1 coin or Rs. 2 coin in her hand; Charm guesses 1 or 2, winning the coin if he guesses the number.

Solution: The matrix corresponding to this game is

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 2 \end{pmatrix}$$

. Therefore, it does not have any saddle point, so it is a non-strictly determind game. Hence the optimal strategies are given by, $p^* = (p_1^*, p_2^*)^t$ and $q^* = (q_1^*, q_2^*)^t$, where

$$p_1^* = \frac{d-c}{(a-b)-(c-d)} = \frac{2}{3}$$

$$p_2^* = \frac{a-b}{(a-b)-(c-d)} = \frac{1}{3},$$
$$q_1^* = \frac{d-b}{(a-b)-(c-d)} = \frac{2}{3},$$
$$q_2^* = \frac{a-c}{(a-b)-(c-d)} = \frac{1}{3}.$$

6. Prove the existence and uniqueness of minimum norm least square solution to Ax = b.

Solution: Let A be an $m \times n$ matrix and $A = UDV^t$ be a singular value decomposition of A. $D = diag(\sigma_1, ..., \sigma_r), r = \rho(A)$. Then the minimum norm least square solution to Ax = b is given by $\bar{x} = VD^+U^t b$, where $D^+ = diag(\frac{1}{\sigma_1}, ..., \frac{1}{\sigma_r})$.

$$||Ax - b||^2 = ||UDV^tx - b||^2 = ||DV^tx - U^tb||^2$$

. Let $y = V^t x$, $c = U^t b$, then ||y|| = ||x||. Now

$$min_{x\in\mathbb{R}^n}||Ax-b||^2 = min_{y\in\mathbb{R}^n}||Dy-c||^2.$$

$$||Dy - c||^{2} = \sum_{i=1}^{r} (\sigma_{i}y_{i} - c_{i})^{2} + \sum_{i>r} c_{i}^{2} \ge \sum_{i>r} c_{i}^{2}$$

. Define the vector \bar{y} as follows: the *i*th entry is $\frac{c_i}{\sigma_i}$ if $i \leq r$ and the *i*th entry is 0 if i > r. Then

$$||D\bar{y} - c||^2 = \sum_{i>r} c_i^2 \le ||Dy - c||^2$$

for all $y \in \mathbb{R}^n$. Now

$$||Dy - c||^2 = \sum_{i > r} c_i^2 \Rightarrow y_i = \frac{c_i}{\sigma_i} \forall i \le r \Rightarrow ||y|| \ge ||\bar{y}||.$$

Hence the proof of existence and uniqueness.

Section II: Answer any two and each question carries 13 marks.

1. (a) Let s_i be the *i*-th singular value of A. Prove that $s_i \leq ||A - B||$ for any matrix B with rank (B) < i (Marks: 7).

Solution: Let A be of order $p \times q$ and $A = VDU^*$ be the singular value decomposition of A, where $D = diag(s_1, ..., s_r)$. Let B be a $p \times q$ matrix such

that rank(B) < i. Let u_i denote the *i*th column of U and v_i denote the *i*th column of V. Let

$$U_1 = [u_1, ..., u_i, 0, ..., 0]$$

and

$$V_1 = [v_1, ..., v_i, 0, ..., 0].$$

Since rank $(V_1^* B U_1) \leq \operatorname{rank}(B) \leq i - 1$, there exists $c \in \mathbb{C}^q$ such that ||c|| = 1, $c \in \operatorname{span}\{e_1, \dots, e_i\}$ and $V^* B U_1(c) = 0$

$$\Rightarrow \sum_{j=1}^{i} c_j < B(u_j), v_k \ge 0 \forall 1 \le k \le i$$
$$\Rightarrow \left\langle B(\sum_{j=1}^{i} c_j u_j), v_k \right\rangle = 0, 1 \le k \le i.$$

Now let $x = \sum_{j=1}^{i} c_j u_j$, then $B(x) \perp v_k \forall 1 \leq k \leq i$. We know $A = \sum_{j=1}^{r} s_j v_j u_j^*$. Then

$$A(x) = \sum_{l,j} s_l c_j v_l u_l^* u_j = \sum_{j=1}^{i} s_j c_j v_j.$$

Now

$$||A(x) - B(x)||^{2} = ||\sum_{j=1}^{i} s_{j}c_{j}v_{j} - \sum_{j=i+1}^{p} \langle B(x), v_{j} \rangle v_{j}||$$
$$= \sum_{j=1}^{i} |s_{j}|^{2}|c_{j}|^{2} + \sum_{j=i+1}^{p} |\langle B(x), v_{j} \rangle v_{j}|^{2}.$$

Hence

$$||A(x) - B(x)|| \ge s_i.$$

As
$$x = \sum_{j=1}^{i} c_j u_j$$
 and $||c|| = 1$, it follows that $||x|| = 1$. Hence $s_i \le ||A - B||$.
(b) For $A = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{3} & 0 & \frac{2}{3} \\ \frac{1}{3} & \frac{2}{3} & 0 \end{pmatrix}$, use Perron-Frobenius theory to compute $\lim_{n\to\infty} A^n$.

