## Your grade: 85%

Your latest: **85%** • Your highest: **85%** • To pass you need at least 80%. We keep your highest score.

Next item

**1.** To help you practice strategies for machine learning, this week we'll present another scenario and ask how you would act. We think this "simulator" of working in a machine learning project will give you an idea of what leading a machine learning project could be like! **1 / 1 point**

You are employed by a startup building self-driving cars. You are in charge of detecting road signs (stop sign, pedestrian crossing sign, construction ahead sign) and traffic signals (red and green lights) in images. The goal is to recognize which of these objects appear in each image. As an example, this image contains a pedestrian crossing sign and red traffic lights.

$$y^{(i)} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} \begin{matrix} \text{“stop sign”} \\ \text{“pedestrian crossing sign”} \\ \text{“construction ahead sign”} \\ \text{“red traffic light”} \\ \text{“green traffic light”} \end{matrix}$$

Your 100,000 labeled images are taken using the front-facing camera of your car. This is also the distribution of data you care most about doing well on. You think you might be able to get a much larger dataset off the internet, which could be helpful for training even if the distribution of internet data is not the same.

Suppose that you came from working with a project for human detection in city parks, so you know that detecting humans in diverse environments can be a difficult problem. What is the first thing you do? Assume each of the steps below would take about an equal amount of time (a few days).

- ○ Leave aside the pedestrian detection, to move faster and then later solve the pedestrian problem alone.
- ○ Start by solving pedestrian detection, since you already have the experience to do this.
- ◉ Train a basic model and proceed with error analysis.
- ○ Spend a few days collecting more data to determine how hard it will be to include more pedestrians in your dataset.

**Correct**
Correct. As discussed in the lecture, it is better to create your first system quickly and then iterate.

**2.** Your goal is to detect road signs (stop sign, pedestrian crossing sign, construction ahead sign) and traffic signals (red and green lights) in images. The goal is to recognize which of these objects appear in each image. You plan to use a deep neural network with ReLU units in the hidden layers. **0 / 1 point**

For the output layer, a softmax activation would be a good choice for the output layer because this is a multi-task learning problem. True/False?

- ○ False
- ◉ True

**Incorrect**

**3.** When trying to determine what strategy to implement to improve the performance of a model, we manually check all images of the training set where the algorithm was successful. True/False? **1 / 1 point**

- ○ True
- ◉ False

**Correct**
Correct. This set should be too large to manually check all the images. It is better to focus on the images that the algorithm got wrong from the dev set. Also, choose a large enough subset that we can manually check.

**4.** After working on the data for several weeks, your team ends up with the following data: **1 / 1 point**

- 100,000 labeled images taken using the front-facing camera of your car.
- 900,000 labeled images of roads downloaded from the internet.
- Each image's labels precisely indicate the presence of any specific road signs and traffic signals or combinations of them. For example, $y^{(i)} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$ means the image contains a stop sign and a red

traffic light.

When using a non fully labeled image such as $y^{(i)} = \begin{bmatrix} 0 \\ ? \\ 1 \\ ? \\ 1 \end{bmatrix}$, which of the following strategies is most appropriate to calculate the loss function to train as a multi-task learning problem?

- ○ Make the missing entries equal to 1.
- ◉ Calculate the loss as $\sum \mathcal{L}(\hat{y}_j^{(i)}, y_j^{(i)})$ where the sum goes over all the know components of $y^{(i)}$.
- ○ It is not possible to use non fully labeled images if we train as a multi-task learning problem.
- ○ Make the missing entries equal to 0.

**Correct**
Correct. We can't use the components of the labels that are missing but we can use the ones we have to train the model.

**5.** The distribution of data you care about contains images from your car's front-facing camera, which comes from a different distribution than the images you were able to find and download off the internet. Which of the following are true about the train/dev/test split? **0.75 / 1 point**

- ☐ The train, dev, and test must come from the same distribution.
- ☐ The dev and test set must come from the front-facing camera.
- ☐ The dev and test sets must contain some images from the internet.
- ☑ The dev and test sets must come from the same distribution.

