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reviewer3@nptel.iitm.ac.in ▼

Courses » Applied Optimization for Wireless, Machine Learning, Big-Data

Announcements Course Ask a Question Progress Mentor FAQ

Unit 12 - Week 10- Application: Compressive Sensing, Sparse Signal Processing, OMP (Orthogonal Matching Pursuit), LASSO (Least Absolute Shrinkage and Selection Operator) for signal estimation

Course outline

How to access the portal

Week 1 :
Introduction to properties of Vectors, Norms, Positive Semi-Definite matrices and Gaussian Random Vectors

DOWNLOAD VIDEOS

Week 2:
Introduction to Convex Optimization – Convex sets, Hyperplanes/ Half-spaces etc. Application: Power constraints in Wireless Systems

Week 3 :
Convex/ Concave Functions

Assignment-10

The due date for submitting this assignment has passed.

As per our records you have not submitted this assignment. **Due on 2018-10-10, 23:59 IST.**

1) Consider a multi-channel estimation problem with pilot matrix \mathbf{X} and received vector $\bar{\mathbf{y}}$ as given below. **1 point**

$$\mathbf{X} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}, \bar{\mathbf{y}} = \begin{bmatrix} 2 \\ 1 \\ 3 \\ -2 \end{bmatrix}$$

The estimate of the channel vector \mathbf{h} is

$\begin{bmatrix} 1 \\ -1 \end{bmatrix}$

$\begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$\begin{bmatrix} 1 \\ \frac{1}{2} \\ 2 \end{bmatrix}$

$\begin{bmatrix} \frac{1}{2} \\ -\frac{1}{2} \end{bmatrix}$

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Multi-User
Wireless,
Cognitive Radio
Systems

Week 4 : Convex
Optimization
problems, Linear
Program,
Application:
Power allocation
in Multi-cell
cooperative
OFDM

Week 5:
Jensen's
Inequality,
Operations that
preserve
Convexity,
Examples,Beamforming
in Multi-antenna
Wireless
Communication

Week-6: Maximal
Ratio Combiner
(MRC), Multi-
antenna
Beamforming
with Interfering
User,
Zero-Forcing
(ZF)
beamforming,Robust
beamformer
Design

Week-7:Optimization
for signal
estimation, LS,
WLS,
Regularization.
Application:
Wireless
channel
estimation,
Image
Reconstruction-
Deblurring,Representatic
of Convex
Optimization
problem

Week 8 :
Application:
Convex
optimization for
Machine
Learning,
Principal
Component
Analysis (PCA),
Support Vector
Machines

Week 9-
Application:

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2) Consider a multi-channel estimation problem with pilot matrix \mathbf{X} as given below. **1 point**

$$\mathbf{X} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}$$

The pseudo-inverse of \mathbf{X} is

$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$

$\frac{1}{4} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$

$\begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \end{bmatrix}$

$\begin{bmatrix} 1 & -1 & -1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$

No, the answer is incorrect.

Score: 0

Accepted Answers:

$\frac{1}{4} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$

3) Consider a multi-channel estimation problem with pilot matrix \mathbf{X} and received vector $\bar{\mathbf{y}}$ as given below. **1 point**

$$\mathbf{X} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}, \bar{\mathbf{y}} = \begin{bmatrix} 2 \\ 1 \\ 3 \\ -2 \end{bmatrix}$$

Let the regularization parameter be $\lambda = 2$. The estimate of the channel vector $\bar{\mathbf{h}}$ is

$\begin{bmatrix} 1 \\ \frac{1}{3} \\ -1 \end{bmatrix}$

$\begin{bmatrix} -\frac{2}{3} \\ -\frac{1}{3} \end{bmatrix}$

$\begin{bmatrix} \frac{1}{2} \\ \frac{4}{3} \end{bmatrix}$

$\begin{bmatrix} \frac{2}{3} \\ -\frac{2}{3} \end{bmatrix}$

No, the answer is incorrect.

Compressive Sensing, Sparse Signal Processing, OMP (Orthogonal Matching Pursuit), LASSO (Least Absolute Shrinkage and Selection Operator) for signal estimation, SVM

Week 10- Application: Compressive Sensing, Sparse Signal Processing, OMP (Orthogonal Matching Pursuit), LASSO (Least Absolute Shrinkage and Selection Operator) for signal estimation

- Lec 62- Practical Application: Approximate Classifier Design
- Lec 63- Concept of Duality
- Lec 64-Relation between optimal value of Primal & Dual Problems, concepts of Duality gap and Strong Duality
- Lec 65-Example problem on Strong Duality
- Lec 66- Karush-Kuhn-Tucker(KKT) conditions
- Lec 67- Application of KKT condition: Optimal MIMO power allocation(Waterfilling)
- Quiz : Assignment-10
- Assignment -10

