IMPERIAL COLLEGE LONDON

DEPARTMENT OF ELECTRICAL AND ELECTRONIC ENGINEERING
EXAMINATIONS 2018

MSc and EEE PART IV: MEng and ACGI

Corrected copy

TOPICS IN LARGE DIMENSIONAL DATA PROCESSING

Tuesday, 15 May 10:00 am

Time allowed: 3:00 hours

There are FOUR questions on this paper.

Answer ALL questions.

All questions carry equal marks

Any special instructions for invigilators and information for candidates are on page 1.

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EE4-66 Topics in Large Dimensional Data Processing

Instructions for Candidates

Answer all questions. Each question carries 20 marks.

1. (Linear Algebra)

(a) Let $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ be a matrix. Let $\boldsymbol{A} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^T$ be its singular value decomposition (SVD), where $\boldsymbol{U} = [\boldsymbol{u}_1, \cdots, \boldsymbol{u}_m]$ and $\boldsymbol{V} = [\boldsymbol{v}_1, \cdots, \boldsymbol{v}_m]$ are the left and right singular vector matrices respectively, and $\boldsymbol{\Sigma} \in \mathbb{R}^{m \times n}$ is the diagonal matrix of which the diagonal entries are the singular values $\sigma_1 \geq \cdots \geq \sigma_{\min(m,n)} \geq 0$.

i State the definition of the eigenvalue decomposition of a square matrix $\boldsymbol{M} \in \mathbb{R}^{m \times m}$. [1]

ii Let $\boldsymbol{B} = \boldsymbol{A}\boldsymbol{A}^T$. State the relationship between the eigenvalue decomposition of the matrix $\boldsymbol{B}$ and the singular value decomposition of the matrix $\boldsymbol{A}$. Justify your answer using the definition of the eigenvalue decomposition. [2]

iii Let $\boldsymbol{A}^\dagger$ be the pseudo-inverse of $\boldsymbol{A}$. Express $\boldsymbol{A}^\dagger$ using the singular value decomposition of $\boldsymbol{A}$. [1]

iv Suppose that $m > n$ and $\text{rank}(\boldsymbol{A}) = n$. For a vector $\boldsymbol{x} \in \mathbb{R}^m$, denote the projection of $\boldsymbol{x}$ on the subspace $\text{span}(\boldsymbol{A})$ by $\boldsymbol{x}_p = \text{proj}(\boldsymbol{x}, \boldsymbol{A})$. Write the formula to compute $\boldsymbol{x}_p$ using the matrices $\boldsymbol{A}$ and $\boldsymbol{A}^\dagger$. [1]

v Prove the projection residue vector $\boldsymbol{x}_r = \boldsymbol{x} - \boldsymbol{x}_p$ is orthogonal to $\boldsymbol{A}$. [2]

vi Prove that the shortest distance between $\boldsymbol{x}$ and any vector $\boldsymbol{v} \in \text{span}(\boldsymbol{A})$ is achieved by $\|\boldsymbol{x} - \boldsymbol{x}_p\|_2$, i.e.,

$$\|\boldsymbol{x} - \boldsymbol{x}_p\|_2 = \min\{\|\boldsymbol{x} - \boldsymbol{v}\| : \boldsymbol{v} \in \text{span}(\boldsymbol{A})\}.$$

[3]

(b)

i For a given square matrix $\boldsymbol{M}$, let $\text{tr}(\boldsymbol{M}) = \sum_i M_{i,i}$ denote its trace function. For any given matrices $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ and $\boldsymbol{B} \in \mathbb{R}^{n \times m}$, prove that $\text{tr}(\boldsymbol{AB}) = \text{tr}(\boldsymbol{BA})$. [2]

ii The Frobenius norm of a matrix $\boldsymbol{A}$ is defined as $\|\boldsymbol{A}\|_F = \sqrt{\sum_{i,j} A_{i,j}^2}$. Express the squared Frobenius norm $\|\boldsymbol{A}\|_F^2$ using the singular values of $\boldsymbol{A}$. Justify your answer. [2]

iii The ℓ_2-norm of a matrix $\boldsymbol{A}$ is defined as

$$\|\boldsymbol{A}\|_2 = \sup\{\|\boldsymbol{A}\boldsymbol{x}\|_2 : \boldsymbol{x} \in \mathbb{R}^n \text{ and } \|\boldsymbol{x}\|_2 = 1\}.$$