Solution: A is a primitive (since A^2 is a positive matrix) and stochastic matrix. So, 1 is the dominant eigenvalue for A and A^t as well. Also let $u = (1, 1, 1)^t$ and v = (1/4, 3/8, 3/8). Then it is easy to see that A(u) = u and $A^t(v) = v$. We also note that $\langle u, v \rangle = 1$. Hence, by perron-Frobenius theory,

$$\lim_{n \to \infty} A^n = uv^t = \begin{pmatrix} 1/4 & 3/8 & 3/8\\ 1/4 & 3/8 & 3/8\\ 1/4 & 3/8 & 3/8 \end{pmatrix}.$$

P.T.O

2. (a) Let $A \ge 0$ be a primitive matrix, v and u be positive eigenvectors for A and A^t with eigenvalue $\lambda = \operatorname{Spr}(A)$. If $u^t v = 1$ and $r = \operatorname{Spr}(A)$, prove that $(\frac{A}{r})^n \to v u^t$ exponentially (Marks: 6).

Solution: Let $M = vu^t$. Note that

$$u^t M = u^t v u^t = u^t$$

and

$$M(v) = vu^t v = v.$$

Now let $W = \langle u \rangle^{\perp}$. For $w \in W$

$$< u, A(w) > = < A^t(u), w > = \lambda < u, w > = 0.$$

Hence $A(w) \in W$ and therefore, W is an invariant subspace for A. Also for $w \in W$,

$$M(w) = vu^t w = 0.$$

Let T be an operator such that T(w) = A(w) for $w \in W$ and T(u) = 0. Then Spr(T) < Spr(A). Let $\beta = Spr(T)$ and $\varepsilon > 0$ be such that $\beta + \varepsilon < \lambda$. Then we know that there exists $N \in \mathbb{N}$ such that

$$||T^n||^{1/n} \le \beta + \varepsilon \ \forall \ n \ge N.$$

i.e. $||T^n|| \le (\beta + \varepsilon)^n \ \forall \ n \ge N.$

Now for $w \in W$,

$$\begin{split} ||\left(\frac{A}{\lambda}\right)^{n}(w)|| &= \left(\frac{1}{\lambda}\right)^{n} ||A^{n}(w)|| = \left(\frac{1}{\lambda}\right)^{n} ||T^{n}(w)|| \\ &\leq \frac{1}{\lambda^{n}} ||T^{n}||||w|| \leq \left(\frac{\beta+\varepsilon}{\lambda}\right)^{n} ||w||, \end{split}$$

which tends to 0 exponentially as $n \to \infty$. This implies that $\left(\frac{A}{\lambda}\right)^n \to M = vu^t$ exponentially, since $\left(\frac{A}{\lambda}\right)^n (v) = v = M(v)$.

(b) Let A and B be two matrices such that $b_{ij} = a_{ij} + r$. Then show that two strategy vectors p and q are optimal for A if and only if they are optimal for B and value of the game B is value of game A plus r.

Solution: Let A and B be $m \times n$ matrices. For any $p = (p_1, ..., p_m)^t$ and $q = (q_1, ..., q_n)$,

$$p^{t}Bq = \sum_{i=1}^{m} \sum_{j=1}^{n} b_{ij}p_{i}q_{j} = \sum_{i=1}^{m} \sum_{j=1}^{n} (a_{ij} + r)p_{i}q_{j} = p^{t}Aq + r.$$

Now let p^* and q^* be an optimal strategy for B. Then

$$pBq^* \le v(B) \le p^*Bq \ \forall \ p \in \mathbb{R}^m, q \in \mathbb{R}^n.$$

Hence by the calculation above,

$$pAq^* + r \le v(B) \le p^*Aq + r \ \forall \ p \in \mathbb{R}^m, q \in \mathbb{R}^n,$$

equivalently,

$$pAq^* \le v(B) - r \le p^*Aq \ \forall \ p \in \mathbb{R}^m, q \in \mathbb{R}^n.$$

This shows that v(A) = v(B) - r. We have also shown that p^* and q^* is also an optimal strategy for A as well. By a similar argument as above it can also be shown that an optimal strategy for A is also an optimal strategy for B.

3. (a) Describe and justify a method to avoid anticycling in LP (Marks: 6).

(b) State and prove a necessary and sufficient condition in terms of the matrix entries for a 2×2 - matrix game to be non-strictly determined.

Solution: Let $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$ be a 2 × 2 matrix corresponding to a matrix game. The game is non-strictly determind if and only if none of the matrix entries is a saddle point. We show that if there is a saddle point then the game is strictly determind, from which the assertion follows. Let a_{12} be a saddle point. Then $a_{12} \leq a_{11}$ and $a_{12} \geq a_{22}$. Then $e_1^t A e_j \geq a_{12}$ for j = 1, 2 and $e_i^t A e_2 \leq a_{12}$ for i = 1, 2. This shows that $v(A) = a_{12}$ with e_1 and e_2 determining an optimal strategy.

(c) Solve the $n \times n$ -game $A = I_n$ (Marks: 3).

Solution: We claim that $p = q = (\frac{1}{n}, ..., \frac{1}{n})^t$ will provide an optimal strategy for this game. If $r = (r_1, ..., r_n)^t$ is any other vector in \mathbb{R}^n with $v_1 + ... + v_n = 1$, then

$$p^t A v = < p, v > = \frac{1}{n}.$$

Similarly,

$$v^t A q = < v, q > = \frac{1}{n}.$$

This shows that $p = q = (\frac{1}{n}, ..., \frac{1}{n})^t$ defines an optimal strategy for this game and $v(A) = v(I_n) = \frac{1}{n}$.