

Error Analysis

Carrying out error analysis

Look at dev examples to evaluate ideas





> 10% occurat

Should you try to make your cat classifier do better on dogs?

Error analysis:

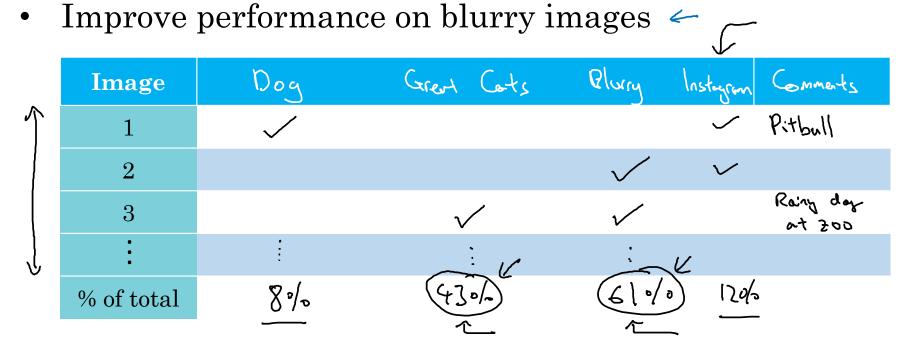
- Get ~100 mislabeled dev set examples.
 Count up how many are dogs.

"(eiling)

Evaluate multiple ideas in parallel

Ideas for cat detection:

- Fix pictures of dogs being recognized as cats <
- Fix great cats (lions, panthers, etc..) being misrecognized <



Create a table in exel like this and go through the images manually that are not good.
See a errorr % of these categories.

Andrew Ng



Error Analysis

Cleaning up Incorrectly labeled data

Incorrectly labeled examples



DL algorithms are quite robust to random errors in the training set.

Systematic errors they are lest rubust to systematic errors

if you have wihite dogs consistenly labeled incorrectly.

Andrew Ng

Error analysis



In this case during error analysis we add one column incorrect label for y

| | • | | | | | | |
|--|------------|-----|--------------|--------------------|---------------------|--------------------------------------|--|
| • | Image | Dog | Great Cat | Blurry | Incorrectly labeled | Comments | |
| \uparrow | | | | | | | |
| | 98 | | | | \checkmark | Labeler missed cat in background | · — |
| | 99 | | \checkmark | | | | |
| 3 number are worth looking in to decide | 100 | | | | \bigcirc | Drawing of a cat; Not a real cat. | \leftarrow |
| whether to look into icorrect labeled | % of total | 8% | 43% | $\underline{61\%}$ | 6% | V | |
| Overall dev set error Errors due incorrect labels 0.6./. | | | | | | 2% | so this is big wrt 2 unlike before 200 so in this case its worth going to fix incorrect |
| | | | | | | 0.6% | |
| Errors due to other causes 9.4% label. | | | | | | | - |
| | | | | 1 | | 2.10/0 | 1.9-/6 |

Goal of dev set is to help you select between two classifiers A & B.

Andrew Ng

Correcting incorrect dev/test set examples

- Apply same process to your dev and test sets to make sure they continue to come from the same distribution
- Consider examining examples your algorithm got right as well as ones it got wrong. (3)
- Train and dev/test data may now come from slightly different distributions.



Error Analysis

Build your first system quickly, then iterate

Speech recognition example



- → Noisy background
 - Café noise
 - → Car noise

- Young children

Accent Guideline:

Build your first Stutten system quickly, then iterate

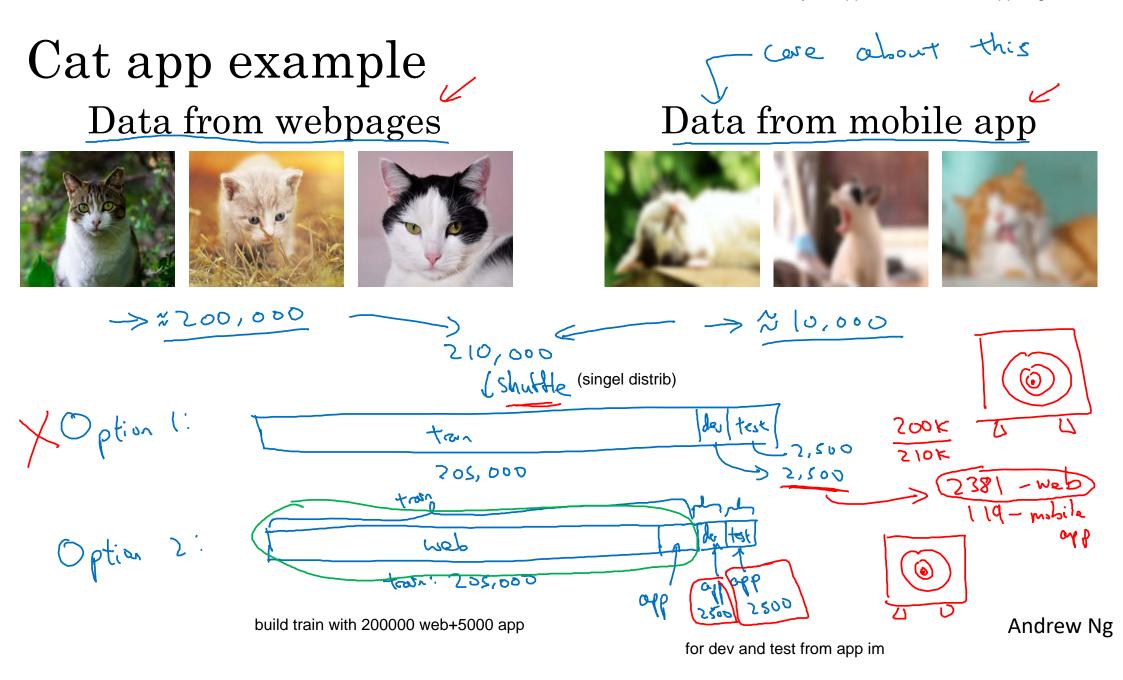
- → Set up dev/test set and metric
 - Build initial system quickly
 - Use Bias/Variance analysis & Error analysis to prioritize next steps.



Mismatched training and dev/test data

Training and testing on different distributions

You want your app to do well on the app img



Say you are building a speech recognizer rearview mirror. (its real product in China)

Speech recognition example

Speak outistel rearries million-



Training

Purchased data ×y

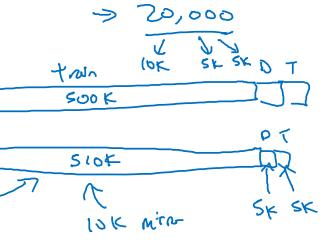
Smart speaker control

Voice keyboard

500,000 utbrances

Dev/test

Speech activated rearview mirror





Mismatched training and dev/test data

Bias and Variance with mismatched data distributions

Should you allways use all the data you have???

Estimating the Bias and Variance really helps your learning algorithm really

helps you prioritize what to work on next. But the way you analyze bias and variance changes when your training set comes from a different distribution that your dev and test sets.

Cat classifier example

Assume humans get $\approx 0\%$ error.

we know bias error is close to 0

Training error

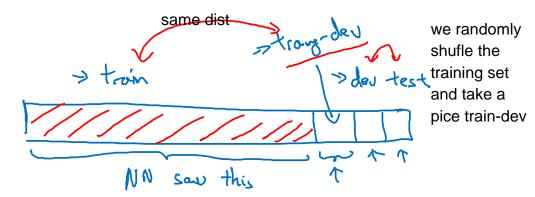
Dev error

So to carry out error analysis you usually look at the training error and the error on the test set. So say the Training error is 1 % and dev set is 10%, if training and dev come from same distrib you say u have a high variance problem. But when the two come from different distrib you can no longer draw this conclusion. Maybe its just becouse dev set is harder due to blury img