Express $\|A\|_2$ using the singular values of A. Justify your answer. [3]

iv The nuclear norm of a matrix A is defined as

$$\|A\|_* = \sum_{i=1}^{\min(m,n)} \sigma_i(A).$$

Let A be symmetric and non-negative definite, i.e., $A = A^T$ and $A \geq 0$. Prove that

$$\|A\|_* = \operatorname{tr}(A)$$

using the singular value decomposition of A. [3]

(Total marks: 20)

2. (Sparse Recovery)

(a) Consider the sparse recovery problem $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x}$ where $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ is a flat matrix, and $\boldsymbol{x} \in \mathbb{R}^n$ is the unknown sparse vector.

i The famous Lasso formulation for sparse recovery is given by

$$\min_{\boldsymbol{x}} \frac{1}{2} \|\boldsymbol{y} - \boldsymbol{A}\boldsymbol{x}\|_2^2 + \lambda \|\boldsymbol{x}\|_1 , \qquad (2.1)$$

where $\lambda > 0$ is a parameter.

A. The soft thresholding function $\eta(\cdot)$ is designed to solve the simplified Lasso problem

$$\min_{\boldsymbol{x}} \frac{1}{2} \|\boldsymbol{x} - \boldsymbol{z}\|_2^2 + \lambda \|\boldsymbol{x}\|_1 . \qquad (2.2)$$

State the form of the soft thresholding function $\eta(\cdot)$. (Derivations are not required.) [1]

B. State the Iterative Shrinkage Thresholding (IST) algorithm to solve the Lasso problem (2.1). (Derivations are not required.) [1]

ii Suppose that the sparsity level S of $\boldsymbol{x}$ is given. The Iterative Hard Thresholding (IHT) algorithm is one of the greedy algorithms designed for sparse recovery.

A. State the hard thresholding function $H_S(\cdot)$. Note that soft thresholding function is designed to solve the simplified Lasso problem (2.2). State the optimisation problem that the hard thresholding function is designed to solve. [2]

B. State the IHT algorithm. Note that IST is designed to solve the Lasso problem (2.1). State the optimisation problem that IHT is designed to solve. [2]

(b) Consider the low-rank matrix recovery problem $\boldsymbol{y} = \mathcal{A}(\boldsymbol{X})$, where $\mathcal{A} : \mathbb{R}^{n_r \times n_c} \to \mathbb{R}^m$ is a linear operator.

i State the counterpart of the IST algorithm designed to solve the low-rank matrix recovery problem. Give the definition of corresponding soft thresholding function used in your algorithm. [2]

ii State the counterpart of the IHT algorithm designed to solve the low-rank matrix recovery problem. Give the definition of corresponding hard thresholding function used in your algorithm. [2]

iii Consider a matrix $\boldsymbol{X}$ with rank 1. The partial observations of $\boldsymbol{X}$ are given as follows:

$$\begin{bmatrix} 1 & ? & ? \\ 1 & -1 & ? \\ ? & 2 & 4 \end{bmatrix}.$$

A. Find the complete $\boldsymbol{X}$ and explain your steps briefly. [3]

B. Let $\boldsymbol{x}_i$ denote the i^{th} column of the matrix $\boldsymbol{X}$. Let $\text{vec}(\boldsymbol{X}) \in \mathbb{R}^9$ be the column vector by stacking the columns of $\boldsymbol{X}$, i.e., $\text{vec}(\boldsymbol{X}) = \left[\boldsymbol{x}_1^T, \boldsymbol{x}_2^T, \boldsymbol{x}_3^T\right]^T$. Find the matrix form $\boldsymbol{A}$ of the linear operator $\mathcal{A}$. Find the observation vector $\boldsymbol{y} = \mathcal{A}(\boldsymbol{X})$. Find the matrix given by $\mathcal{A}^*(\boldsymbol{y})$ where $\mathcal{A}^*$ is the adjoint operator of $\mathcal{A}$ and defined as $\text{vec}(\mathcal{A}^*(\boldsymbol{y})) := \boldsymbol{A}^T\boldsymbol{y}$. [3]

