Week 1: ML Strategy (1)

What is *machine learning strategy?* Lets start with a motivating example.

Introduction to ML strategy

Why ML strategy

Lets say you are working on a **cat classifier**. You have achieved 90% accuracy, but would like to improve performance even further. Your ideas for achieveing this are:

- collect more data
- collect more diverse training set
- train the algorithm longer with gradient descent
- try adam (or other optimizers) instead of gradient descent
- try dropout, add L2 regularization, change network architecture, ...

This list is long, and so it becomes incredibly important to be able to identify ideas that are worth our time, and which ones we can likely discard.

This course will attempt to introduce a framework for making these decisions. In particular, we will focus on the organization of *deep learning-based projects*.

Orthogonalization

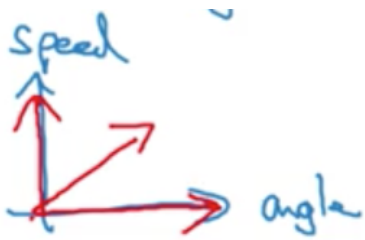
One of the challenges with building deep learning systems is the number of things we can tune to improve performance (*many hyperparameters notwithstanding*).

Take the example of an old TV. They included many nobs for tuning the display position (x-axis position, y-axis position, rotation, etc...).

Orthogonalization in this example refers to the TV designers decision to ensure each nob had one effect on the display and that these effects were *relative* to one another. If these nobs did more than one action and each actions magnitude was not relative to the other, it would become nearly impossible to tune the TV.

Take another example, driving a **car**. Imagine if there was multiple joysticks. One joystick modified 0.3 X steering angle -0.8 speed, and another 2 X steering angle $+0.9$ speed. In theory, by tuning these two nobs we could drive the car, but this would be *much more difficult then separating the inputs into distinct input mechanisms*.

Orthogonal refers to the idea that the *inputs* are aligned to the dimensions we want to control.



[https://postimg.cc/image/t547roobz/]

How does this related to machine learning?

Chain of assumption in examples

For a machine learning system to perform "well", we usually aim to make four things happen:

1. Fit training set well on cost function (for some applications, this means comparing favorably to human-level performance).
2. Fit dev set well on cost function
3. Fit test set well on cost function
4. Performs well in real world.

If we relate back to the TV example, we wanted *one knob* to change each attribute of the display. *In the same way, we can modify knobs for each of our four steps above*:

1. Train a bigger network, change the optimization algorithm, ...
2. Regularization, bigger training set, ...
3. Bigger dev set, ...
4. Change the dev set or the cost function

> **Note**
>
> Andrew said when he trains neural networks, he tends **not** to use **early stopping**. The reason being is that this is not a very **orthogonal** "knob"; it simultaneously effects how well we fit the training set and the dev set.

The whole idea here is that if we keep our "knobs" **orthogonal**, we can more easily come up with solutions to specific problems with our deep neural networks (i.e., if we are getting poor performance on the training set, we may opt to train a bigger [higher variance] network).

Setting up your goal

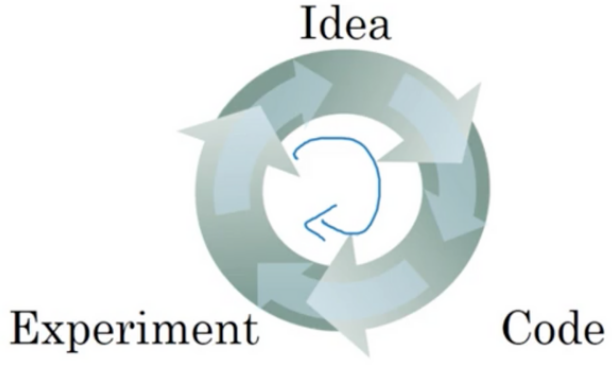
Single number evaluation metric

When tuning neural networks (modifying hyper-parameters, trying different architectures, etc.) you will find that having a _single __evaluation metric___ will allow you to easily and quickly judge if a certain change improved performance.

> **Note**
>
> Andrew recommends deciding on a single, real-valued evaluation metric when starting out on your deep learning project.

Lets look at an example.

As we discussed previously, **applied machine learning** is a very empirical process.



[https://postimg.cc/image/6t6eybcdb/]

Classifier	Precision	Recall
A	95%	90%
B	98%	85%

Lets say that we start with classifier A, and end up with classifier B after some change to the model. We could look at **precision** and **recall** as a means of improvements. What we really want is to improve *both* precision and recall. The problem is that it can become difficult to choose the "best" classifier if we are monitoring two different performance metrics, especially when we are making many modifications to our network.

This is when it becomes important to chose a single performance metric. In this case specifically, we can chose the **F1-score**, the harmonic mean of the precision and recall (less formally, think of this as an average).

Classifier	Precision	Recall	F1 Score
A	95%	90%	92.4%
B	98%	85%	91.0%

[https://postimg.cc/image/uwx6mln4f/]

We can see very quickly that classifier A has a better F1-score, and therefore we chose classifier A over classifier B.

Satisficing and Optimizing metric

It is not always easy to combine all the metrics we care about into a single real-numbered value. Lets introduce **satisficing** and **optimizing** metrics as a solution to this problem.

Lets say we are building a classifier, and we care about both our **accuracy** (measured as F1-score, traditional accuracy or some other metric) *and* the **running time** to classify a new example.

Classifier	Accuracy	Running time
A	90%	80ms
B	92%	95ms
C	95%	1,500ms

[https://postimg.cc/image/aoizsfn67/]

One thing we can do, is to combine accuracy and run-time into a **single-metric**, possibly by taking a weighted linear sum of the two metrics.

> **Note**
>
> As it turns out, this tends to produce a rather artificial solution (no pun intended).

Another way, is to attempt to *maximize accuracy* while subject to the restraint that $\text{running time} \leq 100\text{ms}$. In this case, we say that *accuracy* is an **optimizing** metric (because we want to maximize or minimize it) and *running time* is a **satisficing** metric (because it just needs to meet a certain constraint, i.e., be "good enough").

