

12/15 points (80%)

✓ Congratulations! You passed!

Next Item

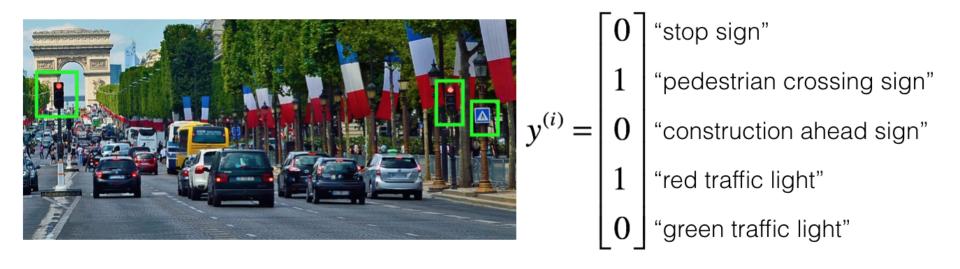


0/1 point

To help you practice strategies for machine learning, in this week we'll present another scenario and ask how you would act. We think this "simulator" of Mailing On Maising in Gas Could be like!

Quiz, 15 questions

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, the above image contains a pedestrian crossing sign and red traffic lights



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, that could be helpful for training even if the distribution of internet data is not the same.

You are just getting started on this project. What is the first thing you do? Assume each of the steps below would take about an equal amount of time (a few days).

- Spend a few days training a basic model and see what mistakes it makes.
- Spend a few days getting the internet data, so that you understand better what data is available.
- Spend a few days checking what is human-level performance for these tasks so that you can get an accurate estimate of Bayes error.

This should not be selected

Quiz, 15 questions



1/1 point

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.

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?

| | True |
|--|------|
|--|------|



False

Correct

Softmax would be a good choice if one and only one of the possibilities (stop sign, speed bump, pedestrian crossing, green light and red light) was present in each image.



1/1 point

3.

You are carrying out error analysis and counting up what errors the algorithm makes. Which of these datasets do you think you should manually go through and carefully examine, one image at a time?

| | | 10,000 | images or | n which th | e algorithn | n made a | mistake |
|--|--|--------|-----------|------------|-------------|----------|---------|
|--|--|--------|-----------|------------|-------------|----------|---------|

- 10,000 randomly chosen images
- 500 images on which the algorithm made a mistake

Autonomous driving (case study)

12/15 points (80%)

Focus on images that the algorithm got wrong. Also, 500 is enough to give you a good initial sense of the error statistics. There's probably no need to look at 10,000, which will take a long time.

500 randomly chosen images



1/1 point

4

After working on the data for several weeks, your team ends up with the following data:

- 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, $y^{(i)}$ =
 - $\begin{bmatrix} 1 \\ 0 \\ 0 \\ means the image contains a stop sign and a red traffic light. \\ 1 \\ \end{bmatrix}$

Because this is a multi-task learning problem, you need to have all your $y^{(i)}$ vectors fully labeled. If one example is equal to $\begin{bmatrix} ? \\ 1 \\ 1 \end{bmatrix}$ then the learning

algorithm will not be able to use that example. True/False?

True

0

False

Autonomous driving (case study)

As seen in the lecture on multi-task learning, you can compute the cost such that it is not influenced by the fact that it is not influenced by the fac



1/1 point

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. How should you split the dataset into train/dev/test sets?

Choose the training set to be the 900,000 images from the internet along with 80,000 images from your car's front-facing camera. The 20,000 remaining images will be split equally in dev and test sets.



Correct

Yes. As seen in lecture, it is important that your dev and test set have the closest possible distribution to "real"-data. It is also important for the training set to contain enough "real"-data to avoid having a data-mismatch problem.

- Choose the training set to be the 900,000 images from the internet along with 20,000 images from your car's front-facing camera. The 80,000 remaining images will be split equally in dev and test sets.
- Mix all the 100,000 images with the 900,000 images you found online. Shuffle everything. Split the 1,000,000 images dataset into 600,000 for the training set, 200,000 for the dev set and 200,000 for the test set.
- Mix all the 100,000 images with the 900,000 images you found online. Shuffle everything. Split the 1,000,000 images dataset into 980,000 for the training set, 10,000 for the dev set and 10,000 for the test set.