**Correct**
Correct. This is required to aim the target where we want to be.

You didn't select all the correct answers

**6.** Assume you've finally chosen the following split between the data: **0 / 1 point**

- ○ You have a high bias.
- ◉ You have a large data-mismatch problem.
- ○ The size of the train-dev set is too high.
- ○ You have a high variance problem.
- ○

| Dataset: | Contains: | Error of the algorithm: |
|---|---|---|
| Training | 940,000 images randomly picked from (900,000 internet images + 60,000 car's front-facing camera images) | 1% |
| Training-Dev | 20,000 images randomly picked from (900,000 internet images + 60,000 car's front-facing camera images) | 5.1% |
| Dev | 20,000 images from your car's front-facing camera | 5.6% |
| Test | 20,000 images from the car's front-facing camera | 6.8% |

You also know that human-level error on the road sign and traffic signals classification task is around 0.5%. Which of the following is true?

**Incorrect**
The training-dev error and the dev error are not that different to come to this conclusion.

**7.** Assume you've finally chosen the following split between the data: **1 / 1 point**

- ○

| Dataset: | Contains: | Error of the algorithm: |
|---|---|---|
| Training | 940,000 images randomly picked from (900,000 internet images + 60,000 car's front-facing camera images) | 2% |
| Training-Dev | 20,000 images randomly picked from (900,000 internet images + 60,000 car's front-facing camera images) | 2.3% |
| Dev | 20,000 images from your car's front-facing camera | 1.3% |
| Test | 20,000 images from the car's front-facing camera | 1.1% |

You also know that human-level error on the road sign and traffic signals classification task is around 0.5%. Based on the information given you conclude that the Bayes error for the dev/test distribution is higher than for the train distribution. True/False?

- ◉ True
- ○ False

Correct
Correct. Notice that the test and dev errors are lower than the train and train-dev errors.

8. You decide to focus on the dev set and check by hand what the errors are due to. Here is a table summarizing your discoveries: 1 / 1 point

| | |
|---|---|
| Overall dev set error | 15.3% |
| Errors due to incorrectly labeled data | 4.1% |
| Errors due to foggy pictures | 2.0% |
| Errors due to partially occluded elements. | 8.2% |
| Errors due to other causes | 1.0% |

In this table, 4.1%, 8.2%, etc. are a fraction of the total dev set (not just examples of your algorithm mislabeled). For example, about 8.2/15.3 = 54% of your errors are due to partially occluded elements in the image.

Which of the following is the correct analysis to determine what to prioritize next?

- ○ You should prioritize getting more foggy pictures since that will be easier to solve.
- ◉ You should weigh how costly it would be to get more images with partially occluded elements, to decide if the team should work on it or not.
- ○ Since 8.2 > 4.1 + 2.0 + 1.0, the priority should be to get more images with partially occluded elements.
- ○ Since there is a high number of incorrectly labeled data in the dev set, you should prioritize fixing the labels on the whole training set.

Correct
Correct. You should consider the tradeoff between the data accessibility and potential improvement of your model trained on this additional data.

9. You can buy a specially designed windshield wiper that helps wipe off some of the raindrops on the front-facing camera. 1 / 1 point

| | |
|---|---|
| Overall dev set error | 15.3% |
| Errors due to incorrectly labeled data | 4.1% |
| Errors due to foggy pictures | 8.0% |
| Errors due to rain drops stuck on your car's front-facing camera | 2.2% |
| Errors due to other causes | 1.0% |

Which of the following statements do you agree with?

- ○ 2.2% would be a reasonable estimate of the minimum amount this windshield wiper could improve performance.
- ○ 2.2% would be a reasonable estimate of how much this windshield wiper will improve performance.
- ◉ 2.2% would be a reasonable estimate of the maximum amount this windshield wiper could improve performance.
- ○ 2.2% would be a reasonable estimate of how much this windshield wiper could worsen performance in the worst case.