More generally, if we have m metrics that we care about, it is reasonable to choose *one* to be our **optimizing metric**, and $m - 1$ to be **satisficing metrics**.

Example: Wake words

We can take a concrete example to illustrate this: **wake words** for **intelligent voice assistants**. We might chose the accuracy of the model (i.e., what percent of the time does it "wake" when a wake word is said) to be out **optimizing metric** s.t. we have

≤ 1 false-positives per 24 hours of operation (our **satisficing metric**).

Summary

To summarize, if there are multiple things you care about, we can set one as the **optimizing metric** that you want to do as well as possible on and one or more as **satisficing metrics** were you'll be satisfied. This idea goes hand-in-hand with the idea of having a single real-valued performance metric whereby we can *quickly* and *easily* chose the best model given a selection of models.

Train/dev/test distributions

The way you set up your train, dev (sometimes called valid) and test sets can have a large impact on your development times and even model performance.

In this video, we are going to focus on the **dev** (sometimes called the **valid** or **hold out** set) and the **test set**. The general workflow in machine learning is to train on the **train** set and test out model performance (e.g., different hyper-parameters or model architectures) on the **dev** set.

Lets look at an example. Say we had data from multiple regions:

- US
- UK
- Other European countries
- South America
- India
- China
- Other Asian countries
- Australia

If we were to build our dev set by choosing data from the first four regions and our test set from the last four regions, our data would likely be **skewed** and our model would likely perform poorly (at least on the **test** set). *Why?*

Imagine the **dev** set as a target, and our job as machine learning engineers is to hit a bullseye. *A dev set that is not representative of the overall general distribution is analogous to moving the bullseye away from its original location moments after we fire our bow*. An ML team could spend months optimizing the model on a dev set, only to achieve very poor performance on a test set!

So for our data above, a much better idea would be to sample data randomly from all regions to build our **dev** and **test** set.

Guidelines

Choose a **dev** set and **test** set (from the same distribution) to reflect data you expect to *get in the future* and *consider important to do well on*.

Size of the dev and test sets

In the last lecture we saw that the dev and test sets should come from the same distributions. *But how large should they be?*

Size of the dev/test sets

The rule of thumb in machine learning is typically 60% **training**, 20% **dev**, and 20% **test** (or 70/30 **train**/**test**). In earlier eras of machine learning, this was pretty reasonable. In the modern machine learning era, we are used to working with *much* larger data set sizes.

For example, imagine we have $1,000,000$ examples. It might be totally reasonable for us to use 98% as our test set, 1% for dev and 1% for **test**.

> **Note**
>
> Note that 1% of 10^6 is 10^4!

Guidelines

Set your **test** set to be big enough to give high confidence in the overall performance of your system.

When to change dev/test sets and metrics

Sometimes during the course of a machine learning project, you will realize that you want to change your evaluation metric (i.e., move the "goal posts"). Lets illustrate this with an example:

Example 1

Imagine we have two models for image classification, and we are using classification performance as our evaluation metric:

- Algorithm A has a **3%** error, but sometimes shows users pornographic images.
- Algorithm B has a **5%** error.

Cleary, algorithm A performs better by our original evaluation metric (classification performance), but showing users pornographic images is *unacceptable*.

\[Error = \frac{1}{m_{dev}}\sum^{m_{dev}}{*i=1} \ell { y*{pred}^{(i)} \ne y^{(i)} }\]

> **Note**
>
> Our error treats all incorrect predictions the same, pornographic or otherwise.

We can think of it like this: our evaluation metric *prefers* algorithm A, but *we* (and our users) prefer algorithm B. When our evaluation metric is no longer ranking the algorithms in the order we would like, it is a sign that we may want to change our evaluation metric. In our specific example, we could solve this by weighting misclassifications

\[Error = \frac{1}{w^{(i)}}\sum^{m_{dev}}{*i=1} w^{(i)}\ell { y*{pred}^{(i)} \ne y^{(i)} }\]

where $w^{(i)}$ is 1 if $x^{(i)}$ is non-porn and 10 (or even 100 or larger) if $x^{(i)}$ is porn.

This is actually an example of **orthogonalization**. We,

1. Define a metric to evaluate our model ("placing the target")
2. (In a completely separate step) Worry about how to do well on this metric.

Example 2

Take the same example as above, but with a new twist. Say we train our classifier on a data set of high quality images. Then, when we deploy our model we notice it performs poorly. We narrow the problem down to the low quality images users are "feeding" to the model. What do we do?

