CSE 446/546 Winter 2024 Final Exam

March 13, 2024

Name ________________________________ **UW NetID** ______________________

Please **wait** to open the exam until you are instructed to begin, and please take out your Husky Card and have it accessible when you turn in your exam.

There are 43 questions on this exam. You will have 1 hour and 50 minutes to complete the exam.

Instructions: This exam consists of a set of short questions (True/False, multiple choice, short answer).

- Each question is worth 1 point unless noted otherwise.
- For each multiple-choice and True/False question, clearly indicate your answer by filling in the letter(s) associated with your choice.
- Multiple choice questions marked with One Answer should only be marked with one answer. All other multiple choice questions are marked Select All , in which case they are "select all that apply" and any number of answers may be selected (**including none, one, or more**).
- For each short answer question, please write your answer in the provided space.
- If you need to change an answer or run out of space, please very clearly indicate what your final answer is and what you would like graded. Responses where we cannot determine the selected option will be marked as incorrect.
- Please remain in your seats for the last 10 minutes of the exam. If you complete the exam before the last 10 minutes, you may turn in your exam and note sheet by handing them to a TA.

1. One Answer In the context of logistic regression, which of the following statements is true about the interpretation of the model coefficients?

   (a) The coefficients represent the **change in the log odds** of the dependent variable for a one-unit change in the predictor variable, holding all other variables constant.

   (b) The coefficients represent the **change in the dependent variable** for a one-unit change in the predictor variable, holding all other variables constant.

   (c) The coefficients are directly proportional to the **probability of the dependent variable being 1**.

   (d) The coefficients represent the probability that the **predictor variable will be present** when the dependent variable is 1.

   Correct answers: (a)

2. One Answer You are working on a machine learning project to classify emails as either spam (1) or not spam (0) using logistic regression. The model has been trained based on emails with labels and several features, including the frequency of specific keywords. For a particular new email, the model's output of the log-odds is 0.4.
   Given the model's output, which of the following options best describes its classification of the email?

   (a) The email is classified as not spam because a positive log-odds score indicates a higher likelihood of the email belonging to the negative class (not spam)

   (b) The email is classified as spam because the log-odds score is positive, indicating that the odds of the email being spam are greater than the odds of it not being spam.

   (c) The email is classified as not spam because the probability of being spam is less than 0.5.

   (d) The email is classified as spam because the probability of it being spam is positive.

   Correct answers: (b)

   Explanation: Note that the log-odds is positive, so $P(Y=+1|X=x) > P(Y=0|X=x)$.

3. Select All In the context of logistic regression used for binary classification, which of the following statements is true?

(a) The model directly outputs class labels (0 or 1)

(b) The model's optimization has a closed-form solution.

(c) The model produces a linear decision boundary with respect to the features.

(d) The model uses the softmax function to output class probabilities.

Correct answers: (c)

4. Select All Which are key properties of the Radial Basis Function kernel?

(a) It works best when features take on categorical values.

(b) It relies on the distance between points in the original feature space.

(c) It relies on the distance between points in infinite-dimensional space.

(d) It implicitly maps to an infinite-dimensional feature space.

(e) It identifies hyperplanes in an infinite-dimensional space.

Correct answers: (b), (d)

5. One Answer Which of the following is **not** a valid kernel?

(a) $K(x, x') = \frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}\|x - x'\|_2^2)$

(b) $K(x, x') = -\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}\|x - x'\|_2^2)$

(c) $K(x, x') = x^\top x'$

(d) $K(x, x') = 1$

Correct answers: (b)

Explanation: Recall that kernel's must be positive semidefinite: $K(x, x') \geq 0$ for all x, x'. This is not true for $K(x, x') = -\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}\|x - x'\|_2^2)$.

6. Select All Which of the following statements about the “kernel trick” are true in the context of machine learning algorithms?

(a) It provides an efficient method for computing and representing high-dimensional feature expansions.