1/1 point

6.

Assume you' Athtomomous driving classestudy data:

12/15 points (80%)

| Quiz, | 15 | questions |
|-------|----|-----------|

| 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) | 8.8% |
| Training- Dev | 20,000 images randomly picked from (900,000 internet images + 60,000 car's front-facing camera images) | 9.1% |
| Dev | 20,000 images from your car's front-facing camera | 14.3% |
| Test | 20,000 images from the car's front-facing camera | 14.8% |

You also know that human-level error on the road sign and traffic signals classification task is around 0.5%. Which of the following are True? (Check all that apply). Your algorithm overfits the dev set because the error of the dev and test sets are very close.

Un-selected is correct

| You hav | e a large avoidable- | bias problem becaus | e your training erro | r is quite a bit higher th | an the human-level error. |
|---------|----------------------|---------------------|----------------------|----------------------------|---------------------------|
|---------|----------------------|---------------------|----------------------|----------------------------|---------------------------|

Correct

| Y | You have a large data-mismatch problem because your model d | loes a lot better on the training-dev set than on the dev set |
|---|---|---|
|---|---|---|

Correct

| Un-s | Quiz, 15 questions (case study) | 12/15 points (80%) |
|-----------------------|--|-------------------------------------|
| | You have a large variance problem because your model is not generalizing well to data from the same transver seen before. | aining distribution but that it has |
| Un-s | selected is correct | |
| ~ | 1/1 point | |
| 7. Based you th | on table from the previous question, a friend thinks that the training data distribution is much easier than ink? | the dev/test distribution. What do |
| | Your friend is right. (I.e., Bayes error for the training data distribution is probably lower than for the dev/t | est distribution.) |
| | Your friend is wrong. (I.e., Bayes error for the training data distribution is probably higher than for the de | v/test distribution.) |
| 0 | There's insufficient information to tell if your friend is right or wrong. | |
| | rect algorithm does better on the distribution of data it trained on. But you don't know if it's because it trained ly is easier. To get a better sense, measure human-level error separately on both distributions. | on that no distribution or if it |



1/1 point

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

| Autonomous driving (case study) Overall dev set error | 12/15 points (80%) 14.3% |
|--|------------------------------------|
| 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% |

In this table, 4.1%, 8.0%, etc.are a fraction of the total dev set (not just examples your algorithm mislabeled). I.e. about 8.0/14.3 = 56% of your errors are due to foggy pictures.

The results from this analysis implies that the team's highest priority should be to bring more foggy pictures into the training set so as to address the 8.0% of errors in that category. True/False?

| | True because it is the largest category of errors. As discussed in lecture, we should prioritize the largest category of error to avoid wasting the team's time. |
|---------------------|--|
| | True because it is greater than the other error categories added together $(8.0 > 4.1 + 2.2 + 1.0)$. |
| 0 | False because this would depend on how easy it is to add this data and how much you think your team thinks it'll help. |
| Corr Corr | ect rect, this is the most appropriate decision in this situation. |

False because data augmentation (synthesizing foggy images by clean/non-foggy images) is more efficient.



1/1 point

| 19 | Structuring Machine Learning Projects - nome Coursera | | |
|--------|---|--|--|
| You ca | an buy a specially designed windshield wiper that help wipe off some of the raindrops on the front- | ont-facing camera. Based on the table from | |
| the p | evious Alestan amous rd riving (Gasae at udy) agree with? Quiz, 15 questions | 12/15 points (80%) | |
| 0 | 2.2% would be a reasonable estimate of the maximum amount this windshield wiper could impro | ove performance. | |
| 2.29 | rect i. You will probably not improve performance by more than 2.2% by solving the raindrops problem. % would be a perfect estimate of the improvement you can achieve by purchasing a specially designal raindrops. | , , | |
| | 2.2% would be a reasonable estimate of the minimum amount this windshield wiper could impro | ove performance. | |
| | 2.2% would be a reasonable estimate of how much this windshield wiper will improve performan | nce. | |
| | 2.2% would be a reasonable estimate of how much this windshield wiper could worsen performa | ance in the worst case. | |



0/1 point

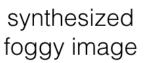
You decide to use data augmentation to address foggy images. You find 1,000 pictures of fog off the internet, and "add" them to clean images to synthesize foggy images driving (case study)

Quiz, 15 questions

12/15 points (80%)

image from front-facing camera











Which of the following statements do you agree with?