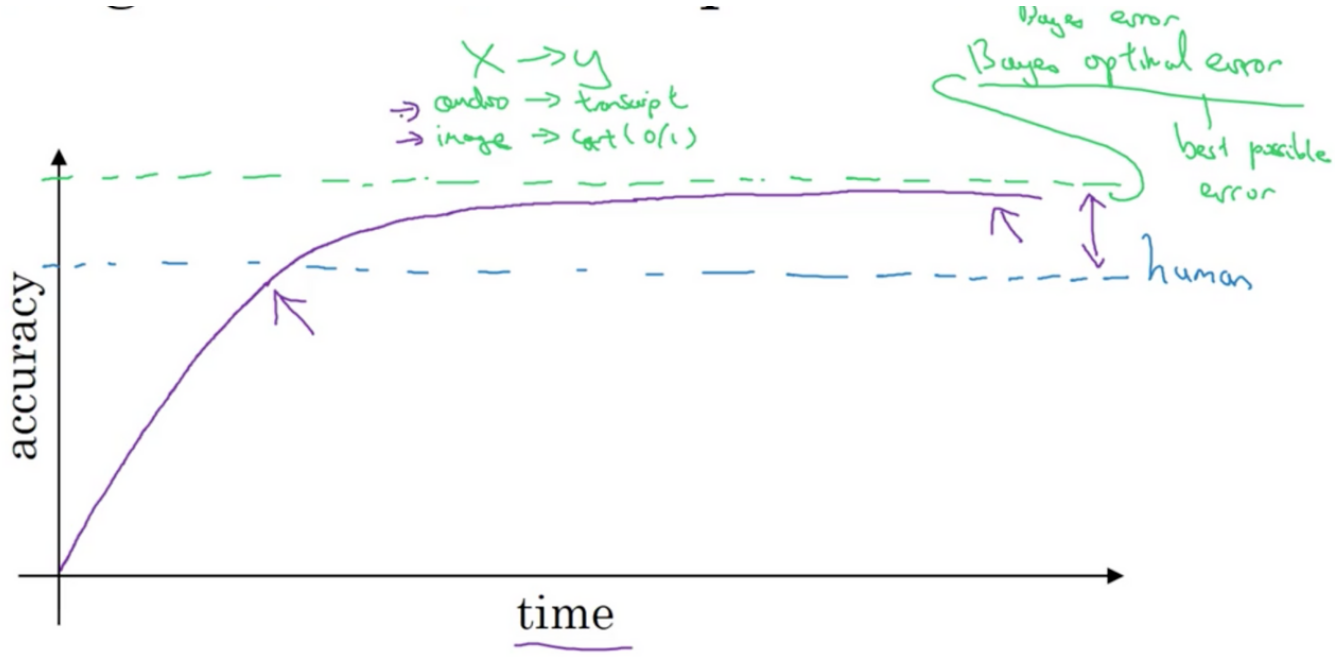
In general: *if doing well on your metric + dev/test set does not correspond to doing well on your application, change your metric and/or dev/test set*.

Comparing to human-level performance

In the last few years, comparing machine learning systems to human level performance have become common place. The reasons for this include:

1. Deep learning based approaches are making extraordinary gains in performance, so our baseline needs to be more stringent.
2. Many of the tasks deep learning is performing well at were thought to be very difficult for machines (e.g. NLP, computer vision). Comparing performance on these tasks to a human baseline is natural.

It is also instructive to look at the performance of machine learning over time (note this is an obvious abstraction)



[https://postimg.cc/image/wm9ztnwof/]

Roughly speaking, performance (e.g., in a research domain or for a certain task) progresses quickly until we reach human-level performance, and tails off quickly. *Why?* mainly because human level performance is typically very close to the **Bayes optimal error** [http://www.wikiwand.com/en/Bayes_error_rate]. Bayes optimal error is the best possible error; there is no way for any function mapping from $x \rightarrow y$ to do any better. A second reason is that so long as ML performs worse than humans for a given task, we can:

- get labeled data from humans
- gain insight from manual error analysis (e.g., why did a person get this right?)
- better analysis of bias/variance

Avoidable bias

Of course, we want our learning algorithm to perform well on the training set, but not *too well*. Knowing where human level performance is can help us decide how well we want to perform on the training set.

Let us again take the example of an image classifier. For this particular data set, assume:

- human-level performance is an error of 1%.
- our classifier is currently achieving 8% classification error on the training set and
- 10% classification on the dev set.

Clearly, it has plenty of room to improve. Specifically, we would want to try to *increase* **variance** and *reduce* **bias**.

> **Note**
>
> For the purposes of computer vision, assume that human-level performance $\approx$ Bayes error.

Now, lets take the same example, but instead, we assume that human-level performance is an error of 7.5% (this example is very contrived, as humans are extremely good at image classification). In this case, we note that our classifier performances nearly as well as a human baseline. We would likely want to to *decrease* **variance** and *increase* **bias** (in order to improve performance on the **dev** set.)

So what did this example show us? When human-level performance (where we are using human-level performance as a proxy for Bayes error) is *very high* relative to our models performance on the train set, we likely want to focus on reducing *"avoidable"* bias (or increasing variance) in order to improve performance on the training set (e.g., by using a bigger network.) When human-level performance is *comparable* to our models performance on the train set, we likely want to focus on increasing bias (or decreasing variance) in order to improve performance on the dev set (e.g., by using a regularization technique or gathering more training data.)

Understanding human-level performance

The term *human-level performance* is used quite casually in many research articles. Lets attempt to define this term more precisely.

Recall from the last lecture that **human-level performance** can be used as a proxy for **Bayes error**. Lets revisit that idea with another example.

Suppose, for a medical image classification example,

- Typical human: 3% error
- Typical doctor: 1% error
- Experienced doctor: 0.7% error
- Team of experienced doctors: 0.5% error

What is "human-level" error? Most likely, we would say **0.5%**, and thus Bayes error is ≤ 0.05. However, in certain contexts we may only wish to perform as well as the typical doctor (i.e., 1% error) and we may deem this *"human-level error"*. The takeaway is that there is sometimes more than one way to determine human-level performance; which way is appropriate will depend on the context in which we expect our algorithm to be deployed. We also note that as the performance of our algorithm improves, we may decide to move the goal posts for human-level performance higher, e.g., in this example by choosing a team of experienced doctors as the baseline. This is useful for solving the problem introduced in the previous lecture: *should I focus on reducing avoidable bias? or should I focus on reducing variance between by training and dev errors.*

Summary

Lets summarize: if you are trying to understand bias and variance when you have a human-level performance baseline:

- Human-level error can be used as a proxy for Bayes' error
- The difference between the training error and the human-level error can be thought of as the **avoidable bias**.
- The difference between the training and dev errors can be thought of as **variance**.
- Which type of error you should focus on reducing depends on how well your model perform compares to (an estimate of) human-level error.
- As our model approaches human-level performance, it becomes harder to determine where we should focus our efforts.

Surpassing human-level performance

Surpassing human-level performance is what many teams in machine learning / deep learning are inevitably trying to do. Lets take a look at a harder example to further develop our intuition for an approach to *matching* or *surpassing* human-level performance.