(b) It implicitly maps to a high-dimensional feature space.

(c) It eliminates the need for regularization.

(d) It can only be used in regression prediction settings.

Correct answers:

Explanation: We gave all students full credit for this question because after the exam we realized that choice (b) was too ambiguous. Our initial intention was to grade (b) as correct. Our rationale was: (a) is incorrect because a major motivation for the kernel trick is that it avoids ever needing to compute or represent high-dimensional feature expansions. (b) is how the kernel trick is typically (always?) used in practice and how the kernel trick was always used in lecture and HWs. However, one *could technically* map to a lower-dimensional feature space. This generally does not make sense to do from the perspective of computational cost. (c) is incorrect–we frequently need regularization with kernel methods, as we saw that kernel regression perfectly fits the training data when no ridge penalty is included. (d) is incorrect–we discussed kernel extensions to PCA in class, and there are many other extensions we did not discuss, e.g., support vector machines for classification.

7. Select All Consider the kernel ridge regression problem.

$$\hat{w} = \arg\min_{w} \frac{1}{n}\sum_{i=1}^{n}(y_i - \phi(x_i)^\top w)^2 + \lambda\|w\|_2^2 \quad \text{becomes} \quad \hat{\alpha} = \arg\min_{\alpha}\|Y - K\alpha\|_2^2 + \lambda\alpha^\top K\alpha$$

Let $\phi(x) : \mathbb{R}^d \to \mathbb{R}^p$ be the feature mapping the kernel matrix K is with respect to. Let n be the number of samples we have. Which of the following statements is true?

(a) Ridge regression can only be kernelized assuming $\alpha \in \text{span}\{x_1, x_2, ..., x_n\}$ where $x_i \in \mathbb{R}^d$ denotes the ith training sample

(b) When $n \ll p$, the kernel method will be more computationally efficient than using regular ridge regression.

(c) There is no closed-form solution if K is positive definite.

(d) The optimal $\hat{w}$ can be obtained after solving for the optimal $\hat{\alpha}$ even though w is not explicitly included in the optimization problem

Correct answers: (b), (d)

8. Select All Assume we have n samples from some distribution P_X, and wish to estimate the variance of P_X, as well as compute a confidence interval on the variance. If $n = 1$ and we draw only a single datapoint $X_1 = 2$ from P_X, which of the following are true?

(a) The bootstrap estimate of the variance is 0.

(b) The bootstrap estimate of the variance is 2.

(c) The bootstrap cannot be applied when we only have $n = 1$ samples.

(d) The bootstrap is likely to give a very poor estimate of the variance in this setting.

Correct answers: (a), (d)

Explanation: Given n samples from a distribution, the bootstrap estimate of the variance is calculated by drawing some number of samples with replacement from this data, computing the variance on these samples, then repeating, and averaging the variance values to get a final estimate. When $n = 1$, however, we will always sample the same point, and so the variance will always be 0, regardless of the distribution's true variance. Thus, in this case, while the bootstrap estimate is well-defined, it is very inaccurate.

9. Select All Which of the following statements about the bootstrap method are true?

(a) It requires a large sample size to be effective and cannot be used effectively with small datasets.

(b) It involves repeatedly sampling with replacement from a dataset to create samples and then calculating the statistic of interest on each sample.

(c) Bootstrap methods can only be applied to estimate the mean of a dataset and do not apply to other statistics like median or variance.

(d) One of the advantages is that it does not make strong parametric assumptions about the distribution of the data.

(e) It can be used to estimate confidence intervals for almost any statistic, regardless of the original data distribution.

Correct answers: (b), (d), (e)

10. Select All Which of the following are advantages of using random forests over decision trees?

(a) The optimal decision tree cannot be efficiently computed, but the optimal random forest can.

(b) Random forests typically have smaller variance than decision trees.

(c) Random forests typically have smaller bias than decision trees.

