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NPTEL

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

Announcements **Course** Ask a Question Progress Mentor FAQ

Unit 8 - Week-6: Maximal Ratio Combiner (MRC), Multi-antenna Beamforming with Interfering User, Zero-Forcing (ZF) beamforming,Robust beamformer Design

Assignment-6

The due date for submitting this assignment has passed.

As per our records you have not submitted this assignment.

Due on 2018-09-12, 23:59 IST.

1) A function f is convex if for any two points $\bar{\mathbf{x}}_1, \bar{\mathbf{x}}_2$ ***1 point***

- $f(\theta\bar{\mathbf{x}}_1 + (1-\theta)\bar{\mathbf{x}}_2) \leq \theta f(\bar{\mathbf{x}}_1) + (1-\theta) f(\bar{\mathbf{x}}_2), \text{ for all } \theta$
- $f(\theta\bar{\mathbf{x}}_1 + (1-\theta)\bar{\mathbf{x}}_2) \geq \theta f(\bar{\mathbf{x}}_1) + (1-\theta) f(\bar{\mathbf{x}}_2), \text{ for all } \theta$
- $f(\theta\bar{\mathbf{x}}_1 + (1-\theta)\bar{\mathbf{x}}_2) \leq \theta f(\bar{\mathbf{x}}_1) + (1-\theta) f(\bar{\mathbf{x}}_2), \text{ for all } 1 \geq \theta \geq 0$
- $f(\theta\bar{\mathbf{x}}_1 + (1-\theta)\bar{\mathbf{x}}_2) \geq \theta f(\bar{\mathbf{x}}_1) + (1-\theta) f(\bar{\mathbf{x}}_2), \text{ for all } 1 \geq \theta \geq 0$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$f(\theta\bar{\mathbf{x}}_1 + (1-\theta)\bar{\mathbf{x}}_2) \leq \theta f(\bar{\mathbf{x}}_1) + (1-\theta) f(\bar{\mathbf{x}}_2), \text{ for all } 1 \geq \theta \geq 0$

2) Which of the following functions is not convex ***1 point***

- $e^{-ax},\ a > 0$
- $x^{\alpha},\ 0 < \alpha < 1$
- $-\ln x$
-

ce De

3) A convex function f satisfies *1 point*

$f(y) \leq f(x) + \frac{df(x)}{dx}(y-x)$

$f(y) = f(x) + \frac{df(x)}{dx}(y-x)$

$f(y) \geq f(x) - \frac{df(x)}{dx}(y-x)$

$f(y) \geq f(x) + \frac{df(x)}{dx}(y-x)$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$f(y) \geq f(x) + \frac{df(x)}{dx}(y-x)$

4) The function $f(\bar{\mathbf{x}})$ of a vector $\bar{\mathbf{x}}$ is convex if *1 point*

$\nabla^2 f(\bar{\mathbf{x}}) \succcurlyeq 0$

$\nabla^2 f(\bar{\mathbf{x}}) \preccurlyeq 0$

$\nabla^2 f(\bar{\mathbf{x}}) = 0$

$\nabla f(\bar{\mathbf{x}}) \nabla^T f(\bar{\mathbf{x}}) \succcurlyeq 0$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$\nabla^2 f(\bar{\mathbf{x}}) \succcurlyeq 0$

5) Consider the MIMO wireless system model given by $\bar{\mathbf{y}} = \mathbf{H}\bar{\mathbf{x}} + \bar{\mathbf{n}}$. The *1 point* quantity $\nabla^2 \| \bar{\mathbf{y}} - \mathbf{H}\bar{\mathbf{x}} \|^2$ is

$2\mathbf{H}\mathbf{H}^T$

$2(\mathbf{H} + \mathbf{H}^T)$

$2\mathbf{H}^T\mathbf{H}$

$(\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$2\mathbf{H}^T\mathbf{H}$

6) Jensen's inequality for a convex function f and random variable X is *1 point*

$f(E\{X\}) \geq E\{f(X)\}$

$f(E\{X\}) \leq E\{f(X)\}$

$f(E\{X\}) \geq f(X)$

$f(E\{X\}) \leq f(X)$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$f(E\{X\}) \leq E\{f(X)\}$

7) Let x be a real-valued random variable which takes values in $\{a_1, a_2, \ldots, a_n\}$ where $a_1 < a_2 < \cdots < a_n$, with $\Pr(x = a_i) = p_i$. The function $\Pr(\alpha \leq x \leq \beta)$ is, *1 point*

Convex

Concave

Quasi-convex

All of the above

No, the answer is incorrect.
Score: 0

Accepted Answers:
All of the above

8) The function $f(x_1, x_2) = x_1 x_2$ is *1 point*

Convex

Concave

Quasi-convex

Quasi-concave

No, the answer is incorrect.
Score: 0

Accepted Answers:
Quasi-concave

9) Consider an AWGN communication channel with output $y = x + n$, where the symbols x are drawn from a BPSK constellation of power P and n denotes white Gaussian noise of power σ^2. The bit-error rate (BER) for this channel as a function of the SNR $\gamma = \frac{P}{\sigma^2}$ is, *1 point*

$Q(\sqrt{\gamma})$

$Q(\gamma)$

$Q^2(\gamma)$

$Q^2(\sqrt{\gamma})$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$Q(\sqrt{\gamma})$

10) The conjugate function $f(\bar{\mathbf{y}})$ of a function $f(\bar{\mathbf{x}})$ is defined as *1 point*

- $\max_{\bar{\mathbf{x}}} \left(\bar{\mathbf{y}}^T\bar{\mathbf{x}} - f(\bar{\mathbf{x}})\right)$
- $\max_{\bar{\mathbf{x}}} \left(f(\bar{\mathbf{x}}) - \bar{\mathbf{y}}^T\bar{\mathbf{x}}\right)$
- $\max_{\bar{\mathbf{x}}} \left(f(\bar{\mathbf{x}}) + \bar{\mathbf{y}}^T\bar{\mathbf{x}}\right)$
- $\min_{\bar{\mathbf{x}}} \left(f(\bar{\mathbf{x}}) - \bar{\mathbf{y}}^T\bar{\mathbf{x}}\right)$

No, the answer is incorrect.
Score: 0

Accepted Answers:
$\max_{\bar{\mathbf{x}}} \left(\bar{\mathbf{y}}^T\bar{\mathbf{x}} - f(\bar{\mathbf{x}})\right)$

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