- team of humans: 0.5% error
- one human: 1.0% error
- training error: 0.3% error
- dev error: 0.4% error

Notice that training error < team of humans error. Does this mean we have *overfit* the data by 0.2%? Or, does this means Bayes' error is actually lower than the team of humans error? We don't really know based on the information given, as to whether we should focus on **bias** or **variance**. This example is meant to illustrate that once we surpass human-level performance, it becomes much less clear how to improve performance further.

Problems where ML significantly surpasses human-level performance

Some example where ML *significantly surpasses human-level performance* include:

- Online advertising,
- Product recommendations
- Logistics (predicting transit time)
- Load approvals

Notice that many of these tasks are learned on **structured data** and do not involve **natural perception tasks**. This appeals to our intuition, as we know humans are *excellent* at natural perception tasks.

> **Note**
>
> We also note that these four tasks have immensely large datasets for learning.

Improving your model performance

You have heard about orthogonalization. How to set up your dev and test sets, human level performance as a proxy for Bayes's error and how to estimate your avoidable bias and variance. Let's pull it all together into a set of guidelines for how to improve the performance of your learning algorithm.

The two fundamental assumptions of supervised learning

1. You can fit the training set (pretty) well, i.e., we can achieve *low avoidable bias*.
2. The training set performance generalizes pretty well to the dev/test set, i.e., variance is *not too bad*.

In the spirit of orthogonalization, there are a certain set of (separate) knobs we can use to improve bias and variance. Often, the difference between the training error and Bayes error (or a human-level proxy) is often illuminating in terms of where large improvement remain to be made.

For reducing bias

- Train a bigger model
- Train longer/better optimization algorithms
- Change/tweak NN architecture/hyperparameter search.

For reducing variance

- Collect more data
- Regularization (L2, dropout, data augmentation)
- Change/tweak NN architecture/hyperparameter search.

Week 2: ML Strategy (2)

Error Analysis

Manually examining mistakes that your algorithm is making can give you insights into what to do next (*especially if your learning algorithm is not yet at the performance of a human*). This process is called **error analysis**. Let's start with an example.

Carrying out error analysis

Take for example our **cat image classifier**, and say we obtain 10% error on our **test set**, much worse than we were hoping to do. Assume further that a colleague notices some of the misclassified examples are actually pictures of dogs. The question becomes, *should you try to make your cat classifier do better on dogs?*

This is where **error analysis** is particularly useful. In this example, we might:

- collect ~100 mislabeled dev set examples
- count up how any many dogs

Lets say we find that 5/100 (5%) mislabeled dev set example are dogs. Thus, the best we could hope to do (if we were to *completely* solve the dog problem) is decrease our error from 10% to 9.5% (a 5% relative drop in error.) We conclude that *this is likely not the best use of our time*. Sometimes, this is called the **ceiling**, i.e., the *maximum* amount of improvement we can expect from *some change* to our algorithm/dataset.

Suppose instead we find 50/500 (50%) mislabeled dev set examples are dogs. Thus, if we solve the dog problem, we could decrease our error from 10% to 5% (a 50% relative drop in error.) We conclude that *solving the dog problem is likely a good use of our time*.

> **Note**
>
> Notice the disproportionate 'payoff' here. It may take < 10 min to manually examine 100 examples from our dev set, but the exercise offers *major* clues as to where to focus our efforts.

Evaluate multiple ideas in parallel

Lets, continue with our cat detection example. Sometimes we might want to evaluate **multiple** ideas in **parallel**. For example, say we have the following ideas:

- fix pictures of dogs being recognized as cats
- fix great cats (lions, panthers, etc..) being misrecognized
- improve performance on blurry images

What can do is create a table, where the *rows* represent the images we plan on evaluating manually, and the *columns* represent the categorizes we think the algorithm may be misrecognizing. It is also helpful to add comments describing the the misclassified example.

Image	Dog	Great Cat	Blurry	Incorrectly labeled	Comments
...					
98				✓	Labeler missed cat in background
99		✓			
100				✓	Drawing of a cat; Not a real cat.
% of total	8%	43%	61%	6%	

As you are part-way through this process, you may also notice another common category of mistake, which you can add to this manual evaluation and repeat.

The conclusion of this process is estimates for:

- which errors we should direct our attention to solving
- how much we should expect performance to improve if reduce the number of errors in each category

Summary

To summarize: when carrying out error analysis, you should find a set of *mislabeled* examples and look at these examples for *false positives* and *false negatives*. Counting up the number of errors that fall into various different categories will often this will help you prioritize, or give you inspiration for new directions to go in for improving your algorithm.

Three numbers to keep your eye on

1. Overall dev set error
2. Errors due to cause of interest / Overall dev set error
3. Error due to other causes / Overall dev set error

If the errors due to other causes >> errors due to cause of interest, it will likely be more productive to ignore our cause of interest for the time being and seek another source of error we can try to minimize.

> **Note**
>
> In this case, *cause of interest* is just our idea for improving our leaning algorithm, e.g., *fix pictures of dogs being recognized as cats*

Cleaning up incorrectly labeled data

In supervised learning, we (typically) have hand-labeled training data. What if we realize that some examples are *incorrectly labeled*? First, lets consider our training set.

> **Note**
>
> In an effort to be less ambiguous, we use **mislabeled** when we are referring to examples the ML algo labeled incorrectly and **incorrectly** labeled when we are referring to examples in the training data set with the wrong label.

Training set

Deep learning algorithms are quite robust to **random** errors in the training set. If the errors are reasonably **random** and the dataset is big enough (i.e., the errors make up only a tiny proportion of all examples) performance of our algorithm is unlikely to be affected.

Systematic errors are much more of a problem. Taking as example our cat classifier again, if labelers mistakingly label all white dogs as cats, this will dramatically impact performance of our classifier, which is likely to labels white dogs as cats with *high degree of confidence*.