(d) Random forests are less prone to overfitting compared to decision trees.

Correct answers: (b), (d)

Explanation: Decision trees can overfit to the data and have high variance, as the decision criteria may very often capture noise, and be very sensitive. In contrast, random forests typically have lower variance, as they are trained on smaller subsets of features and bootstrapped data, thereby reducing the sensitivity to any particular feature of data point.

11. Select All Which of the following is true about k-nearest neighbors (KNN)?

(a) KNN works best with high dimensional data.

(b) When k=1, the training error is always less than or equal to the test error.

(c) The computational cost of making a prediction on a new test point increases with the size of the training dataset.

(d) The effectiveness of KNN is independent of the distance metric used.

Correct answers: (b), (c)

12. One Answer For k-nearest neighbors (KNN), changing k will affect:

(a) Bias

(b) Variance

(c) Both bias and variance

(d) Neither bias nor variance

Correct answers: (c)

13. One Answer In k-nearest neighbors (KNN), having higher dimensional features is always more desirable because it provides more dimensions to calculate the distance between two data points.

(a) True

(b) False

Correct answers: (b)

14. One Answer The training algorithm for k-means clustering is guaranteed to converge to a local minimum of the k-means objective function.

(a) True

(b) False

Correct answers: (a)

15. One Answer The k-means objective function always improves with each successive iteration of the k-means training algorithm until the objective function converges.

(a) True

(b) False

Correct answers: (a)

16. One Answer In k-means clustering, choosing a different set of initial centroids always leads to the same final clusters after convergence.

(a) True

(b) False

Correct answers: (b)

17. One Answer In k-means clustering, if two points are assigned to the same cluster, any point that is a convex combination of those two points must also be assigned to that same cluster. [Hint: recall that a point x_3 is a convex combination of the points x_1 and x_2 if $x_3 = \alpha x_1 + (1 - \alpha) x_2$ for some $0 \leq \alpha \leq 1$]

(a) True

(b) False

Correct answers: (a)

18. One Answer Recall that in a Gaussian mixture model (GMM) with $K = 2$ Gaussians, the "responsibilities" γ_{ik} indicate the probability that the i-th data point was generated by the k-th Gaussian. These responsibilities provide soft cluster assignments.

In a GMM, if two points x_1 and x_2 have responsibilities $\gamma_{1k} \geq p$ and $\gamma_{2k} \geq p$, respectively, then any point x_3 that is a convex combination of x_1 and x_2 must also have a responsibility $\gamma_{3k} \geq p$.

(a) True

(b) False

Correct answers: (b)

19. Select All What are advantages of using a Gaussian mixture model (GMM) to cluster data over k-means clustering?

(a) GMMs are better at handling non-spherical clusters.

(b) There is a closed-form solution that optimizes the GMM loss function, whereas k-means requires an iterative optimization algorithm.

(c) GMMs are better at modeling uncertainty of cluster assignments.

(d) There are no advantages of using a GMM over k-means clustering.

Correct answers: (a), (c)

Explanation: GMMs attempt to fit Gaussian's to the data, learning both the mean and covariance. As they can learn a elliptical covariance, they are often effective at fitting non-spherical clusters, while k-means explicitly learns spherical clusters. Furthermore, GMMs are able to assign likelihood values that each point lies in any given cluster, given that they assume the data is from a Gaussian distribution, something k-means is unable to do.

20. Select All What role(s) does the activation function in a neural network play?

(a) It determines the size of the neural network.

(b) It introduces non-linearity into the network.

(c) It directly minimizes the loss function during training.

(d) It calculates the gradient of the network's weights.

Correct answers: (b)

21. One Answer Consider a neural network being trained to minimize a loss function using backpropagation. If the learning rate is set too high, what is the most likely outcome during the training process?

(a) The network efficiently converges to the global minimum of the loss function, resulting in optimal training performance.

(b) The network's weights oscillate or diverge, potentially causing the loss to increase rather than decrease.

