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Quiz 5

Problem 1

1/1 point (graded)

When gradient descent is used to solve a minimization problem, it is guaranteed to find a local minimum (that may or may not be the global minimum).

● True

○ False

✓

Submit

Problem 2

1/1 point (graded)

You are trying to find the global minimum for a convex function of one variable, $F(w)$. At the current point $w = w_0$, you find that the derivative dF/dw is equal to 2.3. Based on this information, how should you update w?

○ Choose $w > w_0$

● Choose $w < w_0$

○ Choose $w > -w_0$

○ More information is needed

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✓

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Problem 3

1/1 point (graded)

What is the derivative, $\nabla F(\mathbf{w})$, of the function $F(\mathbf{w}) = (3\mathbf{w} \cdot \mathbf{x})$?

○ $\nabla F(\mathbf{w}) = \mathbf{x}$

○ $\nabla F(\mathbf{w}) = \mathbf{w}$

● $\nabla F(\mathbf{w}) \ = 3\mathbf{x}$

○ $\nabla F(\mathbf{w}) \ = 3\mathbf{w}$

✓

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Problem 4

1/1 point (graded)

In the equation $\mathbf{w}_{t+1} = \mathbf{w}_t - \eta_t \nabla L(\mathbf{w}_t)$, what does η_t represent?

○ The direction in which to adjust $\mathbf{w}$ to find a minimum

○ The dimension of the vector $\mathbf{w}$

○ The approximate number of iterations the optimization algorithm has run

● The size of the adjustment made to $\mathbf{w}$

✓

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Problem 5

1/1 point (graded)

True or false: An adjustment to $\mathbf{w}$ in the direction of the gradient is guaranteed to result in a vector of lower cost.

○ True

● False

✓

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Problem 6

1/1 point (graded)

Given a function $L(\mathbf{x}) = 3x_2x_3 + 2x_1x_3 + 2x_1x_2$, compute the gradient $\nabla L(\mathbf{x})$.

○ $\nabla L(\mathbf{x}) = (4x_1, 5x_2, 5x_3)$

● $\nabla L(\mathbf{x}) = (2x_3 + 2x_2, 3x_3 + 2x_1, 3x_2 + 2x_1)$

○ $\nabla L(\mathbf{x}) = (2x_1x_3 + 2x_1x_2, 3x_2x_3 + 2x_1x_2, 3x_2x_3 + 2x_1x_3)$

○ $\nabla L(\mathbf{x}) = (4x_2x_3, 6x_3x_1, 6x_1x_2)$

✓

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Problem 7

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1/1 point (graded)

Stochastic gradient descent is a better alternative to gradient descent in which of the following cases?

☐ There are multiple local minima in a function

☑ There are a large number of data points

☐ The function contains more than 3 variables

☐ The function is discontinuous in at least one location

✓

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Problem 8

1/1 point (graded)

A key difference between gradient descent and stochastic gradient descent is:

○ Stochastic gradient descent takes longer to perform than gradient descent, but can be used on very large data sets

○ Stochastic gradient descent replaces gradient descent when the loss function contains a large number of variables

● Each move made by gradient descent is based on the entire data set, while each move made by stochastic gradient descent is based on a single data point.

○ Gradient descent only makes one pass through the training set, while stochastic gradient descent makes numerous passes before convergence

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Problem 9

1/1 point (graded)

Using mini-batch stochastic gradient descent, a group of data points are used to make adjustments to $\mathbf{w}$. Why might this be preferable to stochastic gradient descent based on a single point?

○ It takes less time to compute adjustments to $\mathbf{w}$

○ It results in a larger adjustment

● The batch-based gradient calculation is a closer approximation to the actual gradient

○ Fewer passes over the training set are required to find a minimum

✓

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Problem 10

1/1 point (graded)

True or false: The negation of any convex function is a concave function.

● True

○ False

✓

Submit

Problem 11

1/1 point (graded)

Given a convex function $f(x)$ and two points in the domain, a and b, which of the true? Select all that apply.

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☑ The line segment connecting $(a, f(a))$ and $(b, f(b))$ must lie above the function at every point on the line connecting a and b

☐ $f(x)$ must be monotonically increasing along the line segment joining a and b

☐ $f(a) > f(b)$ when $a < b$, and $f(b) > f(a)$ when $b < a$

☐ $f(x)$ must have a global minimum between a and b

✓

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Problem 12

1/1 point (graded)

Which of the following functions are convex? Select all that apply.

☑ $y = e^{-x}$

☑ $y = x^2$

☑ $y = 2x$

☐ $y = \sin(x),\ x \in [0, \pi]$

✓

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Problem 13

1/1 point (graded)

True or false: A function whose 2nd derivative is always negative is a convex function.

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○ True

● False

✓

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Problem 14

1/1 point (graded)

The matrix $M = \begin{pmatrix} 2 & 3 \\ 2 & 1 \end{pmatrix}$ has a positive determinant.

○ Yes

● No

✓

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Problem 15

1/1 point (graded)
Given matrix M = \begin{pmatrix} 4 & 1 \\ k & 1 \end{pmatrix} , what value of k results in a singular matrix?

○ k = -4

○ k = -1

○ k = 1

● k = 4

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✓

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Problem 16

1/1 point (graded)

All matrices of the form M = UU^T are always positive semidefinite

● True

○ False

✓

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Problem 17

1/1 point (graded)

The matrix \begin{pmatrix}14 & 7 \\ 7 & 6 \end{pmatrix} is positive semidefinite and follows the form M = UU^T. Which of the following matrices U satisfies this equation?

○ U = \begin{pmatrix} 1 & 4 \\ 1 & 6 \end{pmatrix}

○ U = \begin{pmatrix} 2 & 7 \\ 3 & 1 \end{pmatrix}

○ U = \begin{pmatrix} 3 & 2 & 2 \\ 1 & 4 & 1 \end{pmatrix}

● U = \begin{pmatrix} 1 & 2 & 3 \\ 2 & 1 & 1 \end{pmatrix}

✓

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Problem 18

1/1 point (graded)

A function, F(\textbf z), is convex if which of the following statements hold true?

- ☑ The Hessian, H(\textbf z), is positive semidefinite at all \textbf z
- ☐ F(\textbf z) \ge 0, \forall \textbf z
- ☐ The gradient, \nabla F(\textbf z), is monotonically decreasing
- ☐ The Hessian, H(\textbf z), is symmetric

✓

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Problem 19

1/1 point (graded)

Is the identity matrix positive semidefinite?

- ● Yes
- ○ No

✓

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