Dev/test set

If you suspect that there are many *incorrectly* labeled examples in your dev or test set, you can add another column to your error analysis table where you track these incorrectly labeled examples. Depending on the total percentage of these examples, you can decide if it is worth the time to go through and correct all *incorrectly* labeled examples in your dev or test set.

There are some special considerations when correcting incorrect dev/test set examples, namely:

- apply the same process to your dev and test sets to make sure they continue to come from the same distribution
- considering examining examples your algorithm got right as well as ones it got wrong
- train and dev/test data may now come from different distributions --- this is not necessarily a problem

Build quickly, then iterate

If you are working on a brand new ML system, it is recommended to *build quickly*, then *iterate*. For many problems, there are often tens or hundreds of directions we could reasonably choose to go in.

Building a system quickly breaks down to the following tasks:

1. set up a dev/test set and metric
2. build the initial system quickly and deploy
3. use bias/variance analysis & error analysis to prioritize next steps

A lot of value in this approach lies in the fact that we can quickly build insight to our problem.

> **Note**
>
> Note that this advice applies less when we have significant expertise in a given area and/or there is a significant body of academic work for the same or a very similar task (i.e., face recognition).

Mismatched training and dev/test set

Deep learning algorithms are *extremely data hungry*. Because of this, some teams are tempted into shoving as much information into their training sets as possible. However, this poses a problem when the data sources do not come from the same distributions.

Lets illustrate this again with an example. Take our cat classifier. Say we have ~10,000 images from a **mobile app**, and these are the images (or *type* of images) we hope to do well on. Assume as well that we have ~200,000 images from **webpages**, which have a slightly different underlying distribution than the mobile app images (say, for example, that they are generally higher quality.) *How do we combine these data sets?*

Option 1

We could take the all datasets, combine them, and shuffle them randomly into train/dev/test sets. However, this poses the obvious problem that *many of the examples in our dev set (~95% of them) will be from the webpage dataset*. We are effectively tuning our algorithm to a distribution that is *slightly different* than our target distribution --- data from the mobile app.

Option 2

The second, recommended option, is to comprise the dev/test sets of images *entirely from the target (i.e., mobile data) distribution*. The advantage, is that we are now "aiming the target" in the right place, i.e., the distribution we hope to perform well on. The disadvantage of course, is that the training set comes from a different distribution than our target (dev/test) sets. However, this method is still superior to **option 1**, and we will discuss laters further ways of dealing with this difference in distributions.

> **Note**
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> Note, we can still include examples from the distribution we care about in our training set, assuming we have enough data from this distribution.

Bias and Variance with mismatched data distributions

Estimating the **bias** and **variance** of your learning algorithm can really help you prioritize what to work on next. The way you analyze bias and variance changes when your training set comes from a different distribution than your dev and test sets. Let's see how.

Let's keep using our cat classification example and let's say humans get near perfect performance on this. So, Bayes error, or Bayes optimal error, we know is nearly 0% on this problem. Assume further:

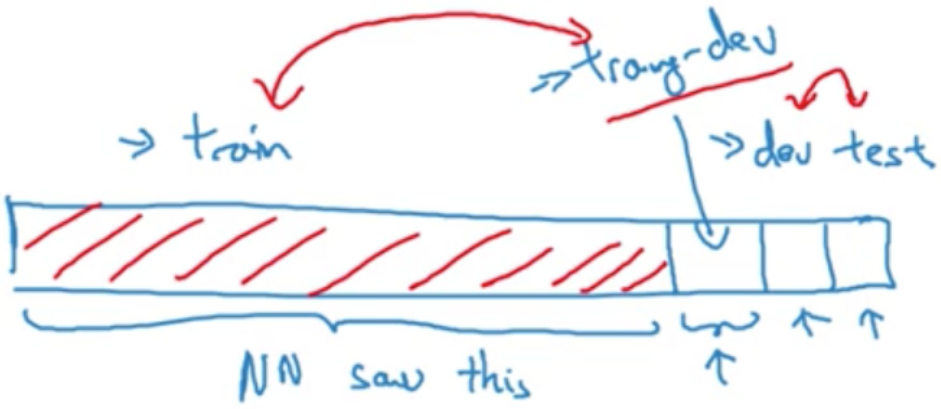
- training error: 1%
- dev error: 10%

If your **dev** data came from the *same distribution* as your **training** set, you would say that you have a large **variance** problem, i.e., your algorithm is not generalizing well from the training set to the dev set. But in the setting where your training data and your dev data comes from a *different distribution*, you can no longer safely draw this conclusion. If the training and dev data come from *different underlying distributions*, then by comparing the training set to the dev set we are actually observing two different changes at the same time:

1. The algorithm *saw* the training data. It did not *see* the dev data
2. The data do not come from the same underlying distribution

In order to tease out these which of these is conributing to the drop in perfromsnce from our train to dev set, it will be useful to define a new piece of data which we'll call the **training-dev** set: a new subset of data with the same distribution as the training set, but not used for training.

Heres what we mean, previously we had train/dev/test sets. What we are going to do instead is randomly shuffle the training set and carve out a part of this shuffled set to be the **training-dev**.



> **Note**
>
> Just as the dev/test sets have the same distribution, the train-dev set and train set have the same distribution.

Now, say we have the following errors:

- training error: 1%
- train-dev error: 9%
- dev error: 10%

We see that training error $<<$ train-dev error $\approx$ dev error. Because the train and train-dev sets come from the same underlying distribution, we can safely conclude that the large increase in error from the train set to the dev set is due to *variance* (i.e., our network is not generalizing well)

Lets look at a counter example. Say we have the following errors:

- training error: 1%
- train-dev error: 1.5%
- dev error: 10%

This is much more likely to be a *data mismatch problem*. Specifically, the algorithm is performing extremely well on the train and train-dev sets, but poorly on the dev set, hinting that the train/train-dev sets likely come from different underlying distributions than the dev set.