(c) The network immediately overfits to the training data, leading to poor generalization on unseen data.

(d) The network's training process significantly slows down, requiring more epochs to reach convergence.

Correct answers: (b)

22. One Answer Increasing the number of hidden layers in a neural network will always decrease prediction error on the training data.

(a) True

(b) False

Correct answers: (b)

23. One Answer When designing a neural network, the depth of the network (i.e., the number of hidden layers) plays a critical role in its performance. Which of the following statements best describes the impact of increasing the network's depth?

(a) Adding more layers to the network always results in better performance on the training data, regardless of the activation function (e.g., linear, ReLU, sigmoid, etc.).

(b) Increasing the depth of the network linearly improves its performance on both training and unseen data, as deeper networks can represent more complex functions.

(c) Adding more layers to the network can improve its ability to learn hierarchical representations of data, which is beneficial for complex pattern recognition tasks, though it may also increase the computational complexity and the risk of overfitting.

(d) Deeper networks are less likely to overfit compared to shallower ones, as they have a greater capacity to generalize from the training data to unseen data.

Correct answers: (c)

Explanation: For choice (a), while it's true that deeper networks can perform better on training data, the assertion that this always results in better performance is misleading. The performance on unseen data does not necessarily improve with depth due to overfitting. For choice (b), the improvement in performance is not guaranteed to be **linear** with the addition of more layers. While deeper networks can represent more complex functions, they also require more data and careful regularization to prevent overfitting. For choice (d), the claim that deeper networks are less likely to overfit is incorrect. In fact, the opposite is often true; deeper networks, due to their higher capacity and complexity, can be more prone to overfitting, especially if not regularized properly or if trained on insufficient data.

24. One Answer In the backpropagation algorithm, after computing the gradient of the loss function with respect to the weights, which step is crucial for updating the weights of a neural network to minimize the loss function?

(a) The weights are updated by setting them directly equal to the negative of the computed gradients to immediately minimize the loss.

(b) The learning rate is applied to the gradients, and this product is then subtracted from the current weights to gradually decrease the loss over iterations.

(c) Each weight's gradient is squared, and this squared gradient is then subtracted from the current weight value to ensure only positive updates.

(d) Gradients are normalized to unit length before being applied to update the weights, ensuring uniform step sizes across all dimensions.

Correct answers: (b)

25. One Answer A narrow and deep neural network will always outperform a wide, shallow neural network if the two networks have an approximately equivalent number of parameters.

(a) True

(b) False

Correct answers: (b)

Explanation: This comparison is made in Homework 3. Model performance is dependent on many factors, one of which is model architecture, and one architecture will never outperform another in all scenarios.

26. One Answer During backpropagation, as the gradient flows backward through a sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$, the gradient will always:

(a) **Decrease** in magnitude, **preserve** sign polarity

(b) **Increase** in magnitude, **preserve** sign polarity

(c) **Decrease** in magnitude, **reverse** sign polarity

(d) **Increase** in magnitude, **reverse** sign polarity

Correct answers: (a)

Explanation: Because the output of the sigmoid is always positive (between 0 and 1), its derivative, $\sigma'(x) = \sigma(x)(1 - \sigma(x))$, will also always be positive. In terms of magnitude, the derivatives will always be inside $(0, 0.25]$ so it's decreasing.

27. (2 points) Note: This question is significantly more time consuming than the others; you may want to finish other questions first.

