Your grade: 100%

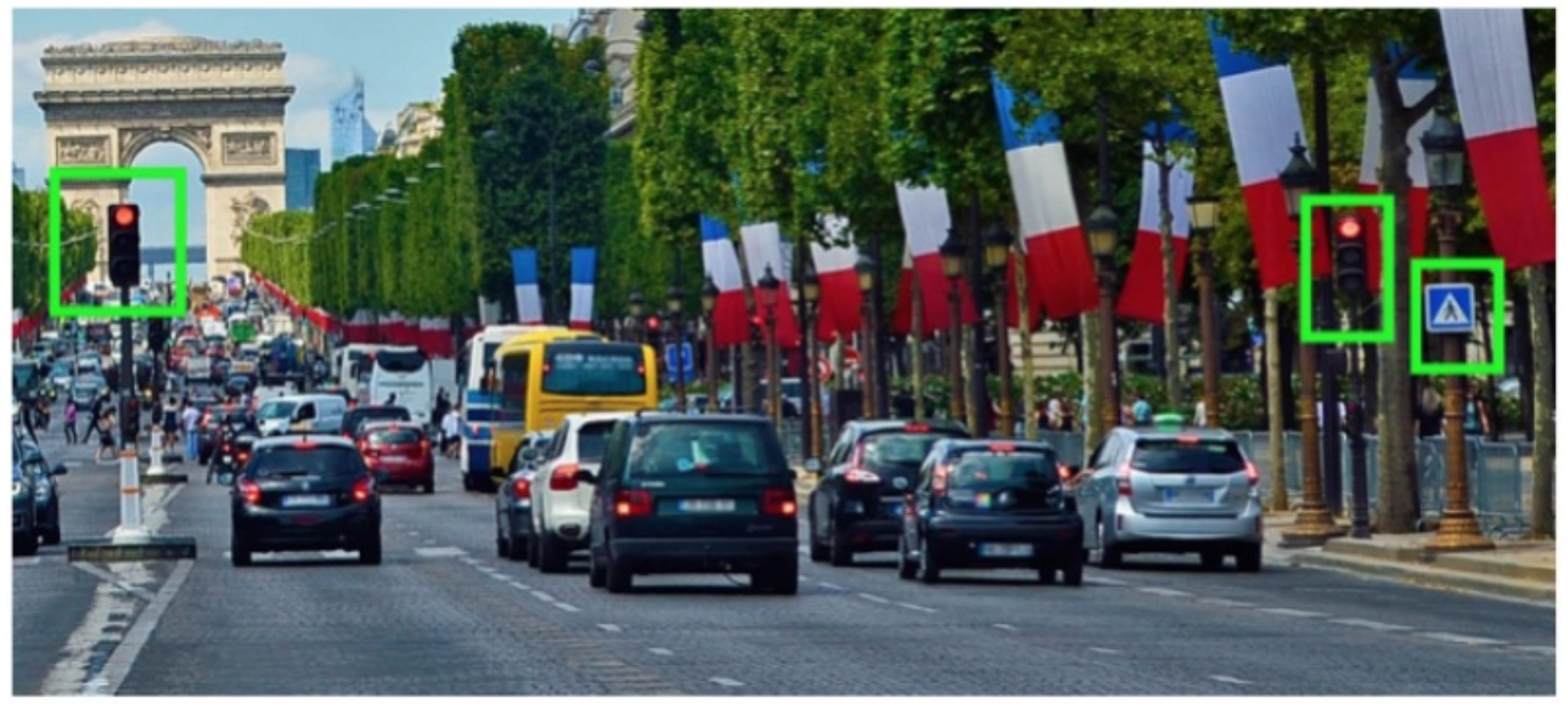
Your latest: **100%** • Your highest: **100%** • To pass you need at least 80%. We keep your highest score.

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.



$$y^{(i)} = \begin{array}{cl} \left[\begin{array}{c} 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{array}\right] & \begin{array}{l} \text{"stop sign"} \\ \text{"pedestrian crossing sign"} \\ \text{"construction ahead sign"} \\ \text{"red traffic light"} \\ \text{"green traffic light"} \end{array} \end{array}$$

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 theinternet, 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).