Finally, one last example. Say we have the following errors:

- Bayes error: $\approx$ 0%
- training error: 10%
- train-dev error: 11%
- dev error: 20%

Here, we likely have two problems. First, we notice an *avoidable bias* problem, suggested by the fact that our training error $>>$ Bayes error. We also have a *data mismatch problem*, suggested by the fact that our training error $\approx$ train-dev error by both are $<<$ our dev error.

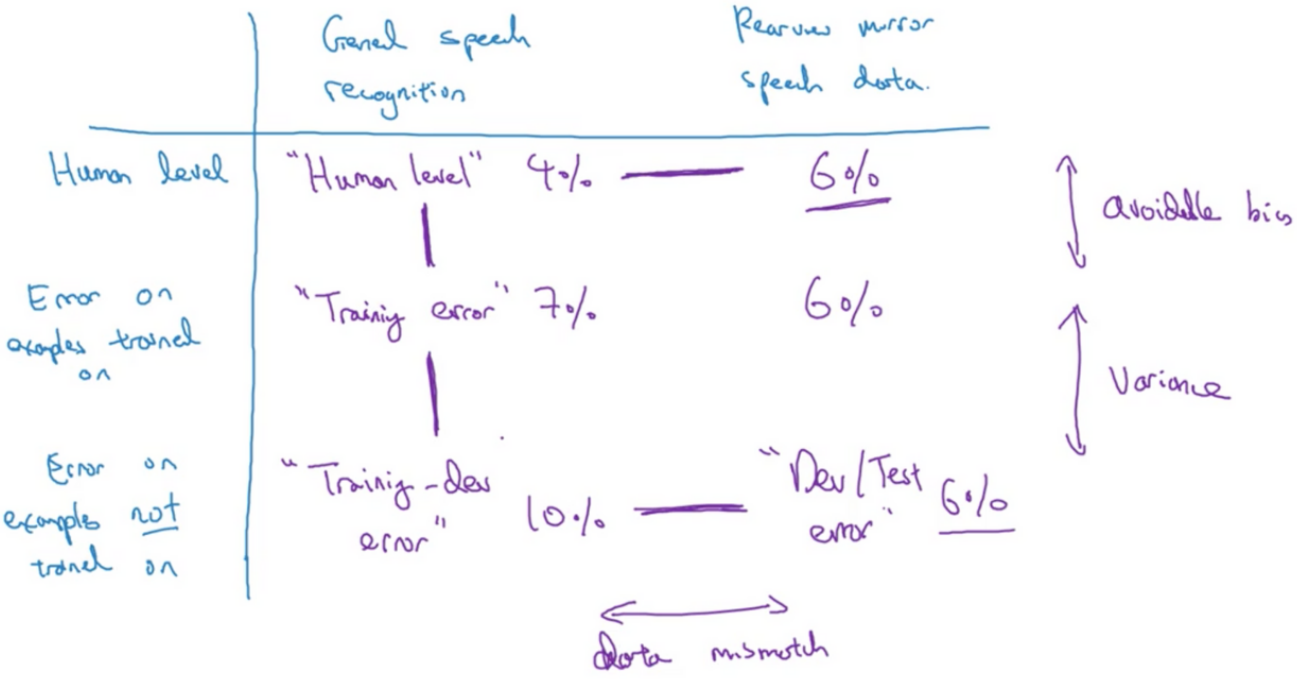
So let's take what we've done and write out the general principles. The *key quantities* your want to look at are: human-level error (or Bayes error), training set error, training-dev set error and the dev set error.

The differences between these errors give us a sense about the **avoidable bias**, the **variance**, and the **data mismatch problem**. Generally,

- training error $>>$ Bayes error: avoidable bias problem
- training error $<<$ train-dev error: variance problem
- training error $\approx$ train-dev error $<<$ dev error: data mismatch problem.

More general formation

We can organize these metrics into a table; where the columns are different datasets (if you have more than one) and the rows are the error for examples the algorithm *was* trained on and examples the algorithm *was not* trained on.



Addressing data mismatch

If your training set comes from a different distribution, than your dev and test set, and if error analysis shows you that you have a data mismatch problem, what can you do? Unfortunately, there are not (completely) systematic solutions to this, but let's look at some things you could try.

Some recommendations:

- carry out manual error analysis to try to understand different between training and dev/test sets.
- *for example, you may find that many of the examples in your dev set are noisy when compared to those in your training set.*
- make training data more similar; or collect more data similar to dev/test sets.
- *for example, you may simulate noise in the training set*

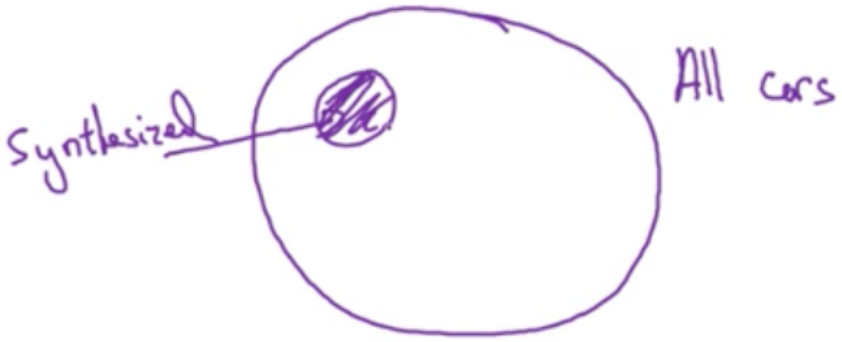
The second point leads us into the idea of **artificial data synthesis**

Artificial data synthesis

In some cases, we may be able to artificially synthesis data to make up for a lack of real data. For example, we can imagine synthesizing images of cars to supplement a dataset of car images for the task of car recognition in photos.

[https://postimg.cc/image/5rexjq01b/]

While artificial data synthesis can be a powerful technique for increasing the size of our dataset (and thus the performance of our learning algorithm), we must be wary of overfitting to the synthesized data. Say for example, the set of "all cars" and "synthesized cars" looked as follows:



[https://postimg.cc/image/3mukint9r/]

In this case, we run a real risk of our algorithm overfitting to the synthesized images.

