Autonomous driving (case study)

Quiz, 15 questions



Congratulations! You passed!

Next Item

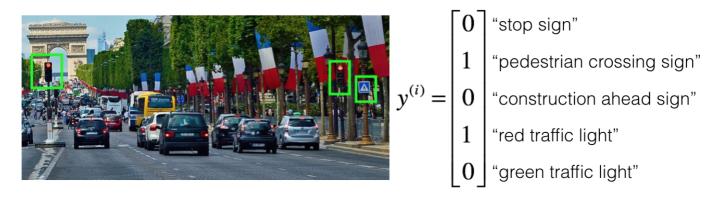


1/1 point

1.

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 working in a machine learning project will give a task of what leading a machine learning project could be like!

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.

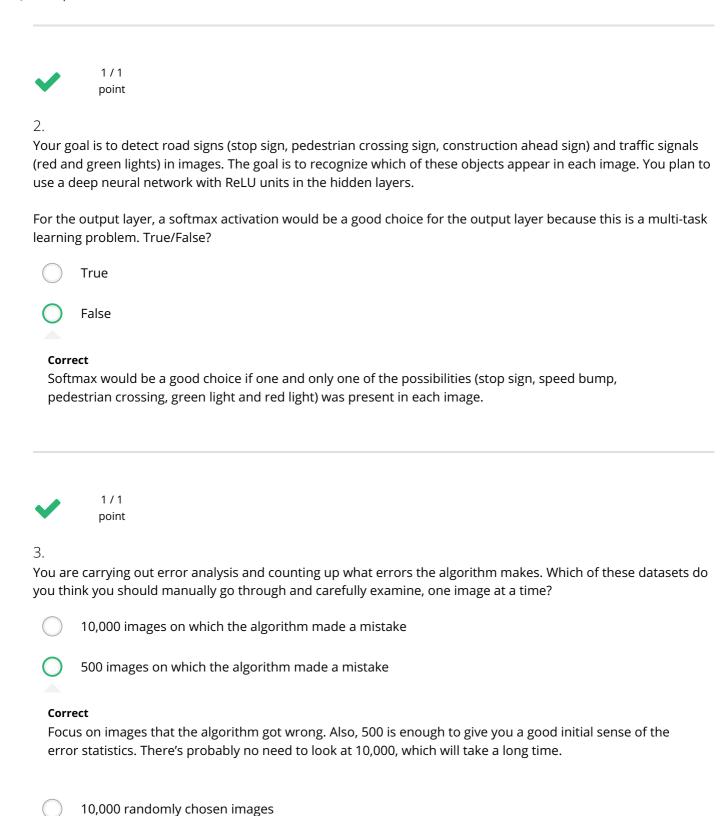
You are just getting started on this project. What is the first thing you do? Assume each of the steps below would take about an equal amount of time (a few days).

	Spend a few days getting the internet data, so that you understand better what data is available.
	Spend a few days collecting more data using the front-facing camera of your car, to better understand how much data per unit time you can collect.
	Spend a few days checking what is human-level performance for these tasks so that you can get an accurate estimate of Bayes error.
0	Spend a few days training a basic model and see what mistakes it makes.

Correct

As discussed in lecture, applied ML is a highly iterative process. If you train a basic model and carry out Automomous (driving sistance standy) will help point you in more promising directions.

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1/1 point

500 randomly chosen images

Autonomous driving (case study) ur team ends up with the following data:

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- 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.

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 $\begin{bmatrix} 0 \\ ? \\ 1 \\ 1 \\ ? \end{bmatrix}$ then the learning algorithm will not be able to use that example. True/False?

True



Correct

As seen in the lecture on multi-task learning, you can compute the cost such that it is not influenced by the fact that some entries haven't been labeled.



0/1 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 20,000 images from your car's front-facing camera. The 80,000 remaining images will be split equally in dev and test sets.

This should not be selected

- 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.
- 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.

Choose the training set to be the 900,000 images from the internet along with 80,000 images from your **Autonomous draining** (cashe study) maining images will be split equally in dev and test sets.

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1/1 point

6.

Assume you've finally chosen the following split between of the data:

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).

You have a large variance problem because your training error is quite higher than the human-level error.

Un-selected is correct

You have a large data-mismatch problem because your model does a lot better on the training-dev set than on the dev set

Correct

Your algorithm overfits the dev set because the error of the dev and test sets are very close.

