## ▲ Try again once you are ready

Grade received 60% To pass 80% or higher

Try again

## **Machine Learning System Design**

Latest Submission Grade 60%

You are working on a spam classification system using regularized logistic regression. "Spam" is a positive class (y = 1) and "not spam" is the negative class (y = 0). You have trained your classifier and there are m = 1000 examples in the cross-validation set. The chart of predicted class vs. actual class is:

1/1 point

	Actual Class: 1	Actual Class: 0
Predicted Class: 1	85	890
Predicted Class: 0	15	10

For reference:

- Accuracy = (true positives + true negatives) / (total examples)
- Precision = (true positives) / (true positives + false positives)
- Recall = (true positives) / (true positives + false negatives)
- $F_1$  score = (2 \* precision \* recall) / (precision + recall)

What is the classifier's recall (as a value from 0 to 1)?

Enter your answer in the box below. If necessary, provide at least two values after the decimal point.

0.85

**⊘** Correct

There are 85 true positives and 15 false negatives, so recall is 85 / (85 + 15) = 0.85.

 Suppose a massive dataset is available for training a learning algorithm. Training on a lot of data is likely to give good performance when two of the following conditions hold true.

0 / 1 point

Which are the two?

Our learning algorithm is able to

represent fairly complex functions (for example, if we

train a neural network or other model with a large

number of parameters).

✓ Correct

You should use a complex, "low bias" algorithm, as it will be able to make use of the large dataset provided. If the model is too simple, it will underfit the large training set.

When we are willing to include high

order polynomial features of x (such as  $x_1^2, x_2^2$ ,

 $x_1x_2$ , etc.).

igotimes This should not be selected

As we saw with neural networks, polynomial features can still be insufficient to capture the complexity of the data, especially if the features are very high-dimensional. Instead, you should use a complex model with many parameters to fit to the large training set.

The classes are not too skewed.

A human expert on the application domain

can confidently predict  $\boldsymbol{y}$  when given only the features  $\boldsymbol{x}$ 

accurately). Suppose you have trained a logistic regression classifier which is outputing  $h_{\theta}(x)$ . 1/1 point Currently, you predict 1 if  $h_{ heta}(x) \geq threshold$ , and predict 0 if  $h_{ heta}(x) < threshold$ , where currently the threshold is set to 0.5.  $\label{thm:continuous} \textit{Suppose you} \ \textbf{decrease} \ \textit{the threshold to 0.3.} \ \textit{Which of the following are true?} \ \textit{Check all that apply.}$ The classifier is likely to have unchanged precision and recall, but higher accuracy. The classifier is likely to have unchanged precision and recall, but lower accuracy. ☐ The classifier is likely to now have higher precision. The classifier is likely to now have higher recall. **⊘** Correct  $Lowering \ the \ threshold \ means \ more \ y=1 \ predictions. \ This \ will \ increase \ the \ number \ of \ true \ positives \ and$ decrease the number of false negatives, so recall will increase. Suppose you are working on a spam classifier, where spam 0 / 1 point emails are positive examples (y = 1) and non-spam emails are negative examples (y=0). You have a training set of emails in which 99% of the emails are non-spam and the other 1% is spam. Which of the following statements are true? Check all that apply. If you always predict non-spam (output y=0), your classifier will have an accuracy of 99%. ✓ Correct Since 99% of the examples are y = 0, always predicting 0 gives an accuracy of 99%. Note, however, that this is not a good spam system, as you will never catch any spam. \\ ☐ If you always predict non-spam (output y=0), your classifier will have 99% accuracy on the training set, but it will do much worse on the cross validation set because it has overfit the training ✓ If you always predict non-spam (output y=0), your classifier will have 99% accuracy on the training set, and it will likely perform similarly on the cross validation set. **⊘** Correct The classifier achieves 99% accuracy on the training set because of how skewed the classes are. We can expect that the cross-validation set will be skewed in the same fashion, so the classifier will have approximately the same accuracy.

A good classifier should have both a

(or more generally, if we have some way to be confident that  $\boldsymbol{x}$  contains sufficient information to predict  $\boldsymbol{y}$ 

high precision and high recall on the cross validation

set.

You didn't select all the correct answers

5.	Which of the following statements are true? Check all that apply.	
	If your model is underfitting the	
	training set, then obtaining more data is likely to	
	help.	
	The "error analysis" process of manually	
	examining the examples which your algorithm got wrong	
	can help suggest what are good steps to take (e.g.,	
	developing new features) to improve your algorithm's	
	performance.	
	<ul> <li>Correct         This process of error analysis is crucial in developing high performance learning systems, as the space of possible improvements to your system is very large, and it gives you direction about what to work on next.     </li> </ul>	
After training a logistic regression		
	classifier, you <b>must</b> use 0.5 as your threshold	
	for predicting whether an example is positive or	
	negative.	
Using a <b>very large</b> training set		
	makes it unlikely for model to overfit the training	
	data.	
	<ul> <li>Correct         A sufficiently large training set will not be overfit, as the model cannot overfit some of the examples without doing poorly on the others.     </li> </ul>	
lt is a good idea to spend a lot of time		
	collecting a large amount of data before building	
	your first version of a learning algorithm.	

1/1 point