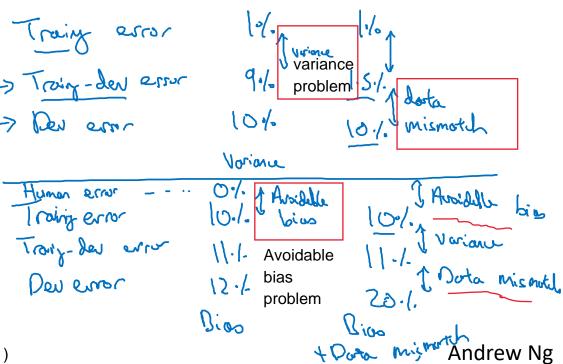
Training-dev set: Same: we def this distribution as training new subset set, but not used for training

So when you pass from the training set to the dev set, two things change:

- 1. the alg saw data in training set but not in dev set(variance part of problem)
- 2. the distrib of data in dev set is different since u change two things at the same time its diffictult to know of this 9% increase in error how much of it is due to



Now u just train on red part, you dont run backprop on train-dev part



Bias/variance on mismatched training and dev/test sets Here is an examples of number

Human level
Traing set error
Traing-der set error
> Der error
> Test error

to/. Jaroidable bios

70/s of variance
10.1. Javan mismath
12.1/s Javan degree of suchthy
12.1/s to dow set.

legree of overgitting to dev set

this happens u find more data into dev set

Reasure milror More general formulation Rearview mirrorr speech data General speech recognition Genel speech recognition Rearum misor Human level Human level" avoidale Varione

Andrew Ng



Mismatched training and dev/test data

Addressing data mismatch

Addressing data mismatch

 Carry out manual error analysis to try to understand difference between training and dev/test sets

Try to figure out how u dev set is different from test set

→ • Make training data more similar; or collect more data similar to dev/test sets

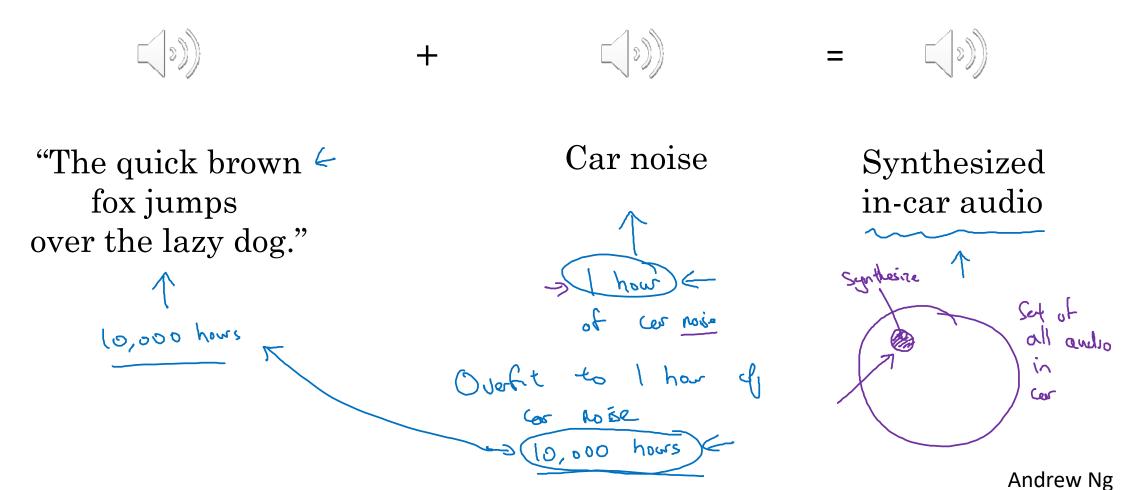


Try make training data more similar to training set.