A commonly used activation function in neural networks is the ReLU function, defined as

$$\mathsf{ReLU}(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}.$$

Consider the following neural network with input $x \in \mathbb{R}^d$ and output $y \in \mathbb{R}$ defined as:

$$z = \mathsf{ReLU}(W^{(0)}x + b^{(0)})$$
$$y = W^{(1)}z + b^{(1)}$$

for parameters $W^{(0)} \in \mathbb{R}^{h \times d}, b^{(0)} \in \mathbb{R}^h, W^{(1)} \in \mathbb{R}^{1 \times h}, b^{(1)} \in \mathbb{R}$, and where ReLU is applied element-wise to the vector $W^{(0)}x + b^{(0)}$. Let $W_i^{(1)}$ denote the ith element of $W^{(1)}$, and $W_i^{(0)\top}$ denote the ith row of $W^{(0)}$. For simplicity, assume that each element of $W^{(0)}x + b^{(0)}$ is non-zero.

What is $\frac{dy}{dW_i^{(0)}}$? You may write your answer in terms of $W_i^{(0)}$ and $W_i^{(1)}$.

Answer: ____________________________

What is $\frac{dy}{dW^{(0)}}$? You may write your answer in terms of $\frac{dy}{dW_i^{(0)}}$.

Answer: ____________________________

Explanation: Note that this problem is very similar to Problem 2.1(d) of Section 8. Please see the solutions to that problem for additional discussion.

First note that, by the chain rule, we have

$$\frac{dy}{dW_i^{(0)}} = \frac{dy}{dz_i}\frac{dz_i}{dW_i^{(0)}}.$$

It is straightforward to see that $\frac{dy}{dz_i} = W_i^{(1)}$. Since the ReLU is only active when it's argument is > 0, we have $\frac{dz_i}{dW_i^{(0)}} = 0$ unless $W_i^{(0)}x + b_i^{(0)}$. Otherwise, we have $z_i = W_i^{(0)}x + b_i^{(0)}$, and we see that the derivative of this with respect to $W_i^{(0)}$ is x. This then gives:

$$\frac{dy}{dW_i^{(0)}} = \begin{cases} W_i^{(1)} \cdot x & \text{if } (W_i^{(0)})^\top x + b_i^{(0)} > 0 \\ 0 & \text{if } (W_i^{(0)})^\top x + b_i^{(0)} \leq 0 \end{cases}$$

Note that $\frac{dy}{dW_i^{(0)}} \in \mathbb{R}^d$, since y is 1-dimensional and $W_i^{(0)}$ is d-dimensional. By the same reasoning, we have $\frac{dy}{dW^{(0)}} \in \mathbb{R}^{h \times d}$, and the rows of $\frac{dy}{dW^{(0)}}$ are simply $\frac{dy}{dW_i^{(0)}}^\top$, giving

$$\frac{dy}{dW^{(0)}} = \begin{bmatrix} \frac{dy}{dW_1^{(0)}}^\top \\ \frac{dy}{dW_2^{(0)}}^\top \\ \vdots \\ \frac{dy}{dW_h^{(0)}}^\top \end{bmatrix}$$

28. Select All Which of the following statements about PCA are True?

(a) PCA identifies the directions in feature space that minimize the variance of the projected data.

(b) PCA identifies the directions in feature space that minimize the reconstruction error between the original data and its projection onto the principal components.

(c) All principal component directions are orthogonal to one another.

(d) The first principal component direction is the eigenvector of the data covariance matrix that has the smallest eigenvalue.

(e) The principal component directions can be found from a singular value decomposition of the data matrix.

Correct answers: (b), (c), (e)

Explanation: B, C, and E are correct. Full credit is given if all of {B, C, E} are indicated AND no incorrect choices are indicated. Partial credit is given if any of {B, C, E} are indicated AND no incorrect choices are indicated. No credit is given otherwise.
– A is incorrect because PCA identifies the directions that MAXIMIZE the variance of the projected data.
– D is incorrect because the first principal component direction is the eigenvector of the data covariance matrix that has the LARGEST eigenvalue.

29. Select All Which of the following statements about PCA are True?

(a) For samples in d-dimensions, the top d principal components can fully reconstruct the original samples

(b) For samples in d-dimension, it's impossible to fully reconstruct the samples using top q principal components when $q < d$.

(c) Standard cross-validation techniques can be used to identify q, the optimal dimensionality of the PCA projection.