Learning from multiple tasks

Transfer learning

One of the most powerful ideas in deep learning is that you can take knowledge the neural network has learned from *one task* and apply that knowledge to a *separate task*. So for example, maybe you could have the neural network learn to recognize objects like cats and then use parts of that knowledge to help you do a better job reading X-ray scans. This is called **transfer learning**. Let's take a look.

Lets say you have trained a neural network for **image recognition**. If you want to take this neural network and *transfer* it to a different task, say radiology diagnosis, one method would be to *delete* the last layer, and re-randomly initialize the weights feeding into the output layer.

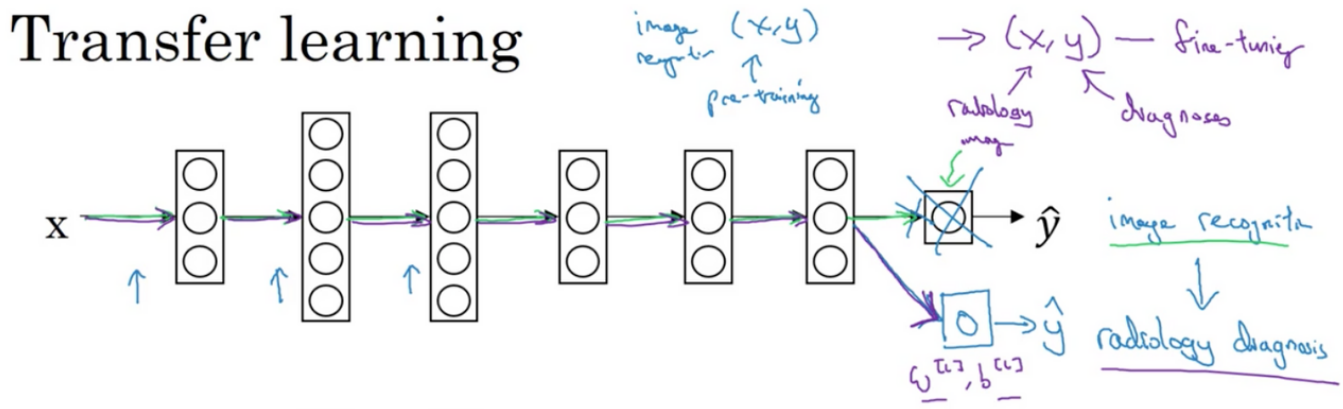
To be concrete:

- during the first phase of training when you're training on an image recognition task, you train all of the usual parameters for the neural network, all the weights, all the layers
- having trained that neural network, what you now do to implement transfer learning is swap in a new data set X, Y, where now these are radiology images and diagnoses pairs.
- finally, initialize the last layers' weights randomly and retrain the neural network on this new data set.

We have a couple options on how we retrain the dataset.

- If the radiology dataset is **small**: we should likely *"freeze"* the transferred layers and only train the output layer.
- If the radiology dataset is **large**: we should likely train all layers.

> **Note**
>
> Sometimes, we call the process of training on the first dataset **pre-training**, and the process of training on the second dataset **fine-tuning**.



The idea is that learning from a very large image data set allows us to transfer some fundamental knowledge for the task of computer vision (i.e., extracting features such as lines/edges, small objects, etc.)

> **Note**
>
> Note that transfer learning is **not** confined to computer vision examples, recent research has shown much success deploying transfer learning for NLP tasks.

When does transfer learning make sense?

Transfer learning makes sense when you have a *lot of data for the problem you're transferring **from** and usually relatively less data for the problem you're transferring **to***.

So for our example, let's say you have a *million* examples for image recognition task. Thats a lot of data to learn low level features or to learn a lot of useful features in the earlier layers in neural network. But for the radiology task, assume we only a hundred examples. So a lot of knowledge you learn from image recognition can be transferred and can really help you get going with radiology recognition even if you don't have enough data to perform well for the radiology diagnosis task.

If you're trying to learn from some **Task A** and transfer some of the knowledge to some **Task B**, then transfer learning makes sense when:

- Task A and B have the same input X.
- you have a lot more data for Task A than for Task B --- all this is under the assumption that what you really want to do well on is Task B.
- transfer learning will tend to make more sense if you suspect that low level features from Task A could be helpful for learning Task B.

Multi-task learning

Whereas in transfer learning, you have a sequential process where you learn from task A and then transfer that to task B --- in multi-task learning, you start off simultaneously, trying to have one neural network do several things at the same time. The idea is that shared information from each of these tasks improves performance on *all* tasks. Let's look at an example.

Simplified autonomous driving example

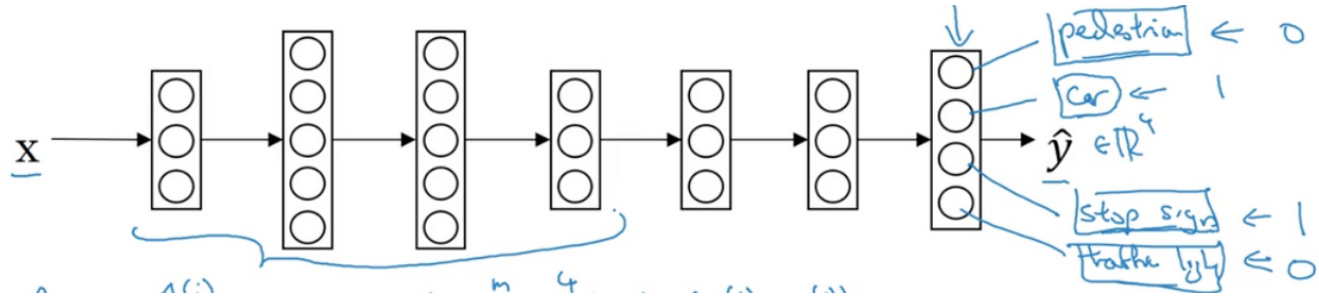
Let's say you're building an autonomous vehicle. Then your self driving car would need to detect several different things such as *pedestrians*, *other cars*, *stop signs*, *traffic lights* etc.

