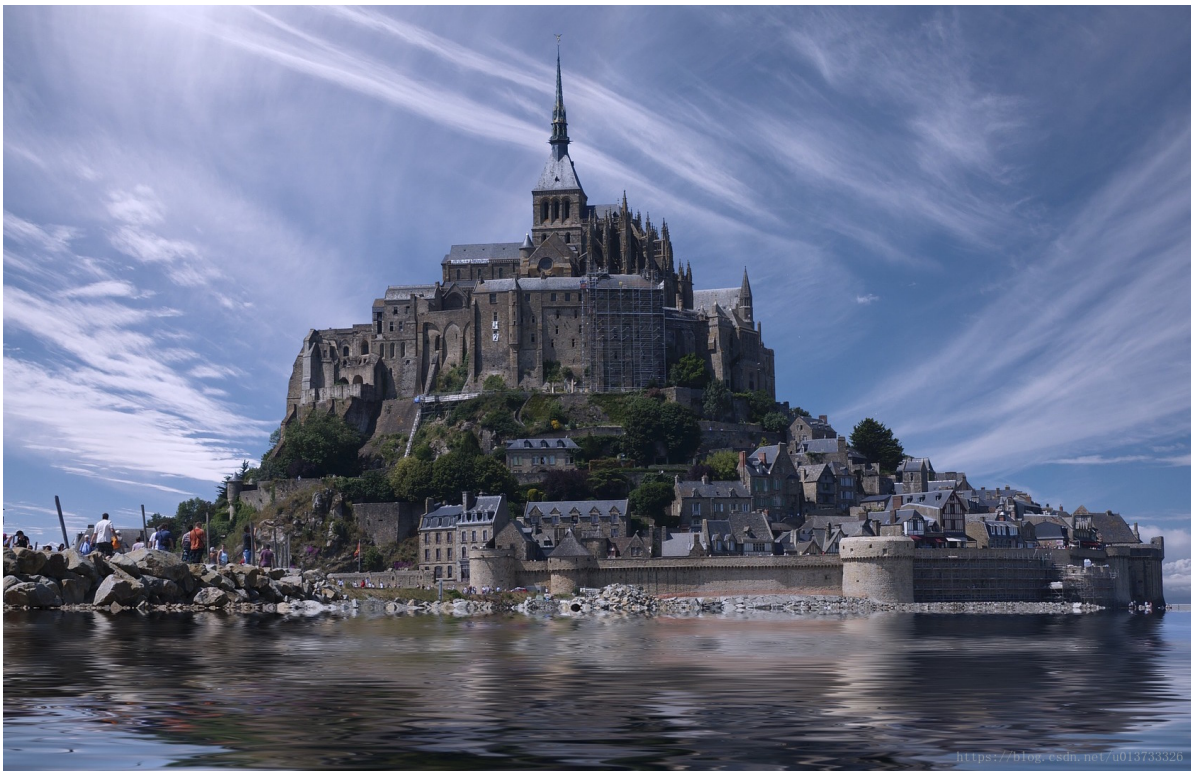
# Bird recognition in the city of Peacetopia (case study)

## 1. Question 1

## Problem Statement

This example is adapted from a real production application, but with details disguised to protect confidentiality.




You are a famous researcher in the City of Peacetopia. The people of Peacetopia have a common characteristic: they are afraid of birds. To save them, you have to **build an algorithm that will detect any bird flying over Peacetopia** and alert the population.

The City Council gives you a dataset of 10,000,000 images of the sky above Peacetopia, taken from the city's security cameras. They are labelled:

- y = 0: There is no bird on the image
- y = 1: There is a bird on the image

Your goal is to build an algorithm able to classify new images taken by security cameras from Peacetopia.

There are a lot of decisions to make:

- What is the evaluation metric?
- How do you structure your data into train/dev/test sets?

## Metric of success

The City Council tells you the following that they want an algorithm that

1. Has high accuracy
2. Runs quickly and takes only a short time to classify a new image.

   > 优化指标是精确度，满足指标是判断速度

3. Can fit in a small amount of memory, so that it can run in a small processor that the city will attach to many different security cameras.