Correct answers: (a)

30. One Answer Throughout this course, we have seen that the solution to linear regression problems can be written as $\widehat{\theta} = (X^\top X)^{-1} X^\top Y$, for data matrices $X \in \mathbb{R}^{n \times d}$ and $Y \in \mathbb{R}^n$. Let $X = U \Sigma V^\top$ denote the SVD of X. What is $\widehat{\theta}$ in terms of U, Σ, V, and Y? Note that this suggests that one way to solve a least squares problem is to simply compute the SVD of X.

(a) $V(\Sigma^\top \Sigma)^{-1} \Sigma^\top U^\top Y$

(b) $V \Sigma^{-1} U^\top Y$

(c) $U \Sigma^\top (\Sigma^\top \Sigma)^{-1} V^\top Y$

(d) $U(\Sigma^\top \Sigma)^{-1} \Sigma^\top V^\top Y$

Correct answers: (a)

Explanation: Recall that U and V are both orthogonal. Thus, $X^\top X = V \Sigma^\top \Sigma V^\top$, and $(X^\top X)^{-1} = V(\Sigma^\top \Sigma)^{-1} V^\top$. Noticing that $V^\top X^\top = \Sigma^\top U^\top$, the result follows.

As an aside, note that $\Sigma^\top \Sigma$ is diagonal. It is significantly easier to invert a diagonal matrix than a non-diagonal one (we can simply invert each element in the diagonal individually), so in general it is much easier to invert $(\Sigma^\top \Sigma)^{-1}$ than $(X^\top X)^{-1}$. Thus, if we know the SVD of X, we can compute the least-squares estimate very efficiently! (No free lunch here, though, as it's often expensive to compute the SVD of X).

31. Consider the following matrix X and convolutional neural network (CNN) filter F.

$$X = \begin{array}{|c|c|c|c|}\hline 8 & 17 & 8 & 16 \\ \hline 13 & 7 & 10 & 5 \\ \hline 12 & 0 & 13 & 17 \\ \hline 7 & 11 & 11 & 9 \\ \hline \end{array} \qquad F = \begin{array}{|c|c|}\hline 1 & 0 \\ \hline 0 & 1 \\ \hline \end{array}$$

Apply the filter F to matrix X with Padding = 1 (padding with zeros) and stride = 2. Write the resulting matrix below in the grid of the correct size. Only write answers in one matrix, otherwise the problem will be graded as incorrect.

Explanation:

$$\begin{array}{|c|c|c|}\hline 8 & 8 & 0 \\ \hline 12 & 20 & 5 \\ \hline 0 & 11 & 9 \\ \hline \end{array}$$

Zero padding means we add zeros all the way around the matrix, this will make it look like the following:

$$\begin{array}{|c|c|c|c|c|c|}\hline 0 & 0 & 0 & 0 & 0 & 0 \\ \hline 0 & 8 & 17 & 8 & 16 & 0 \\ \hline 0 & 13 & 7 & 10 & 5 & 0 \\ \hline 0 & 12 & 0 & 13 & 17 & 0 \\ \hline 0 & 7 & 11 & 11 & 9 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 0 \\ \hline \end{array}$$

We then get 8 as the first position because $1(0) + 0(0) + 0(0) + 8(1) = 8$. Then, the filter moves over two spaces because of stride = 2 to compute the next number and so on.

32. Give one main reason we might use a convolutional neural network over a fully connected one. Briefly explain why the CNN architecture makes that advantage possible.

Answer: ____

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Explanation: Particularly for image data, we might use CNNs over fully connected networks since CNNs often have much fewer parameters, are better at capturing local patterns, and are better at feature extraction.

33. Select All Which of the following functions are convex?

(a) $f(x) = x^\top Ax$, where A is a symmetric matrix and $x \in \mathbb{R}^d$.