One of the techniques u can use is artificial data sintesis.

Artificial data synthesis

: Make u data look like it has been recorded inside a car



if u just add hat 1 h of car noise t all 10000 h then u have a risk to overfit to car noise.

Need to find 10000 h of car noise, hard!!

Artificial data synthesis

use computer graphics to generate those img

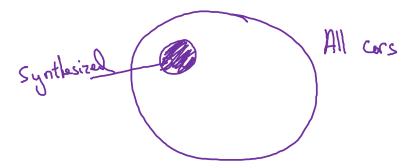
Car recognition:







WSD cons



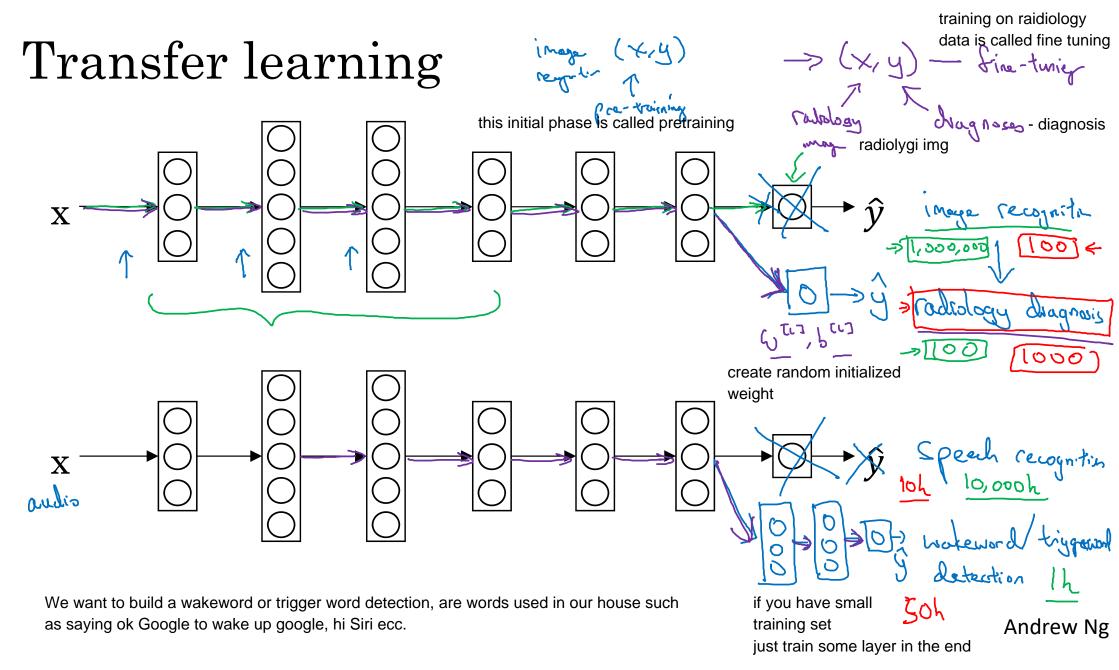
Andrew Ng



Learning from multiple tasks

Transfer learning

The NN has learned from one task and applying it to other task. U have a NN that recognises cats and then use to do a better job reading x-ray scans. This is called transfer learning.

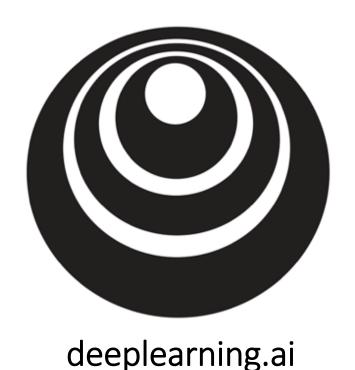


When does transfer learning make sense?? It makes sense when u have a lot of data for the problem you are transfering from, and usually less data for the problem you're transfering to. It would not make sense if the amount of data u have is inverse.