   > 满足指标再加一个内存占用

**Note**: Having three evaluation metrics makes it harder for you to quickly choose between two different algorithms, and will slow down the speed with which your team can iterate. True/False?

- **True**
- False

> 要求多了，搞起来也费劲点。但是其实也有好处，那就是方向明确，而且一开始要求多了后期甲方应该也不好改，有利于开发团队专心工作。

# 2. Question 2

After further discussions, the city narrows down its criteria to:

- "We need an algorithm that can let us know a bird is flying over Peacetopia as accurately as possible."
- "We want the trained model to take no more than 10sec to classify a new image."
- "We want the model to fit in 10MB of memory."

> 阿这，我上面的满足指标想得太早了，原来刚才客户需求那么高啊。。。
>
> 还好降低需求了

If you had the three following models, which one would you choose?

☐ A

| Test Accuracy | Runtime | Memory size |
| --- | --- | --- |
| 97% | 1 sec | 3MB |

- [ ] B

| Test Accuracy | Runtime | Memory size |
| --- | --- | --- |
| 99% | 13 sec | 9MB |

- [ ] C

| Test Accuracy | Runtime | Memory size |
| --- | --- | --- |
| 97% | 3 sec | 2MB |

- [x] D

| Test Accuracy | Runtime | Memory size |
| --- | --- | --- |
| 98% | 9 sec | 9MB |

> 在满足了满足指标的模型中，D的优化指标最高

# 3. Question 3

Based on the city's requests, which of the following would you say is true?

- [x] Accuracy is an optimizing metric; running time and memory size are a satisficing metrics.
- Accuracy is a satisficing metric; running time and memory size are an optimizing metric.
- Accuracy, running time and memory size are all optimizing metrics because you want to do well on all three.
- Accuracy, running time and memory size are all satisficing metrics because you have to do sufficiently well on all three for your system to be acceptable.

> 毫无疑问，前面已经推断出来了

# 4. Question 4

# Structuring your data

Before implementing your algorithm, you need to split your data into train/dev/test sets. Which of these do you think is the best choice?

- [ ] A

| Train | Dev | Test |
| --- | --- | --- |
| 3,333,334 | 3,333,333 | 3,333,333 |

- [ ] B

| Train | Dev | Test |
| --- | --- | --- |
| 6,000,000 | 3,000,000 | 1,000,000 |

- [x] C

| Train | Dev | Test |
| --- | --- | --- |
| 9,500,000 | 250,000 | 250,000 |

- [ ] D

| Train | Dev | Test |
| --- | --- | --- |
| 6,000,000 | 1,000,000 | 3,000,000 |

> 选C就好啦，其实开发集啥的能有100,000样本就已经很多了。。

## 5. Question 5

After setting up your train/dev/test sets, the City Council comes across another 1,000,000 images, called the “citizens’ data”. Apparently the citizens of Peacetopia are so scared of birds that they volunteered to take pictures of the sky and label them, thus contributing these additional 1,000,000 images. These images are different from the distribution of images the City Council had originally given you, but you think it could help your algorithm.

You should not add the citizens’ data to the training set, because this will cause the training and dev/test set distributions to become different, thus hurting dev and test set performance. True/False?

- [ ] True
- [x] False

> 如果使用正则化的话应该没事的吧。而且如果按比例把这些数据加到三个数据集里应该也是没事的吧。

## 6. Question 6

One member of the City Council knows a little about machine learning, and thinks you should add the 1,000,000 citizens’ data images to the test set. You object because:

- [x] This would cause the dev and test set distributions to become different. This is a bad idea because you’re not aiming where you want to hit.
- [ ] The 1,000,000 citizens’ data images do not have a consistent x–>y mapping as the rest of the data (similar to the New York City/Detroit housing prices example from lecture).
- [ ] A bigger test set will slow down the speed of iterating because of the computational expense of evaluating models on the test set.
- [x] The test set no longer reflects the distribution of data (security cameras) you most care about.

