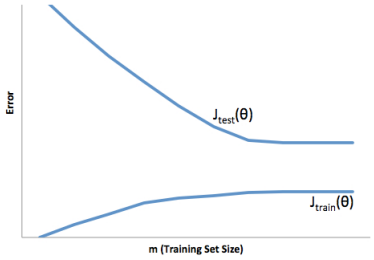
1 point

1. 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 neither?




- ( ) High bias
- (•) Neither
- ( ) High variance

1 point

2. Suppose you have implemented regularized logistic regression to classify what object is in an image (i.e., to do object 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.

- [ ] Try decreasing the regularization parameter $\lambda$.
- [x] Try using a smaller set of features.
- [x] Try evaluating the hypothesis on a cross validation set rather than the test set.
- [x] Try increasing the regularization parameter $\lambda$.

1 point

3. Suppose you have implemented regularized logistic regression to predict what items customers will purchase on a web 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.

- [x] Try to obtain and use additional features.
- [ ] Try using a smaller set of features.
- [x] Try adding polynomial features.
- [ ] Try increasing the regularization parameter $\lambda$.

1 point

4. Which of the following statements are true? Check all that apply.

- [ ] It is okay to use data from the test set to choose the regularization parameter $\lambda$ , but not the model parameters ($\theta$).
- [x] 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.
- [x] 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 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.

1 point

5. Which of the following statements are true? Check all that apply.

- [x] When debugging learning algorithms, it is useful to plot a learning curve to understand if there is a high bias or high variance problem.
- [x] If a learning algorithm is suffering from high bias, only adding more training examples may **not** improve the test error significantly.
- [x] We always prefer models with high variance (over those with high bias) as they

We always prefer models with high variance (over those with high bias) as they will able to better fit the training set.

If a learning algorithm is suffering from high variance, adding more training examples is likely to improve the test error.

I, **Marin Sarbulescu**, understand that submitting work that isn't my own may result in permanent failure of this course or deactivation of my Coursera account.

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