- So long as the synthesized fog looks realistic to the human eye, you can be confident that the synthesized data is accurately capturing the distribution of real foggy images (or a subset of it), since human vision is very accurate for the problem you're solving.
- There is little risk of overfitting to the 1,000 pictures of fog so long as you are combing it with a much larger (>>1,000) of clean/non-foggy images.

This should not be selected

Adding synthesized images that look like real foggy pictures taken from the front-facing camera of your car to training dataset won't help the model improve because it will introduce avoidable-bias.



point

| After agree | orking Autten Amepus driying (Case study) the incorrectly labeled data on the dev set. Which of these statements do you with? (Chick anthropply). |
|-------------|--|
| | You should also correct the incorrectly labeled data in the test set, so that the dev and test sets continue to come from the same distribution |
| | |
| Corr | ect |
| | because you want to make sure that your dev and test data come from the same distribution for your algorithm to make your team's ative development process is efficient. |
| | |
| | You should correct incorrectly labeled data in the training set as well so as to avoid your training set now being even more different from your dev set. |
| | |
| Un-s | elected is correct |
| | |
| | You should not correct the incorrectly labeled data in the test set, so that the dev and test sets continue to come from the same distribution |
| | |
| Un-s | elected is correct |
| | |
| | You should not correct incorrectly labeled data in the training set as it does not worth the time. |
| Corr | ect . |
| | e, deep learning algorithms are quite robust to having slightly different train and dev distributions. |
| | |
| | |

V

1/1 point 12. So factour al philiphon pous participes of the light. One of your colleagues in the startup is starting to work on recognizing a yellow traffic light. (知神中医院里尼斯 an orange light rather than a yellow light; we'll use the US convention of calling it yellow.) Images containing yellow lights are quite rare, and she doesn't have enough data to build a good model. She hopes you can help her out using transfer learning.

What do you tell your colleague?



She should try using weights pre-trained on your dataset, and fine-tuning further with the yellow-light dataset.

Correct

Yes. You have trained your model on a huge dataset, and she has a small dataset. Although your labels are different, the parameters of your model have been trained to recognize many characteristics of road and traffic images which will be useful for her problem. This is a perfect case for transfer learning, she can start with a model with the same architecture as yours, change what is after the last hidden layer and initialize it with your trained parameters.

- If she has (say) 10,000 images of yellow lights, randomly sample 10,000 images from your dataset and put your and her data together. This prevents your dataset from "swamping" the yellow lights dataset.
- You cannot help her because the distribution of data you have is different from hers, and is also lacking the yellow label.
- Recommend that she try multi-task learning instead of transfer learning using all the data.



0/1

point

13.

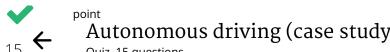
Another colleague wants to use microphones placed outside the car to better hear if there're other vehicles around you. For example, if there is a police vehicle behind you, you would be able to hear their siren. However, they don't have much to train this audio system. How can you help?

Transfer learning from your vision dataset could help your colleague get going faster. Multi-task learning seems significantly less promising.



This should not be selected

| \ | Multi-task learning from your vision dataset could help your colleague get going faster. Transfer learning seems significantly less — promising Quiz, 15 questions |
|---|--|
| | Either transfer learning or multi-task learning could help our colleague get going faster. |
| | Neither transfer learning nor multi-task learning seems promising. |
| ~ | 1/1 point |
| 14. To recognize red and green lights, you have been using this approach: | |
| • (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). | |
| A teammate proposes a different, two-step approach: | |
| • (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. | |
| Between these two, Approach B is more of an end-to-end approach because it has distinct steps for the input end and the output end. True/False? | |
| | True |
| 0 | False |
| Corr Yes. | ect (A) is an end-to-end approach as it maps directly the input (x) to the output (y). |
| | |



Autonomous driving (case study) 12/15 points (80%) Quiz, 15 questions Approach A (in the question above) tends to be more promising than approach B if you have a _____ (fill in the blank). Large training set 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. Multi-task learning problem. Large bias problem. Problem with a high Bayes error.