> A的想法就是要三集同分布。D的想法是原来的分布是监控摄像头，后加入的是市民拍摄，而我们关注的是监控摄像头的判断精准度，因此如果把市民拍摄的数据加入会导致精准度下降。要加也是同分布加入到三个集合中。

## 7. Question 7

You train a system, and its errors are as follows (error = 100%-Accuracy):

| **Training set error** | **4.0%** |
| --- | --- |
| Dev set error | 4.5% |

This suggests that one good avenue for improving performance is to train a bigger network so as to drive down the 4.0% training error. Do you agree?

- [ ] Yes, because having 4.0% training error shows you have high bias.
- [ ] Yes, because this shows your bias is higher than your variance.
- [ ] No, because this shows your variance is higher than your bias.
- [x] No, because there is insufficient information to tell.

> 我们需要贝叶斯误差，或者人类级别误差也行。这样才能判断这个训练集错误率是否达到极限了

## 8. Question 8

You ask a few people to label the dataset so as to find out what is human-level performance. You find the following levels of accuracy:

| **Bird watching expert #1** | **0.3% error** |
|---|---|
| Bird watching expert #2 | 0.5% error |
| Normal person #1 (not a bird watching expert) | 1.0% error |
| Normal person #2 (not a bird watching expert) | 1.2% error |

If your goal is to have "human-level performance" be a proxy (or estimate) for Bayes error, how would you define "human-level performance"?

- [ ] 0.0% (because it is impossible to do better than this)
- [x] 0.3% (accuracy of expert #1)
- [ ] 0.4% (average of 0.3 and 0.5)
- [ ] 0.75% (average of all four numbers above)

> 要用已知最低错误率当作贝叶斯误差的估计

## 9. Question 9

Which of the following statements do you agree with?

- [x] A learning algorithm's performance can be better than human-level performance but it can never be better than Bayes error.
- [ ] A learning algorithm's performance can never be better than human-level performance but it can be better than Bayes error.
- [ ] A learning algorithm's performance can never be better than human-level performance nor better than Bayes error.
- [ ] A learning algorithm's performance can be better than human-level performance and better than Bayes error.

## 10. Question 10

You find that a team of ornithologists debating and discussing an image gets an even better 0.1% performance, so you define that as "human-level performance." After working further on your algorithm, you end up with the following:

| **Human-level performance** | **0.1%** |
|---|---|
| Training set error | 2.0% |
| Dev set error | 2.1% |

Based on the evidence you have, which two of the following four options seem the most promising to try? (Check two options.)

- [ ] Try increasing regularization.
- [ ] Get a bigger training set to reduce variance.
- [x] Try decreasing regularization.
- [x] Train a bigger model to try to do better on the training set.

> 这两个都是减小偏差的做法

# 11. Question 11

You also evaluate your model on the test set, and find the following:

| **Human-level performance** | **0.1%** |
|---|---|
| Training set error | 2.0% |
| Dev set error | 2.1% |
| Test set error | 7.0% |

What does this mean? (Check the two best options.)

- [ ] You have underfit to the dev set.
- [x] You should try to get a bigger dev set.
- [ ] You should get a bigger test set.
- [x] You have overfit to the dev set.

> D是错误原因，B是解决方案

# 12. Question 12

After working on this project for a year, you finally achieve:

| **Human-level performance** | **0.10%** |
|---|---|
| Training set error | 0.05% |
| Dev set error | 0.05% |

What can you conclude? (Check all that apply.)

- [x] It is now harder to measure avoidable bias, thus progress will be slower going forward.
- [ ] This is a statistical anomaly (or must be the result of statistical noise) since it should not be possible to surpass human-level performance.
- [ ] With only 0.09% further progress to make, you should quickly be able to close the remaining gap to 0%
- [x] If the test set is big enough for the 0.05% error estimate to be accurate, this implies Bayes error is ≤0.05

> B错，在这种任务上超越人类是可能的
>
> C错，因为贝叶斯误差未知，错误率的最小值不一定是0%

## 13. Question 13

It turns out Peacetopia has hired one of your competitors to build a system as well. Your system and your competitor both deliver systems with about the same running time and memory size. However, your system has higher accuracy! However, when Peacetopia tries out your and your competitor's systems, they conclude they actually like your competitor's system better, because even though you have higher overall accuracy, you have more false negatives (failing to raise an alarm when a bird is in the air). What should you do?

