✓ **Congratulations! You passed!**   Next Item

1. If you have 10,000,000 examples, how would you split the train/dev/test set?

1 / 1 points

- ◉ 98% train . 1% dev . 1% test

  Correct

- ○ 33% train . 33% dev . 33% test
- ○ 60% train . 20% dev . 20% test

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2. The dev and test set should:

1 / 1 points

- ◉ Come from the same distribution

  Correct

- ○ Come from different distributions
- ○ Be identical to each other (same (x,y) pairs)
- ○ **Have the same number of examples**

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3. If your Neural Network model seems to have high bias, what of the following would be promising things to try? (Check all that apply.)

1 / 1 points

- ☑ Make the Neural Network deeper

  Correct

- ☐ Get more test data

  Un-selected is correct

- ☐ Get more training data

  Un-selected is correct

- ☑ Increase the number of units in each hidden layer

  Correct

- ☐ Add regularization

  Un-selected is correct

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4. You are working on an automated check-out kiosk for a supermarket, and are building a classifier for apples, bananas and oranges. Suppose your classifier obtains a training set error of 0.5%, and a dev set error of 7%. Which of the following are promising things to try to improve your classifier? (Check all that apply.)

1 / 1 points

- ☑ Increase the regularization parameter lambda

  Correct

- ☐ Decrease the regularization parameter lambda

  Un-selected is correct

- ☑ Get more training data

  Correct

- ☐ Use a bigger neural network

  Un-selected is correct

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5. What is weight decay?

1 / 1 points

- ◉ A regularization technique (such as L2 regularization) that results in gradient descent shrinking the weights on every iteration.

  Correct

- ○ Gradual corruption of the weights in the neural network if it is trained on noisy data.
- ○ The process of gradually decreasing the learning rate during training.
- ○ A technique to avoid vanishing gradient by imposing a ceiling on the values of the weights.

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6. What happens when you increase the regularization hyperparameter lambda?

1 / 1 points

- ◉ Weights are pushed toward becoming smaller (closer to 0)

  Correct

- ○ Weights are pushed toward becoming bigger (further from 0)
- ○ Doubling lambda should roughly result in doubling the weights
- ○ Gradient descent taking bigger steps with each iteration (proportional to lambda)

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7. With the inverted dropout technique, at test time:

1 / 1 points

- ○ You apply dropout (randomly eliminating units) but keep the 1/keep_prob factor in the calculations used in training.
- ◉ You do not apply dropout (do not randomly eliminate units) and do not keep the 1/keep_prob factor in the calculations used in training

  Correct

- ○ You do not apply dropout (do not randomly eliminate units), but keep the 1/keep_prob factor in the calculations used in training.
- ○ You apply dropout (randomly eliminating units) and do not keep the 1/keep_prob factor in the calculations used in training

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8. Increasing the parameter keep_prob from (say) 0.5 to 0.6 will likely cause the following: (Check the two that apply)

1 / 1 points

- ☐ Increasing the regularization effect

  Un-selected is correct

- ☑ Reducing the regularization effect

  Correct

- ☐ Causing the neural network to end up with a higher training set error

  Un-selected is correct

- ☑ Causing the neural network to end up with a lower training set error

  Correct

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9. Which of these techniques are useful for reducing variance (reducing overfitting)? (Check all that apply.)

1 / 1 points

- ☐ Exploding gradient

  Un-selected is correct

- ☐ Vanishing gradient

  Un-selected is correct

- ☐ Xavier initialization

  Un-selected is correct

- ☑ Dropout

  Correct

- ☑ L2 regularization

  Correct

- ☑ Data augmentation

  Correct

- ☐ Gradient Checking

  Un-selected is correct

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10. Why do we normalize the inputs x?

1 / 1 points

- ○ It makes it easier to visualize the data
- ○ It makes the parameter initialization faster
- ◉ It makes the cost function faster to optimize

  Correct

- ○ Normalization is another word for regularization--It helps to reduce variance