When transfer learning makes sense

Transh from A -> B

- Task A and B have the same input x.
- You have a lot more data for $\underbrace{Task A}_{\uparrow}$ than $\underbrace{Task B}_{\uparrow}$.
- Low level features from A could be helpful for learning B.



Learning from multiple tasks

Multi-task learning

In multitasking you have one NN trying to do several things at the same time and each of these tasks helps the other tasks thats look at an example

Simplified autonomous driving example

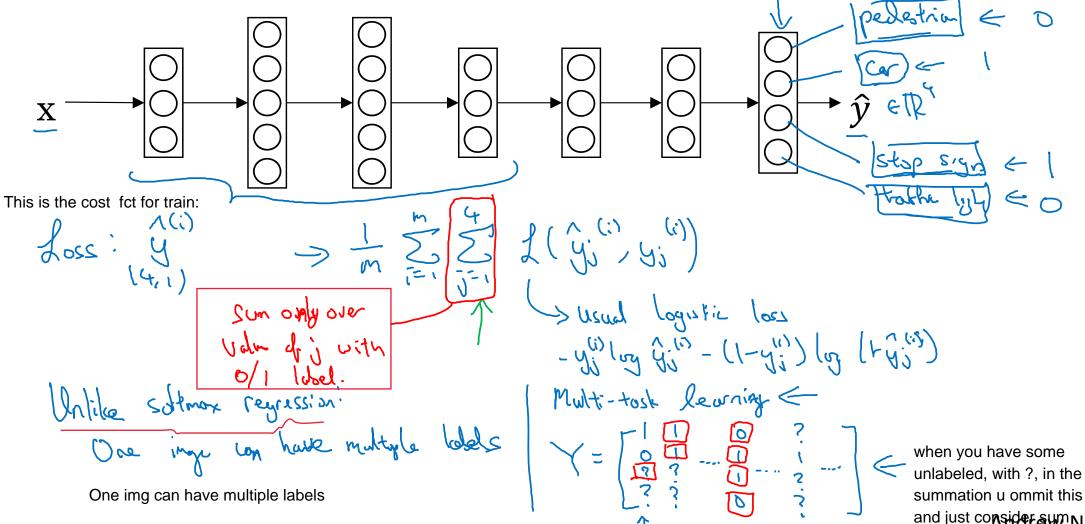


input x i

So now Y is (4,n) matrix and not a (1,n) matrix like before So what you can do is to train a NN to predict these values Y

Neural network architecture

You can do multiclassification



If we do min that cost function we are performing

Multiclass classification learning

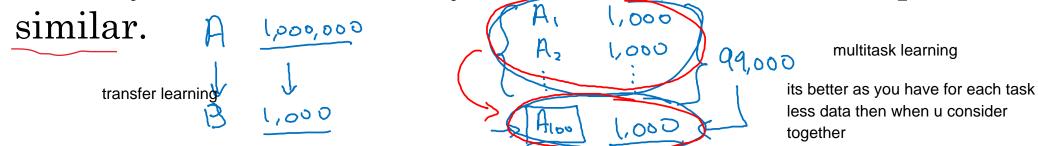
You could have done four separate NN to do this, but like this you get better performance

and just consider swn Ng over 0/1 label

When multi-task learning makes sense

• Training on a set of tasks that could benefit from having shared lower-level features.

Usually: Amount of data you have for each task is quite



• Can train a big enough neural network to do well on all the tasks.

The only time when multitask learning does hurt performace is when the NN is not big enough.



End-to-end deep learning

What is end-to-end deep learning

There have been some learning systems that require multipe stages of processing, what end to end does is to take all of these stages an replace with a single NN

What is end-to-end learning?

thats take speech recogn ex:

Speech recognition example

take imput x(audio clip)

MECC

Mu

Phonemes > Words > transcript

audio > phonemes > phonemes > transcript

Touscript

10,0004

speech recognition involves several phases like using MFCC extract som low level features then use ML to find phonemes (which are the basic units of sound, so for ex word cat is made of three sounds c a t. Then you string together phonemes to form individual words and then you string those together to form the transcripts of the audio clips.