- [ ] Look at all the models you've developed during the development process and find the one with the lowest false negative error rate.
- [ ] Ask your team to take into account both accuracy and false negative rate during development.
- [x] Rethink the appropriate metric for this task, and ask your team to tune to the new metric.
- [ ] Pick false negative rate as the new metric, and use this new metric to drive all further development.

> 这类似于广告公司推送猫猫准确率高，但是出错的时候会出涩图，这太危险了。

## 14. Question 14

You've handily beaten your competitor, and your system is now deployed in Peacetopia and is protecting the citizens from birds! But over the last few months, a new species of bird has been slowly migrating into the area, so the performance of your system slowly degrades because your data is being tested on a new type of data.

You have only 1,000 images of the new species of bird. The city expects a better system from you within the next 3 months. Which of these should you do first?

- [x] Use the data you have to define a new evaluation metric (using a new dev/test set) taking into account the new species, and use that to drive further progress for your team.
- [ ] Put the 1,000 images into the training set so as to try to do better on these birds.
- [ ] Try data augmentation/data synthesis to get more images of the new type of bird.
- [ ] Add the 1,000 images into your dataset and reshuffle into a new train/dev/test split.

> 把1000张图加入三集或增强后加入三集都是沧海一粟，应当赶快调整目标，重新分析整个系统

## 15. Question 15

The City Council thinks that having more Cats in the city would help scare off birds. They are so happy with your work on the Bird detector that they also hire you to build a Cat detector. (Wow Cat detectors are just incredibly useful aren't they.) Because of years of working on Cat detectors, you have such a huge dataset of 100,000,000 cat images that training on this data takes about two weeks. Which of the statements do you agree with? (Check all that agree.)

- [x] Needing two weeks to train will limit the speed at which you can iterate.
- [x] Buying faster computers could speed up your teams' iteration speed and thus your team's productivity.
- [x] If 100,000,000 examples is enough to build a good enough Cat detector, you might be better of training with just 10,000,000 examples to gain a ≈10x improvement in how quickly you can run experiments, even if each model performs a bit worse because it's trained on less data.

- [ ] Having built a good Bird detector, you should be able to take the same model and hyperparameters and just apply it to the Cat dataset, so there is no need to iterate.

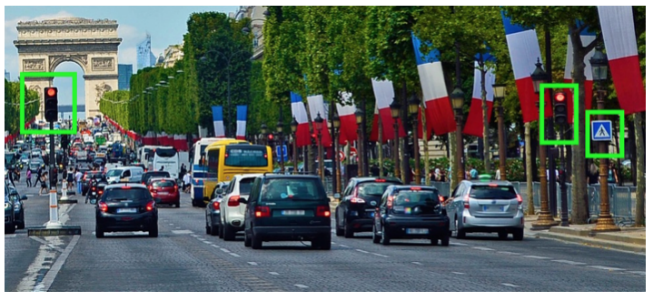
> 第四个选项直接用鸟探测器去探测猫，这太蠢了。前三个都对，我们不仅要考虑效果，还要考虑实际的作业时间等情况。

# Autonomous driving (case study)

## 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



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



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, 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.**

> 机器学习是一个高速迭代的过程，我们应该先做出基本模型，然后从问题出发，逐渐改善现有模型。

Spend a few days checking what is human-level performance for these tasks so that you can get an accurate estimate of Bayes error.

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.

As discussed in lecture, applied ML is a highly iterative process. If you train a basic model and carry out error analysis (see what mistakes it makes) it will help point you in more promising directions.

## 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**

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.

> softmax是识别图片中的单个目标，以及他所属的种类。
>
> 现在的目标是识别图片中属于某几个种类的所有目标，这和softmax完全不同

## 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 randomly chosen images

**500 images on which the algorithm made a mistake**

10,000 images on which the algorithm made a mistake

500 randomly chosen images

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.

