

1. Guidelines for questions types:
 - (a) (0 points) Multiple choice, **single** answer.
 - A. Mark only **one** the most correct answer.
 - B. Mark only one the most correct answer.**
 - (b) (0 points) Multiple choice, **multiple** answer.
 - Mark **all** the most correct answers.
 - Mark **all** the most correct answers.
 - (c) (0 points) Numerical answer
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Modeling

1. Which of the following best describes the primary difference between a loss function and an evaluation metric in supervised learning?
 - A. A loss function is used during training to compute gradients and update model parameters; an evaluation metric is used after (or during) training to assess model performance on validation/test data.**
 - B. A loss function is only defined for classification tasks, while an evaluation metric is only defined for regression tasks.
 - C. A loss function is minimized during model training, while an evaluation metric is maximized during model training.
 - D. A loss function is maximized during model training, while an evaluation metric is minimized during model training.
2. What is correct about gradient descent algorithm:
 - A learning rate that is too high may cause parameters to oscillate or even diverge.**
 - Guarantees convergence to a global minimum.
 - Choosing a very small learning rate can make GD converge extremely slowly, even though it may still reach a minimum.**
 - Always requires second-order derivatives (the Hessian) to compute its updates.
3. There are two confusion matrices:

		Predicted	
		Yes	No
Actual	Yes	50	10
	No	10	30

		Predicted	
		Yes	No
Actual	Yes	60	0
	No	20	20

Which metric emphasizes the performance difference?

- Accuracy
- Precision**
- Recall**
- Specificity**

Solution:

$$\underbrace{\begin{bmatrix} x[1] \\ x[2] \\ \vdots \\ x[L-2] \\ x[L-1] \end{bmatrix}}_{\mathbf{y}} = \mu + a_1 \begin{bmatrix} x[0] \\ x[1] \\ \vdots \\ x[L-3] \\ x[L-2] \end{bmatrix} = \underbrace{\begin{bmatrix} \mu & a_1 \end{bmatrix}}_{\mathbf{a}} \underbrace{\begin{bmatrix} 1 & x[0] \\ 1 & x[1] \\ \vdots \\ 1 & x[L-3] \\ 1 & x[L-2] \end{bmatrix}}_{\mathbf{X}}$$

$$\hat{\mathbf{a}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

$$\mathbf{X}^T \mathbf{X} = \begin{bmatrix} N-1 & \sum_n^{L-2} x[n] \\ \sum_n^{L-2} x[n] & \sum_n^{L-2} x^2[n] \end{bmatrix}$$

$$(\mathbf{X}^T \mathbf{X})^{-1} = \frac{1}{N \sum_n^{L-2} x^2[n] - \left(\sum_n^{L-2} x[n] \right)^2} \begin{bmatrix} \sum_n^{L-2} x^2[n] & - \sum_n^{L-2} x[n] \\ - \sum_n^{L-2} x[n] & N \end{bmatrix}$$

$$\mathbf{X}^T \mathbf{y} = \begin{bmatrix} \sum_{n=1}^L x[n] \\ \sum_{n=0}^L x[n]x[n-1] \end{bmatrix}$$