Correct
Yes. You will probably not improve performance by more than 2.2% by solving the raindrops problem. If your dataset was infinitely big, 2.2% would be a perfect estimate of the improvement you can achieve by purchasing a specially designed windshield wiper that removes the raindrops.

10. You decide to use data augmentation to address foggy images. You find 1,000 pictures of fog off the internet, and "add" them to clean images to synthesize foggy days, like this: 1 / 1 point


We can't use this data since they have a different distribution from the ones we used (internet and front-facing camera). True/False?

- ◉ False
- ○ True

Correct
Correct. The new synthesized images are added to the training set and as long as they look realistic to the human eye this will be useful data to train the model.

**11.** After working further on the problem, you've decided to correct the incorrectly labeled data. Your team corrects the labels of the wrongly predicted images on the dev set. 1 / 1 point

You have to correct the labels of the test so test and dev sets have the same distribution, but you won't change the labels on the train set because most models are robust enough they don't get severely affected by the difference in distributions. True/False?

- False, the test set should be changed, but also the train set to keep the same distribution between the train, dev, and test sets.
- True, as pointed out, we must keep dev and test with the same distribution. And the labels at training should be fixed only in case of a systematic error.
- False, the test set shouldn't be changed since we want to know how the model performs in real data.

Correct
Correct! To successfully train a model, the dev set and test set should come from the same distribution. Also, the deep learning models are robust enough to handle a small change in distributions, but if the errors are systematic they can significantly affect the training of the model.

**12.** One of your colleagues at the startup is starting a project to classify road signs as stop, dangerous curve, construction ahead, dead-end, and speed limit signs. Given how specific the signs are, he has only a small dataset and hasn't been able to create a good model. You offer your help providing the trained weights (parameters) of your model to transfer knowledge. 1 / 1 point

But your colleague points out that his problem has more specific items than the ones you used to train your model. This makes the transfer of knowledge impossible. True/False?

- True
- False

Correct
Correct. The model can benefit from the pre-trained model since there are many features learned by your model that can be used in the new problem.

**13.** Another colleague wants to use microphones placed outside the car to better hear if there are other vehicles around you. For example, if there is a police vehicle behind you, you would be able to hear their siren. However, they don't have much to train this audio system. How can you help? 1 / 1 point

- Transfer learning from your vision dataset could help your colleague get going faster. Multi-task learning seems significantly less promising.
- Multi-task learning from your vision dataset could help your colleague get going faster. Transfer learning seems significantly less promising.
- Either transfer learning or multi-task learning could help our colleague get going faster.
- Neither transfer learning nor multi-task learning seems promising.

Correct
Yes. The problem he is trying to solve is quite different from yours. The different dataset structures make it probably impossible to use transfer learning or multi-task learning.

**14.** When building a system to detect cattle crossing a road from images taken with the front-facing camera of a truck, the designers had a large dataset of images. Which of the following might be a reason to use an end-to-end approach? 1 / 1 point

- It requires less computational resources.
- This approach will make use of useful hand-designed components.
- There is a large dataset available.
- That is the default approach on computer vision tasks.

Correct
Correct. To get good results when using an end-to-end approach, it is necessary to have a big dataset.

**15.** Consider the following two approaches, A and B: 1 / 1 point

- **(A)** Input an image (x) to a neural network and have it directly learn a mapping to make a prediction as to whether there's a red light and/or green light (y).
- **(B)** In this two-step approach, you would first (i) detect the traffic light in the image (if any), then (ii) determine the color of the illuminated lamp in the traffic light.

Approach A tends to be more promising than approach B if you have a _____ (fill in the blank).

- (●) Large training set
- ( ) Large bias problem.
- ( ) Multi-task learning problem.
- ( ) Problem with a high Bayes error.

**Correct**
Yes. In many fields, it has been observed that end-to-end learning works better in practice, but requires a large amount of data.