Advice for Applying Machine Learning

TOTAL POINTS S

| You train a learning algorithm, and find that it has unacceptably high error on the test set. You plot the learning curve, and obtain the figure below. Is the algorithm suffering from high bias, high variance, or | 1 point |
|---|---------|
| neither? | |
| | |
| | |
| | |
| $J_{\text{test}}(\theta)$ | |
| (est, -) | |
| $J_{train}(\theta)$ | |
| | |
| | |
| m (Training Set Size) | |
| High bias | |
| Neither | |
| High variance | |
| | |
| Suppose you have implemented regularized logistic regression | 1 point |
| to classify what object is in an image (i.e., to do object | Тропк |
| | |
| recognition). However, when you test your hypothesis on a new | |
| set of images, you find that it makes unacceptably large | |
| errors with its predictions on the new images. However, your | |
| hypothesis performs well (has low error) on the | |
| training set. Which of the following are promising steps to | |
| take? Check all that apply. | |
| Use fewer training examples. | |
| | |
| Get more training examples. | |
| Try using a smaller set of features. | |
| ☐ Try adding polynomial features. | |
| | |
| Suppose you have implemented regularized logistic regression | 1 point |
| to predict what items customers will purchase on a web | Тропк |
| | |
| shopping site. However, when you test your hypothesis on a new | |
| set of customers, you find that it makes unacceptably large | |
| errors in its predictions. Furthermore, the hypothesis | |
| performs poorly on the training set. Which of the | |
| following might be promising steps to take? Check all that | |
| apply. | |
| Use fewer training examples. | |
| | |
| Try evaluating the hypothesis on a cross validation set rather than the test set. | |
| $igspace$ Try decreasing the regularization parameter λ . | |
| ✓ Try adding polynomial features. | |
| | |
| Which of the following statements are true? Check all that apply. | 1 point |
| | 1 point |
| It is okay to use data from the test set to choose the regularization parameter λ , but not the model parameters (θ) . | |
| | |
| Suppose you are training a logistic regression classifier using polynomial features and want to select what degree polynomial (denoted d in the lecture videos) to use. After training the classifier on the | |
| entire training set, you decide to use a subset of the training examples as a validation set. This will work just as well as having a validation set that is separate (disjoint) from the training set. | |
| | |
| A typical split of a dataset into training, validation and test sets might be 60% training set, 20% validation set, and 20% test set. | |
| Suppose you are using linear regression to predict housing prices, and your dataset comes sorted in | |
| order of increasing sizes of houses. It is then important to randomly shuffle the dataset before | |
| splitting it into training, validation and test sets, so that we don't have all the smallest houses going into the training set, and all the largest houses going into the test set. | |
| | |
| Which of the following statements are true? Check all that apply. | 1 point |
| | 1 point |
| When debugging learning algorithms, it is useful to plot a learning curve to understand if there is a high bias or high variance problem. | |
| | |
| If a learning algorithm is suffering from high bias, only adding more training examples may not improve the test error significantly. | |

| If a neural network has much lower training error than test error, then adding more layers will h bring the test error down because we can fit the test set better. | elp | |
|---|------|--------|
| A model with more parameters is more prone to overfitting and typically has higher variance. | | |
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