Un-selected is correct

You have a large avoidable-bias problem because your training error is quite a bit higher than the

You have a large variance problem because your model is not generalizing well to data from the same

training distribution but that it has never seen before.

human-level error.

Correct

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1/1 point

7.

Based on table from the previous question, a friend thinks that the training data distribution is much easier than the dev/test distribution. What do you think?

- Your friend is right. (I.e., Bayes error for the training data distribution is probably lower than for the dev/test distribution.)
- Your friend is wrong. (I.e., Bayes error for the training data distribution is probably higher than for the dev/test distribution.)
- There's insufficient information to tell if your friend is right or wrong.

Correct

The algorithm does better on the distribution of data it trained on. But you don't know if it's because it trained on that no distribution or if it really is easier. To get a better sense, measure human-level error separately on both distributions.



1/1 point

8.

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:

Overall dev set error	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.

1/1 point

10.

You decide to use data augmentation to address foggy images. You find 1,000 pictures of fog off the internet, and Automomous driving (same study) days, like this:

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image from front-facing camera



foggy image from the internet



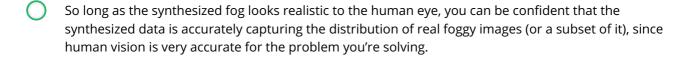
synthesized foggy image



Which of the following statements do you agree with?

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.

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.





Yes. If the synthesized images look realistic, then the model will just see them as if you had added useful data to identify road signs and traffic signals in a foggy weather. I will very likely help.

0.50 / 1 point

11.

After working further on the problem, you've decided to correct the incorrectly labeled data on the dev set. Which of these statements do you agree with? (Check all that apply).

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

Correct

Yes 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 iterative 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.

This should not be selected

No, deep learning algorithms are quite robust to having slightly different train and dev distributions.

Ouiz 15 aug	mous driving (case study) You should not correct the incorrectly labeled data in the test set, so that the dev and test sets continue stions to come from the same distribution
Un-se	lected is correct
	You should not correct incorrectly labeled data in the training set as it does not worth the time.
✓	1 / 1 point
to work use the enough	our algorithm only recognizes red and green traffic lights. One of your colleagues in the startup is starting on recognizing a yellow traffic light. (Some countries call it an orange light rather than a yellow light; we'll US convention of calling it yellow.) Images containing yellow lights are quite rare, and she doesn't have data to build a good model. She hopes you can help her out using transfer learning.
0	Syou tell your colleague? She should try using weights pre-trained on your dataset, and fine-tuning further with the yellow-light dataset.
are di and ti start v	You have trained your model on a huge dataset, and she has a small dataset. Although your labels different, the parameters of your model have been trained to recognize many characteristics of road raffic images which will be useful for her problem. This is a perfect case for transfer learning, she can with a model with the same architecture as yours, change what is after the last hidden layer and ize 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.
	1/1

/

point

13.

019/1/8	Structuring Machine Learning Projects - Home Coursera
Autono	colleague wants to use microphones placed outside the car to better hear if there're other vehicles MOUSE STIPLES (GASC STILL) hicle behind you, you would be able to hear their siren. However, it have much to train this audio system. How can you help?
Quiz; 13 ques	strons.
	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.
Correc	et
Yes. T	he problem he is trying to solve is quite different from yours. The different dataset structures make bably impossible to use transfer learning or multi-task learning.
~	1/1 point
14. To recog	gnize red and green lights, you have been using this approach:
	put an image (x) to a neural network and have it directly learn a mapping to make a prediction as to ner there's a red light and/or green light (y).
A teamn	nate proposes a different, two-step approach:
	this two-step approach, you would first (i) detect the traffic light in the image (if any), then (ii) determine blor of the illuminated lamp in the traffic light.
	n these two, Approach B is more of an end-to-end approach because it has distinct steps for the input end output end. True/False?
	True
	False
Comme	
Correc Yes. (A	A) is an end-to-end approach as it maps directly the input (x) to the output (y).



1/1 point

15.

2019/1/8	Structuring Machine Learning Projects - Home Coursera
Approa Autann	ach A (in the question above) tends to be more promising than approach B if you have a (fill in the omous $driving$ (case $study$)
Quiz, 15 que	estions Large training set
	ect In many fields, it has been observed that end-to-end learning works better in practice, but requires a e amount of data.
	Multi-task learning problem.
	Large bias problem.
	Problem with a high Bayes error.