(b) The logistic function $\sigma(x) = \frac{1}{1+e^{-x}}$, where $x \in \mathbb{R}$.

(c) The L2 regularization term $f(x) = \lambda \|x\|_2^2$, where $\lambda > 0$ and $x \in \mathbb{R}^d$.

(d) The L1 regularization term $f(x) = \lambda \|x\|_1$, where $\lambda > 0$ and $x \in \mathbb{R}^d$.

(e) The regularization term $f(x) = \lambda \sum_{i=1}^{d} \sqrt{x_i}$, where $\lambda > 0, x_i > 0$.

Correct answers: (c), (d)

Explanation: $f(x) = x^\top Ax$ is convex $\iff$ $A \succeq 0$. Not all symmetric matrices are positive semidefinite (e.g., $A = -I$).

34. Select All Which of the following statements are true for a convex function $f(x)$? You may assume that $f(x)$ is defined and is twice differentiable for all values of x.

(a) If you pick any two points on the graph of $f(x)$, the line segment connecting them will not lay underneath the graph.

(b) Every local minimum of $f(x)$ is also a global minimum.

(c) $f(x)$ must have at least one sharp corner or point, like the tip of a triangle.

(d) The second derivative of $f(x)$ is always negative.

(e) There is a unique value of x that minimizes $f(x)$.

Correct answers: (a), (b)

Explanation: Answer choices (a) and (b) follow from the definition of a convex function. Choice (c) is incorrect, as its not a requirement for a convex function to have a sharp corner or point. Convex functions can be perfectly smooth. Further, the question states the the function is twice differentiable, which means there are no sharp corners or points. Choice (d) is also incorrect, as a function is convex if and only if its second derivative is always non-negative. Choice (e) is not correct since a convex function may have multiple (connected) global minima. Also, consider the special case where $f(x)$ is a hyperplane (which is a convex function). A hyperplane with nonzero slope has no finite x that minimizes $f(x)$. A hyperplane with zero slope is minimized at every x, so again there is no unique value of x that minimizes $f(x)$.

35. One Answer Suppose you train a linear regression model to approximate the quadratic function $g(x) = 7x^2 + 3$. What is the most likely outcome?

(a) The model will have high bias and high variance

(b) The model will have high bias and low variance

(c) The model will have low bias and high variance

(d) The model will have low bias and low variance

Correct answers: (b)

36. One Answer Suppose you train a polynomial regression model of degree $d = 4$ to approximate the linear function $g(x) = 3x + 2$. What is the most likely outcome?

(a) The model will have high bias and high variance

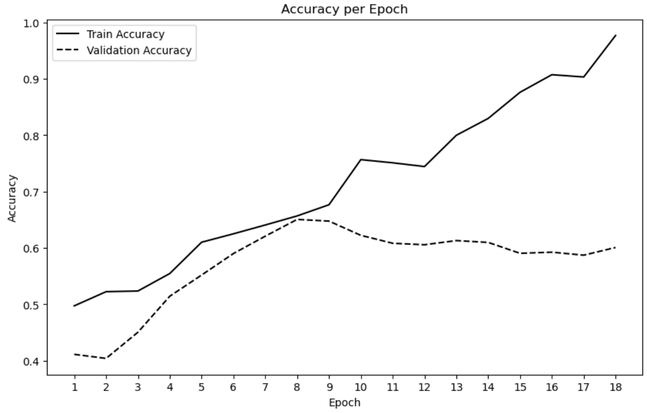
(b) The model will have high bias and low variance

(c) The model will have low bias and high variance

(d) The model will have low bias and low variance

Correct answers: (c)

37. Consider the following accuracy plot generated while training a neural network.



Which **one** of these options would be most likely to improve the validation accuracy of your model?

1. Increase the learning rate
2. Decrease the learning rate
3. Increase regularization
4. Decrease regularization
5. Increase the number of epochs
6. Decrease the number of epochs
7. None of the above

Choose one option and explain how it would help improve the model (2 sentences). If none of these options are likely to change the model's performance, explain why (2 sentences).