Score: 0

Accepted Answers:

$$\begin{bmatrix} \frac{2}{3} \\ -\frac{2}{3} \end{bmatrix}$$

4) The standard form of a convex optimization problem is

1 point

$\min g_0(\bar{\mathbf{x}})$ where $g_0(\bar{\mathbf{x}})$ is any function

$\min g_0(\bar{\mathbf{x}})$

s.t. $g_i(\bar{\mathbf{x}}) \leq 0, i = 1, 2, \dots, l$

$\tilde{g}_j(\bar{\mathbf{x}}) = 0, j = 1, 2, \dots, m$

where $g_i(\bar{\mathbf{x}})$ are convex and $\tilde{g}_j(\bar{\mathbf{x}})$ are affine

$\min g_0(\bar{\mathbf{x}})$

s.t. $g_i(\bar{\mathbf{x}}) \leq 0, i = 1, 2, \dots, l$

$\tilde{g}_j(\bar{\mathbf{x}}) = 0, j = 1, 2, \dots, m$

where $g_i(\bar{\mathbf{x}}), \tilde{g}_j(\bar{\mathbf{x}})$ are any convex functions

$\min g_0(\bar{\mathbf{x}})$

s.t. $g_i(\bar{\mathbf{x}}) = 0, i = 1, 2, \dots, l$

where $g_i(\bar{\mathbf{x}})$ are any convex functions

No, the answer is incorrect.

Score: 0

Accepted Answers:

$\min g_0(\bar{\mathbf{x}})$

s.t. $g_i(\bar{\mathbf{x}}) \leq 0, i = 1, 2, \dots, l$

$\tilde{g}_j(\bar{\mathbf{x}}) = 0, j = 1, 2, \dots, m$

where $g_i(\bar{\mathbf{x}})$ are convex and $\tilde{g}_j(\bar{\mathbf{x}})$ are affine

5) The convex optimization problem below can be equivalently recast as

1 point

$$\begin{aligned} \min \quad & \|\bar{\mathbf{x}}\|_{\infty} \\ \text{s.t.} \quad & \bar{\mathbf{x}} \in \mathcal{S} \end{aligned}$$

$\min \bar{\mathbf{1}}^T \bar{\mathbf{t}}$

s.t. $-\bar{\mathbf{t}} \leq \bar{\mathbf{x}} \leq \bar{\mathbf{t}}$

$\bar{\mathbf{x}} \in \mathcal{S}$

$\min \|\bar{\mathbf{x}}\|_1$

$\bar{\mathbf{x}} \in \mathcal{S}$

$\min t$

s.t. $-t\bar{\mathbf{1}} \leq \bar{\mathbf{x}} \leq t\bar{\mathbf{1}}$

$\bar{\mathbf{x}} \in \mathcal{S}$

$\min t$

s.t. $-t \leq \bar{\mathbf{1}}^T \bar{\mathbf{x}} \leq t$

$\bar{\mathbf{x}} \in \mathcal{S}$

Solution

Week 11 :
Application:
Radar for target
detection, Array
Processing,
MUSIC,
MIMO-Radar
Schemes for
Enhanced Target
Detection

Week 12:
Application:
Convex
optimization for
Big Data
Analytics,
Recommender
systems, User
Rating
Prediction and
Optimization for
Finance

Transcripts

No, the answer is incorrect.**Score: 0****Accepted Answers:**

$$\min t$$

$$\text{s.t. } -t\mathbf{1} \leq \bar{\mathbf{x}} \leq t\mathbf{1}$$

$$\bar{\mathbf{x}} \in \mathcal{S}$$

6) Consider the multi base station cooperation problem in a wireless communication **1 point** system with P_{ij}, g_{ij} denoting the transmit power and power gain from base station i to user j . Total number of base stations is M and number of users is K . The optimization problem to minimize the sum transmit power while ensuring minimum received power \tilde{P} at all users is



$$\min t$$

$$\text{s.t. } \sum_{i=1}^M \sum_{j=1}^K P_{ij} \leq t$$

$$\sum_{i=1}^M P_{ij} g_{ij} \geq \tilde{P}, j = 1, 2, \dots, K$$



$$\min t$$

$$\text{s.t. } \sum_{i=1}^M P_{ij} g_{ij} < t, j = 1, 2, \dots, K$$

$$\sum_{i=1}^M \sum_{j=1}^K P_{ij} \geq \tilde{P}$$



$$\min t$$

$$\text{s.t. } \sum_{j=1}^K P_{ij} g_{ij} \geq \tilde{P}, j = i = 1, 2, \dots, M$$

$$\sum_{i=1}^M \sum_{j=1}^K P_{ij} = t$$



$$\min t$$

$$\text{s.t. } \sum_{j=1}^K P_{ij} g_{ij} = t, i = 1, 2, \dots, M$$

$$\sum_{i=1}^M \sum_{j=1}^K P_{ij} \geq \tilde{P}$$

No, the answer is incorrect.**Score: 0****Accepted Answers:**

$$\min t$$

$$\text{s.t. } \sum_{i=1}^M \sum_{j=1}^K P_{ij} \leq t$$

$$\sum_{i=1}^M P_{ij} g_{ij} \geq \tilde{P}, j = 1, 2, \dots, K$$

7) The constraint $\Pr(\bar{\mathbf{c}}^T \bar{\mathbf{x}} \leq d) \geq \eta$ where $\bar{\mathbf{c}}$ is Gaussian with mean $\bar{\boldsymbol{\mu}}$ and covariance **1 point** matrix $\Sigma = \tilde{\Sigma} \tilde{\Sigma}^T$ can be equivalently represented as