(c) Consider the blind deconvolution problem $y(t) = \sum_\tau h(\tau)\, x(t-\tau)$ where both $h(t)$ and $x(t)$ are unknown time series. For simplicity, assume that $h(t) = 0$ for $t \notin \{1, 2, 3\}$ and write $\boldsymbol{h} = [h(1), h(2), h(3)]^T$. Assume that $x(t) = 0$ for $t \notin \{1, 2, 3\}$ and write $\boldsymbol{x} = [x(1), x(2), x(3)]^T$. As a result, $y(t) = 0$ for $t \notin \{1, \cdots, 5\}$.

Find the convex optimisation formulation for solving the blind deconvolution problem. Find the matrix form $\boldsymbol{A}$ of the linear operator $\mathcal{A}$ involved in your formulation. [4]

(Total marks: 20)

3. (Convex Optimisation)

(a)

i State the definition of a convex set $S \subset \mathbb{R}^n$. [2]

ii State the definition of a convex function $f: \mathbb{R}^n \to \mathbb{R}$. [2]

iii State the standard form of a convex optimisation problem (with equality and inequality constraints). [2]

iv Let $\boldsymbol{Q}$ be positive definite. Solve the following quadratic optimisation problem by minimising its Lagrangian with respect to $\boldsymbol{x}$:

$$\min_{\boldsymbol{x}} \frac{1}{2}\boldsymbol{x}^T \boldsymbol{Q}\boldsymbol{x} + \boldsymbol{c}^T\boldsymbol{x}$$
$$\text{subject to } \boldsymbol{A}\boldsymbol{x} = \boldsymbol{0}.$$

[3]

(b) The α-sublevel set of a function $f: \mathbb{R}^n \to \mathbb{R}$ is defined as

$$C_\alpha = \{\boldsymbol{x} \in \mathbb{R}^n : f(\boldsymbol{x}) \le \alpha\}.$$

i Prove that sublevel sets of a convex function f are convex. [2]

ii For a given $y \in \mathbb{R}^+$, define $f(\boldsymbol{x}) = \left(y - \|\boldsymbol{x}\|_2^2\right)^2$ where $\|\boldsymbol{x}\|_2^2 = \sum_i x_i^2$. Show that it is not convex by studying the sublevel set C_0. [2]

(c) As an extension of Problem 3.(b)ii, the function $f(\boldsymbol{x}) = \sum_i \left(y_i - \left(\boldsymbol{a}_i^T\boldsymbol{x}\right)^2\right)^2$ is not convex. The following presents a recently developed technique to optimise it.

i Show that $f(\boldsymbol{x}) = \sum_i (y_i - \mathrm{tr}(\boldsymbol{X}\boldsymbol{A}_i))^2$ where $\boldsymbol{X} = \boldsymbol{x}\boldsymbol{x}^T$ and $\boldsymbol{A}_i = \boldsymbol{a}_i\boldsymbol{a}_i^T$. You are allowed to use the fact that $\mathrm{tr}(\boldsymbol{A}\boldsymbol{B}) = \mathrm{tr}(\boldsymbol{B}\boldsymbol{A})$. [2]

ii To solve the original optimisation problem

$$\min_{\boldsymbol{x}} \sum_i \left(y_i - \left(\boldsymbol{a}_i^T\boldsymbol{x}\right)^2\right)^2, \tag{3.3}$$

one can solve the following optimisation problem

$$\min_{\boldsymbol{X}} \sum_i (y_i - \mathrm{tr}(\boldsymbol{X}\boldsymbol{A}_i))^2 + \lambda \mathrm{tr}(\boldsymbol{X})$$
$$\text{subject to } \boldsymbol{X} = \boldsymbol{X}^T,\ \boldsymbol{X} \succeq 0, \tag{3.4}$$

where $X \geq 0$ denotes that the matrix X is non-negative definite.