Our input to the learning algorithm could be a single image, our our label for that example, $y^{(i)}$ might be a four-dimensional column vector, where 0 at position j represents absence of that object from the image and 1 represents presence.

> **Note**

E.g., a 0 at the first index of $y^{(i)}$ might specify absence of a pedestrian in the image.

Our neural network architecture would then involve a single input and output layer. The twist is that the output layer would have j number of nodes, one per object we want to recognize.



To account for this, our cost function will need to sum over the individual loss functions for each of the objects we wish to recongize:

$$Cost = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{m} \ell(\hat{y}_j^{(i)}, y_j^{(i)})$$

Note

Were ℓ is our logisitc loss.

Unlike traditional softmax regression, one image can have multiple labels. This, in essense, is **multi-task** learning, as we are preforming multiple tasks with the same neural network (sets of weights/biases).

When does multi-task learning make sense?

Typically (but with some exceptions) when the following hold:

- Training on a set of tasks that could benefit from having shared lower-level features.
- Amount of data you have for each task is quite similar.
- Can train a big enough neural network to do well on all the tasks

Note

The last point is important. We typically need to "scale-up" the neural network in multi-task learning, as we will need a high variance model to be able to perform well on multiple tasks and typically more data --- as opposed to single tasks.

End-to-end deep learning

One of the most exciting recent developments in deep learning has been the rise of **end-to-end deep** learning. So what is the end-to-end learning? Briefly, there have been some data processing systems, or learning systems that require *multiple stages of processing*. In contrast, end-to-end deep learning attempts to replace those multiple stages with a single neural network. Let's look at some examples.

What is end-to-end deep learning?

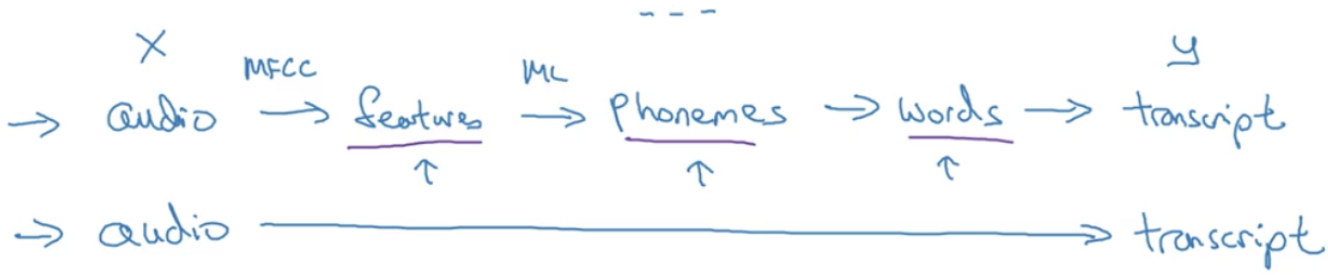
Speech recognition example

At a high level, the task of speech recognition requires receiving as input some audio singles containing spoken words, and mapping that to a transcript containing those words.

Traditionally, speech recognition involved many stages of processing:

1. First, you would extract "hand-designed" features from the audio clip
2. Feed these features into a ML algorithm which would extract phonemes
3. Concatenate these phonemes to form words and then transcripts

In contrast to this step-by-step pipeline, **end-to-end deep learning** seeks to model all these tasks with a single network given a set of inputs.



The more traditional, **hand-crafted** approach tends to *outperform* the **end-to-end approach** when *our dataset is small*, but this relationship flips as the dataset grows larger. Indeed, one of the biggest barriers to using end-to-end deep learning approaches is that large datasets which map our input to our final downstream task are *rare*.

> **Note**
>
> Think about this for a second and it makes perfect sense, its only recently in the era of deep learning that datasets have begun to map inputs to downstream outputs, skipping many of the intermediate levels of representation (images $\Rightarrow$ labels, audio clips $\Rightarrow$ transcripts.)

One example where end-to-end deep learning currently works very well is **machine translation** (massive, parallel corpuses have made end-to-end solutions feasible.)

Summary

When end-to-end deep learning works, it can work really well and can simplify the system, removing the need to build many hand-designed individual components. But it's also not panacea, *it doesn't always work*.

Whether or not to use end-to-end learning

Let's say in building a machine learning system you're trying to decide whether or not to use an end-to-end approach. Let's take a look at some of the pros and cons of end-to-end deep learning so that you can come away with some guidelines on whether or not an end-to-end approach seems promising for your application.

Pros and cons of end-to-end deep learning

Pros:

1. *let the data speak*: if you have enough labeled data, your network (given that it is large enough) should be able to a mapping from $x \rightarrow y$, with out having to rely on a humans preconceived notions or forcing the model to use some representation of the relationship between inputs an outputs.
2. *less hand-designing of components needed*: end-to-end deep learning seeks to model the entire task with a single learning algorithm, which typically involves little in the way of hand-designing components.

Cons:

1. *likely need a large amount of data for end-to-end learning to work well*
2. *excludes potentially useful hand-designed components*: if we have only a small training set, our learning algorithm likely does not have enough examples to learn representations that perform well. Although deep learning practitioners often

speak despairingly about hand-crafted features or components, they allow us to inject priors into our model, which is particularly useful when we do not have a lot of labeled data.

> **Note**
>
> Note: hand-designed components and features are a double-edged sword. Poorly designed components may actually harm performance of the model by forcing the model to obey incorrect assumptions about the data.

Should I use end-to-end deep learning?

The key question we need to ask ourselves when considering on using end-to-end deep learning is:

Do you have sufficient data to learn a function of the complexity needed to map x to y?

Unfortunately, we do not have a formal definition of **complexity** --- we have to rely on our intuition.