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

Correct
It's most efficient to create a basic system and iterate based on what the errors reveal.

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.

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Suppose that you use a sigmoid function for the output layer, and the output $\hat{y}$ has shape (5, 1).

Which of the following best describes the cost function?

- ○ $\frac{\exp \hat{y}_j^{(i)}}{\sum_{j=1}^{5} \exp \hat{y}_j^{(i)}}$
- ○ $\frac{1}{m} \sum_{i=1}^{m} \left(-y^{(i)} \log \hat{y}^{(i)} - (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}\right)$
- ○ $\frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{5} \mathcal{L}(\hat{y}_i^{(j)}, y_i^{(j)})$
- ◉ $\frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{5} \mathcal{L}(\hat{y}_j^{(i)}, y_j^{i})$

Correct
Yes! Here you compare each component (each possible object) of the prediction $\hat{y}$ with the respective component of the label y, and sum over the individual losses. This is appropriate because multiple objects can be present in each image.

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

- ( ) True
- (•) False

Correct
The training set is typically very large, and manually checking all the successful images would be time-consuming and inefficient. It's more effective to focus on the errors in the dev set to understand where the model needs improvement.

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 0.

- ○ 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 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 $y^{(i)}$.

Correct
You can't use the components of the labels that are missing, but you can use the ones you have to train the model. This allows you to leverage partially labeled data effectively.

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.

1 / 1 point

How should you split the dataset into train/dev/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 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 car's front-facing camera. The 20,000 remaining images will be split equally in dev and 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.

Correct
Yes. 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.

6. 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)	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?**

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

Correct
The large difference between the training-dev error and the training error indicates that the model is not generalizing well to unseen data from the same distribution, which is a sign of high variance.

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1 / 1 point

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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%

Human-level error on this task is approximately 0.5%. (Bayes error is the lowest possible error rate for a task. Human-level error is a good estimation of Bayes error.)

True or False: Based on this, the Bayes error for the car camera images (Dev/Test) is higher than the Bayes error for the mixed internet/car images (Training).

- (●) False
- ( ) True

Correct
The Dev/Test errors (1.3% and 1.1%) are lower than the Training/Training-Dev errors (2% and 2.3%). This indicates the car camera images are likely inherently easier for the algorithm to learn, thus having a lower Bayes error.

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?

- ○ 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.
- ◉ 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.
- ○ You should prioritize getting more foggy pictures since that will be easier to solve.

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

9. 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	3.0%
Errors due to partially occluded elements.	7.2%
Errors due to other causes	1.0%

In this table, 4.1%, 7.2%, etc. are a fraction of the total dev set (not just examples of your algorithm mislabeled). For example, about 7.2/15.3 = 47% of your errors are due to partially occluded elements.

You find out that there is an anti-reflective film that eliminates sun reflection, but it is quite costly.

Which one of the following gives the best description of what the investment in the film can do to the model?

- ○ The film will reduce at least 7.2% of the dev set error.
- ◉ The film will reduce the dev set error with 7.2% at the most.
- ○ The overall test set error will be reduced by at most 7.2%.

Correct
Yes. Remember that this 7.2% gives us an estimate for the ceiling of how much the error can be reduced when the cause is fixed.