A. Verify the optimisation problem (3.4) is convex. Show your arguments. [3]

B. Explain the motivations of the terms involved in (3.4). [2]

(Total marks: 20)

4. (Performance Analysis)

Consider the problem $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x}_0$ where $\boldsymbol{A} \in \mathbb{R}^{m \times n}$ is a flat matrix, and $\boldsymbol{x}_0 \in \mathbb{R}^n$ is the unknown S-sparse vector. Assume that the columns of $\boldsymbol{A}$ have been normalised, i.e., $\|\boldsymbol{a}_i\|_2 = 1$, $\forall i$.

(a) State the definition of the mutual coherence constance $\mu(\boldsymbol{A})$ of the matrix $\boldsymbol{A}$. [1]

(b)

i State the definitions of Restricted Isometry Property (RIP) and Restricted Isometry Constant (RIC). [3]

ii RIP implies the near orthogonality of two disjoint submatrices of $\boldsymbol{A}$. Specifically, let $\mathcal{I}, \mathcal{J} \subset \{1, \cdots, n\}$. Assume that $|\mathcal{I}| = k$, $|\mathcal{J}| = \ell$ and $\mathcal{I} \bigcap \mathcal{J} = \phi$. RIP implies that for all $\boldsymbol{a} \in \mathbb{R}^k$ and $\boldsymbol{b} \in \mathbb{R}^\ell$,

$$|\langle \boldsymbol{A}_{\mathcal{I}}\boldsymbol{a}, \boldsymbol{A}_{\mathcal{J}}\boldsymbol{b} \rangle| \leq c \|\boldsymbol{a}\|_2 \|\boldsymbol{b}\|_2, \tag{4.5}$$

for some constant c. Write c in terms of RIC. (No proof is needed.) [1]

iii If $\boldsymbol{A}$ satisfies the RIP with the RIC $\delta_{2S} < 1$, then the solution of the sparse recovery problem is unique, that is, there does not exist another S-sparse vector $\boldsymbol{x}' \neq \boldsymbol{x}_0$ such that $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x}'$. Prove this claim. [3]

(c) The Gershgorin circle theorem states the following: for any square matrix $\boldsymbol{M}$, every eigenvalue of $\boldsymbol{M}$ satisfies

$$\lambda(\boldsymbol{M}) \in \left[M_{i,i} - \sum_{j \neq i} |M_{i,j}|, M_{i,i} + \sum_{j \neq i} |M_{i,j}| \right].$$

Consider square matrices of the form $\boldsymbol{M} = \boldsymbol{A}_{\mathcal{I}}^T \boldsymbol{A}_{\mathcal{I}}$ where $\boldsymbol{A}_{\mathcal{I}}$ is an S-column submatrix of $\boldsymbol{A}$. Prove that the following relationship between the RIC δ_S and the mutual coherence constant μ.

$$\delta_S \leq S\mu.$$

[3]

(d) Let $\boldsymbol{c} = \boldsymbol{A}^T\boldsymbol{y}$. Define

$$i^* = \arg\max_i |c_i| = \arg\max_i |\boldsymbol{a}_i^T \boldsymbol{y}|.$$

We seek for an RIP condition to guarantee that $i^* \in \mathcal{T} := \operatorname{supp}(\boldsymbol{x}_0)$ via the following steps.

i For an $i \notin \mathcal{T}$, find an upper bound bound of $\left|\boldsymbol{a}_i^T \boldsymbol{y}\right|$ in terms of the RIP constant δ_{S+1} and $\|\boldsymbol{x}_0\|_2$. [3]

ii Find a lower bound of

$$\max_{i \in \mathcal{T}} \left|\boldsymbol{a}_i^T \boldsymbol{y}\right|$$

in terms of the RIP constant δ_{S+1} and $\|\boldsymbol{x}_0\|_2$. You may need the fact that

$$\max_{i \in \mathcal{T}} |x_{0,i}| \geq \frac{1}{\sqrt{S}} \|\boldsymbol{x}_0\|.$$

[3]

iii Establish an RIP condition to guarantee that $i^* \in \mathcal{T}$. [3]

(Total marks: 20)

Desk 172 - question
on paper