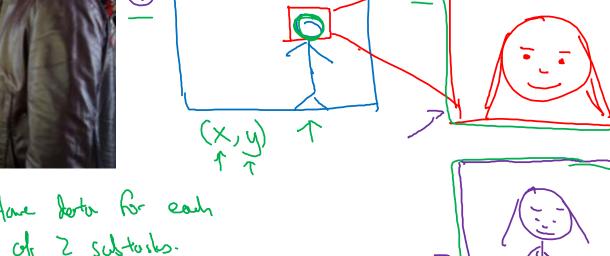
Andrew Ng

So in contrast to the pipeline with a lot of stages what end to end deep learning does is you can train a huge NN to just input the audio clip and have directly the trascript. The challenge is that you need a lot of data for it to work well, so for ex if you are training on 3000 h of data then the traditional pipeline works really well, its only when you have like 10000 h to 100000 h of data then end to end learning works well. There are also intermediate approaches where you go from audio to phonemes to other stages and then to transcript.

Face recognition



[Image courtesy of Baidu]



Andrew Ng

you do multitask, first you identify the person then zoom into the face and crop the face pic and feed to NN So why the two step works better:

- 1. each of the two problems you're solving is actually much simpler
- 2. you have a lot of data for each of the two sub-tasks. In particular ther is a lot of data you can obtain for phase detection

More examples

Machine translation

Estimating child's age:





End-to-end deep learning

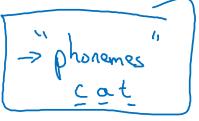
Whether to use end-to-end learning

Pros and cons of end-to-end deep learning

Pros:

• Let the data speak

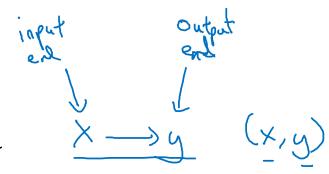




Less hand-designing of components needed

Cons:

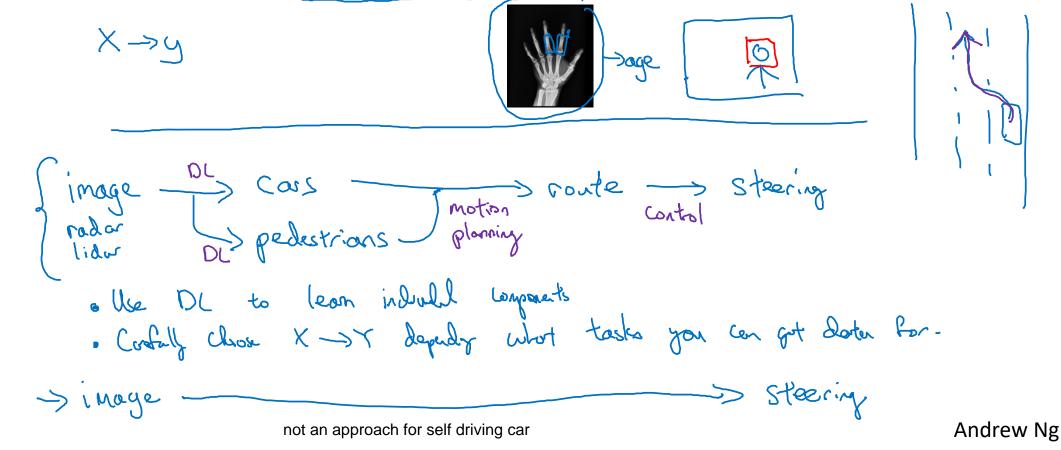
May need large amount of data



• Excludes potentially useful hand-designed components

Applying end-to-end deep learning

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



You need to be mindful where u apply end to end deep learning