

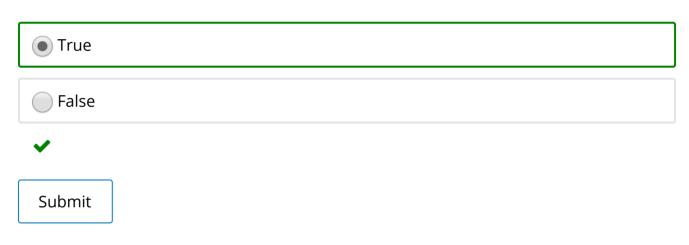
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# Quiz 5

## 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).

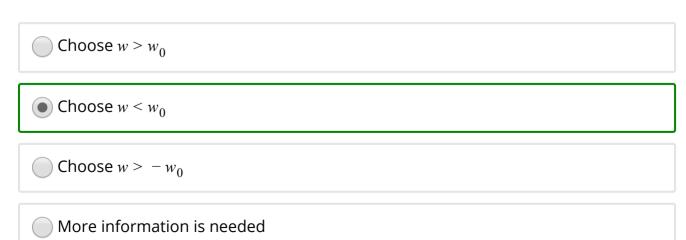


# Problem 2

1/1 point (graded)

Processing math: 72%

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?



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## Problem 3

1/1 point (graded)

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

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



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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  $\eta_t$  represent?

- $\overline{\phantom{a}}$  The direction in which to adjust  ${f w}$  to find a minimum
- The dimension of the vector w
- The approximate number of iterations the optimization algorithm has run
- lacktriangle The size of the adjustment made to f w



## Problem 5

1/1 point (graded)

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







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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  $\nabla L(\mathbf{x})$ .

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



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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 w. Why might this be preferable to stochastic gradient descent based on a single point?

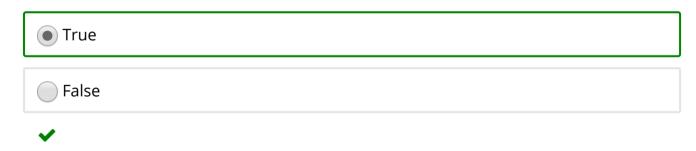
It takes less time to compute adjustments to w
It results in a larger adjustment
The batch-based gradient calculation is a closer approximation to the actual gradient
Fewer passes over the training set are required to find a minimum

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#### Problem 10

1/1 point (graded)

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



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# Problem 11

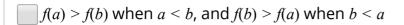
1/1 point (graded)

Given a convex function f(x) and two points in the domain, a and b, which of the Processing math: 72% | true? Select all that apply.



 $\checkmark$  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(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.

	T	r	u	e





## 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?





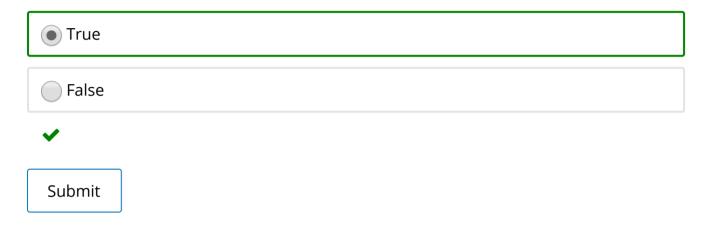




## Problem 16

1/1 point (graded)

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



## 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?

- $U = \left( \frac{1 \& 4 \land 1 \& 6 \land pmatrix}{1 \& 4 \land 1 \& 6 \land pmatrix} \right)$ 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  I/1 point (graded) s the identity matrix positive semidefinite?	
<ul><li>Yes</li></ul>	
○ No	
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