> 误差分析的时候应该只看错的，同时表格记录
>
> 同时别把自己累坏了

## 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)=【1，0，0，1，0】^Tmeans 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【0，？，1，1，？】then the learning algorithm will not be able to use that example. True/False?

True

**False**

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.

这种情况下只要忽略违背标记的数据就好了

## 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.**

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 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 980,000 for the training set, 10,000 for the dev set and 10,000 for the test set.

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.

> 开发集和测试集必须针对现实生活、实际使用。同时为了产生好结果，训练集里现实生活分布的样本不能占比太少

## 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 model is not generalizing well to data from the same training distribution but that it has never seen before.

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

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

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

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

> 分布问题和偏差问题解决之前，还不能确定方差问题。迭代要一步步来

## 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.**

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.

> 无法确定是因为分布，还是因为真的简单，使得训练集与开发集结果不同。也许我们需要先在两个集合上估算贝叶斯误差。

## 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.

True because it is greater than the other error categories added together (8.0 > 4.1+2.2+1.0).

**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.**

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

> 我本来想选正确，但是答案说错误也有道理。我没有考虑到雾天样本的易得性，以及将雾天判断强化的必要性。也许雾天的自动驾驶又是另外一个复杂系统了。

## 9

You can buy a specially designed windshield wiper that help wipe off some of the raindrops on the front-facing camera. Based on the table from the previous question, which of the following statements do you agree with?

**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 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.

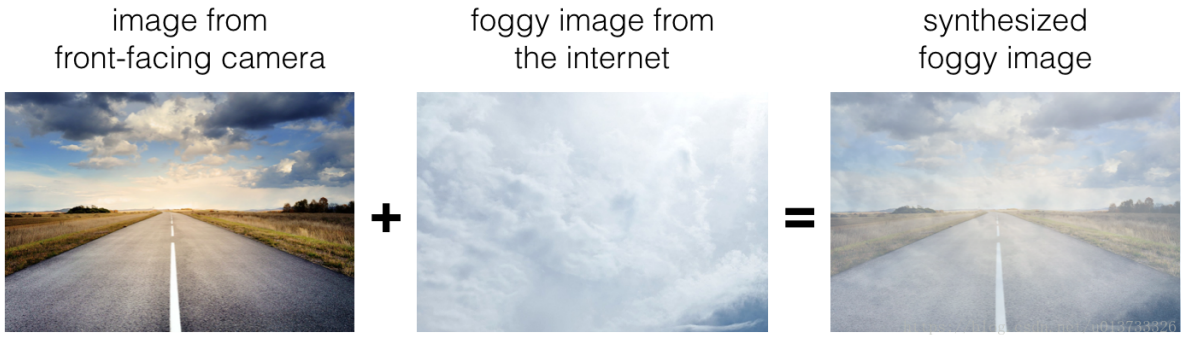
2.2% would be a reasonable estimate of how much this windshield wiper could worsen performance in the worst case.

> 不不不，2.2%不是合理的估计。2.2%是在不损坏镜头情况下的最好估计，这已经很难了，你再损坏镜头，修正掉这2.2%误差就更难了。

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:




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.**

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.

## 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**

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.

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

**You should not 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.**

> 开发集和测试集用来评判训练效果，因此标签必须作对。训练集中的少量标签错误无伤大雅，因为深度学习算法对这种轻微的错误鲁棒性很好，他会从大量的正确案例中逐渐抹除掉错误标签的负面影响

## 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 call it 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.**

> 这完全就是迁移学习应该的做法

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.

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.

## 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.

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.**

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.

> 我搞图像，他搞声音，我们的低维度特征差异很大，不符合迁移学习和多任务学习的应用条件

## 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

**False**

Yes. (A) is an end-to-end approach as it maps directly the input (x) to the output (y).

## 15

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**

Multi-task learning problem.

Large bias problem.

Problem with a high Bayes error.

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

> 端到端学习在使用超大训练集的时候通常会更有可能成功（比起传统的分步方法）