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

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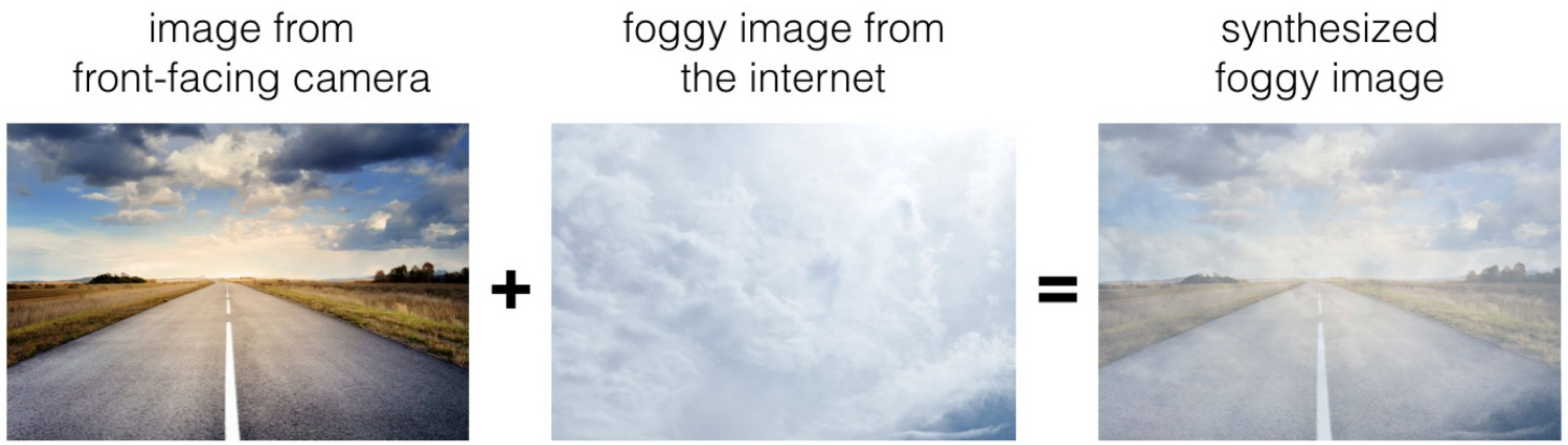

True or False: We can't use this data since they have a different distribution from the ones we used (internet and front-facing camera).

- (●) False
- ( ) True

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

True or False: You need to correct the labels of the test set so that the 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 that they aren't severely affected by the difference in distributions.

- ( ) False, the test set shouldn't be changed since we want to know how the model performs with uncorrected or original data.

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- ○ False, the test set shouldn't be changed since we want to know how the model performs with uncorrected or original data.
- ○ 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. The labels in the training set should be fixed only in case of a systematic error.

Correct
To successfully train a model, the dev set and test set should come from the same distribution. Also, 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. So far, your algorithm only recognizes red and green traffic lights. One of your colleagues in the startup is starting to work on recognizing a yellow traffic light. Some countries refer to it as an orange light; however, we will 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.

1 / 1 point

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.
- ○ You cannot help her because the distribution of data you have is different from her's and is also lacking the yellow label.

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1 / 1 point

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.
- ( ) You cannot help her because the distribution of data you have is different from her's and is also lacking the yellow label.
- ( ) Recommend that she try multi-task learning instead of transfer learning using all the data.
- ( ) 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.

Correct
You have trained your model on a large 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.

13. 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. He has approximately 30,000 examples of each image and 30,000 images without a sign.

1 / 1 point

True or False: This case could benefit from using multi-task learning.

- ( ) False
- (◉) True

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1 / 1 point

True or False: This case could benefit from using multi-task learning.

- ○ False
- ◉ True

Correct
Multi-task learning is suitable here due to the shared high-level features among the required road signs.

14. You want to recognize red and green lights in images. You have two approaches:

1 / 1 point

- **Approach 1**: Input an image (x) into a neural network that directly predicts whether a red or green light is present (y).
- **Approach 2**: First, detect the traffic light in the image (if any). Then, determine the color of the illuminated lamp.

Which approach is a better example of an end-to-end approach?

- ◉ Approach 1
- ○ Approach 2

Correct
Approach 1 directly maps the input (x) to the output (y) in a single step, which is the definition of an end-to-end approach.

- **Approach 2**: First, detect the traffic light in the image (if any). Then, determine the color of the illuminated lamp.

Which approach is a better example of an end-to-end approach?

- (x) Approach 1
- ( ) Approach 2

Correct
Approach 1 directly maps the input (x) to the output (y) in a single step, which is the definition of an end-to-end approach.

15. To recognize a stop sign, you use the following approach: 1 / 1 point

First, localize any traffic sign in an image. **After that**, determine if the sign is a stop sign or not.

This is a better approach than an end-to-end model for which of the following cases? **Choose the best answer**.

- ( ) There are available models which we can use to transfer knowledge.
- (x) There is not enough data to train a big neural network.
- ( ) The problem has a high Bayes error.
- ( ) There is a large amount of data.

Correct
When data is limited, a two-step approach can be more effective than training a large end-to-end model.