$$|\bar{\mathbf{x}}^T \bar{\boldsymbol{\mu}}| \leq \frac{1}{\eta} (d - \bar{\mathbf{x}}^T \Sigma \bar{\mathbf{x}})$$



$$|\bar{\mathbf{x}}^T \bar{\mathbf{c}}| Q(\eta - 1) \leq (d\bar{\mathbf{c}} + \bar{\boldsymbol{\mu}})^T \Sigma (d\bar{\mathbf{c}} + \bar{\boldsymbol{\mu}})$$



$$\|\tilde{\Sigma}^T \bar{\mathbf{x}}\| \leq \frac{1}{Q^{-1}(1-\eta)} (d - \bar{\mathbf{x}}^T \bar{\boldsymbol{\mu}})$$



$$\bar{\mathbf{x}}^T \tilde{\Sigma} \bar{\mathbf{x}} + \bar{\mathbf{x}}^T \bar{\boldsymbol{\mu}} \leq dQ^{-1}(1-\eta)$$

No, the answer is incorrect.

Score: 0

Accepted Answers:

$$\|\tilde{\Sigma}^T \bar{\mathbf{x}}\| \leq \frac{1}{Q^{-1}(1-\eta)} (d - \bar{\mathbf{x}}^T \bar{\boldsymbol{\mu}})$$

8) The robust linear program $\min \bar{\mathbf{c}}^T \bar{\mathbf{x}}$, s.t. $\bar{\mathbf{a}}^T \bar{\mathbf{x}} \leq b$ for all $\bar{\mathbf{a}} \in \{\hat{\mathbf{a}} + \mathbf{P}\bar{\mathbf{u}} \mid \|\bar{\mathbf{u}}\| \leq 1\}$ can be represented equivalently as

1 point



$$\min \bar{\mathbf{c}}^T \bar{\mathbf{x}}, \text{ s.t. } \hat{\mathbf{a}}^T \bar{\mathbf{x}} - \|\mathbf{P}\mathbf{P}^T \bar{\mathbf{x}}\| \leq b$$



$$\min \bar{\mathbf{c}}^T \bar{\mathbf{x}}, \text{ s.t. } |\hat{\mathbf{a}}^T \bar{\mathbf{x}}|^2 + \bar{\mathbf{x}}^T \mathbf{P}\mathbf{P}^T \bar{\mathbf{x}} \leq b$$



$$\min \bar{\mathbf{c}}^T \bar{\mathbf{x}}, \text{ s.t. } \hat{\mathbf{a}}^T \bar{\mathbf{x}} \leq b$$



$$\min \bar{\mathbf{c}}^T \bar{\mathbf{x}}, \text{ s.t. } \hat{\mathbf{a}}^T \bar{\mathbf{x}} + \|\mathbf{P}^T \bar{\mathbf{x}}\| \leq b$$

No, the answer is incorrect.

Score: 0

Accepted Answers:

$$\min \bar{\mathbf{c}}^T \bar{\mathbf{x}}, \text{ s.t. } \hat{\mathbf{a}}^T \bar{\mathbf{x}} + \|\mathbf{P}^T \bar{\mathbf{x}}\| \leq b$$

9) The optimal vector $\bar{\mathbf{v}}$ that is the solution to the optimization problem $\max \bar{\mathbf{v}}^T \mathbf{G} \bar{\mathbf{v}}$, s.t. $\|\bar{\mathbf{v}}\| \leq 1$, where \mathbf{G} is a PSD matrix, is

0 points



Any eigenvector of \mathbf{G}



Unit-norm eigenvector of \mathbf{G} corresponding to minimum eigenvalue



Unit-norm eigenvector of \mathbf{G} corresponding to maximum eigenvalue



Eigenvector of \mathbf{G} corresponding to eigenvalue = 1

No, the answer is incorrect.

Score: 0

Accepted Answers:

Unit-norm eigenvector of \mathbf{G} corresponding to minimum eigenvalue

10) Consider a MIMO channel with channel matrix given as \mathbf{H} . The optimal receive and transmit beamformers for this channel are given as

1 point



Principal eigenvectors of $\mathbf{H}\mathbf{H}^H$ and $\mathbf{H}^H\mathbf{H}$ respectively



Principal eigenvectors of $\mathbf{H}^H\mathbf{H}$ and $\mathbf{H}\mathbf{H}^H$ respectively



Principal eigenvectors of \mathbf{H}^H and \mathbf{H} respectively



Principal eigenvectors of \mathbf{H} and \mathbf{H}^H respectively

No, the answer is incorrect.

Score: 0

Accepted Answers:

Principal eigenvectors of $\mathbf{H}\mathbf{H}^H$ and $\mathbf{H}^H\mathbf{H}$ respectively

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