Answer: ____

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Explanation: This model is overfitting, so increasing regularization is the most likely to decrease the variance by adding in bias. Another option is decreasing the number of epochs as that is another form of regularization.

38. Select All Which of the following statements about Maximum Likelihood Estimation (MLE) are true?

(a) MLE requires probabilistic assumptions to be made about the data.

(b) Linear regression can be viewed as a MLE problem.

(c) Logistic regression can be viewed as a MLE problem.

(d) MLE guarantees that the estimated parameters are unbiased.

(e) MLE is always equivalent to minimizing the squared reconstruction error.

Correct answers: (a), (b), (c)

39. In the context of machine learning, how does k-fold cross-validation enhance the reliability of a model's performance evaluation compared to using a single train-test split, and what is one potential downside of using this method?

Answer: ______________________________

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Explanation: K-fold cross-validation improves reliability by dividing the dataset into 'k' equal parts, training the model 'k' times with each part serving as the test set once, thereby reducing bias and variance in the performance estimation. However, it can be computationally expensive, especially for large datasets or complex models, as it requires the model to be trained multiple times.

40. Select All Which of the statements about cross-validation are true?

(a) The goal of cross-validation is to estimate the training error.

(b) Leave-one-out cross-validation is equivalent to k-fold cross-validation when k is equal to the total number of training data points n.

(c) Leave-one-out cross-validation is always faster than k-fold cross-validation.

(d) k-fold cross-validation will always produce the same estimate of error, regardless of the choice of k.

Correct answers: (b)

41. Select All In which setting(s) might logistic regression be more suitable than k-nearest neighbors (KNN)?

(a) If your targets y_i take on continuous values.

(b) If you want to understand the relationship between your features x_i and your targets y_i.

(c) If you care most about minimizing the time required to train your model.

(d) If you care most about minimizing the time required to make predictions with your model.

Correct answers: (b), (d)

Explanation: a - incorrect as for logistic regression you have class output which isn't continuous.
b - Correct as you can see what features are given the most weight with logistic regression while knn is just distances.
c - Incorrect as the train time for knn is O(1), it's the prediction time that takes the time
d - Correct as predictions are a single calculation for logistic regression but scale with the amount of data you have for knn.

42. Select All Ridge regression reduces overfitting by:

(a) Penalizing the L1 norm of the model parameters.

(b) Penalizing the L2 norm of the model parameters.

(c) Increasing model complexity to better fit the training data.

(d) Encouraging sparsity in the model parameters.

Correct answers: (b)

43. Select All Which of the following statements about ridge regression are **incorrect**?

(a) Ridge regression introduces a penalty term to the linear regression cost function by controlling the magnitudes of the coefficient values.

(b) The regularization term in ridge regression helps in reducing model complexity by setting some coefficients to exactly zero.

(c) The ridge regression parameter estimate will be equivalent to the Ordinary Least Squares parameter estimate when $\lambda = 0$ in the case that $X^T X$ is full rank (where X is the training data matrix).

(d) The choice of the regularization hyperparameter (λ) in ridge regression can significantly impact the model's bias-variance trade-off.

Correct answers: (b)

Explanation: In ridge regression, the regularization term adds a penalty to the linear regression cost function, which helps control the magnitudes of the coefficient values. It aims to minimize the sum of squared errors while keeping all coefficients in the model. Ridge regression is often used when you want to reduce the impact of multicollinearity without eliminating any predictors from the model.

In contrast, LASSO also adds a penalty term to the linear regression cost function but uses $\mathcal{L}_1$ regularization. LASSO has the property of variable selection, which means it can set some coefficients exactly to zero. This makes LASSO useful for feature selection, as it can effectively eliminate certain predictors from the model. Unlike ridge regression, LASSO encourages sparsity in the coefficient matrix.