Setting up your goal

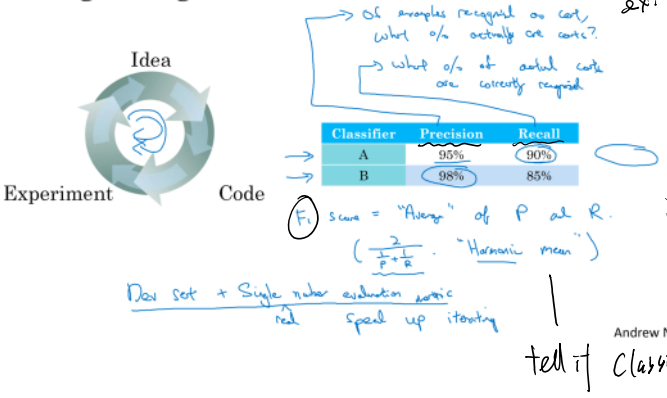
Tuesday, June 5, 2018 3:21 PM

singlenum

set up a number that can evaluate performance

Using a single number evaluation metric

ex: cat classifier



Single # evaluation metric.

problem: better precision, worse recall, or reverse.

例 $F_1 = \frac{2}{\frac{1}{P}+\frac{1}{R}}$

tell if Classifier A or B is better — speed up iterating.

Another example

Algorithm	US	China	India	Other
A	3%	7%	5%	9%
B	5%	6%	5%	10%
C	2%	3%	4%	5%
D	5%	8%	7%	2%
E	4%	5%	2%	4%
F	7%	11%	8%	12%

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What if the algorithms have different performance (ranking) in different test sets (US, China, India, Other)?

Take average

satisficing

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Setting up your goal

Satisficing and optimizing metrics

Another cat classification example

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

optimizing: Accuracy; satisficing: Running time

cost = accuracy − 0.5 × running time

maximize accuracy
subject to running time ≤ 100 ms.

N metrics: 1 optimizing
N-1 satisficing

voice
Wakewords / Trigger words
Alexa, OK Google,
Hey Siri, nihaobaidu
你好百度

accuracy.
#false positive

maximize accuracy.
s.t. ≤ 1 false positive
every 24 hours.

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有不同的 criteria : Accuracy, run time
what to do ? Define cost function, then set constraint
如 — run time 不能超过 xx 时, 找 max accuracy.

traindevtest

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Setting up your goal

Train/dev/test distributions

Cat classification dev/test sets

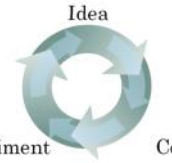
Regions:

- US
- UK
- Other Europe
- South America

Dev

- India
- China
- Other Asia
- Australia

Test



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Dev and test sets should come from the same distribution

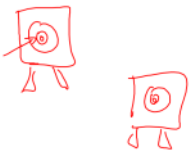
otherwise ML learn models that do not get good performance on the test set (WRONG TARGET)

True story (details changed)

A real world example

Optimizing on dev set on loan approvals for medium income zip codes

Tested on low income zip codes



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Guideline

Same distribution

Choose a dev set and test set to reflect data you expect to get in the future and consider important to do well on.

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Setting up your goal

Size of dev and test sets

rule of thumb.

Reasonable for smaller size of data.

Size of test set

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

10,000
100,000

Train + Dev. No test set.

train	~~test~~ dev

can do train + ~~test~~ dev. with No test set

⇒ Not recommended

Take away: the 70/30 rule ~~NOT~~ no longer work

trend: assignment ~~[illegible]~~ more data to training set.

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changeset

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Setting up your goal

When to change dev/test sets and metrics

If your evaluation matrix don't give you results that make sense

⇒ use a different matrix

Criteria

还是取决根据需求定义

Cat dataset examples

Metric + Dev : Prefer A
You/users : Prefer B.

→ Metric: classification error

Algorithm A: 3% error → + pornographic → 不过为啥把两个给混起来?

✓ Algorithm B: 5% error

$$\text{Error}: \frac{1}{\sum_i w^{(i)}} \cancel{\frac{1}{m_{dev}}} \sum_{i=1}^{m_{dev}} w^{(i)} \, I\{ y_{pred}^{(i)} \neq y^{(i)} \}$$

y_{pred} ← predicted value (0/1)

$$\rightarrow w^{(i)} = \begin{cases} 1 & \text{if } x^{(i)} \text{ is non-porn} \\ 10 & \text{if } x^{(i)} \text{ is porn} \end{cases}$$

penalize 把porn misclassify 成 cat 的行为.

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Orthogonalization for cat pictures: anti-porn

1. So far we've only discussed how to define a metric to evaluate classifiers. ← Place target
2. Worry separately about how to do well on this metric.

Aim/shoot at target

$$J = \frac{1}{\sum w^{(i)}} \sum_{i=1}^{m} w^{(i)} \mathcal{L}\left(\hat{y}^{(i)}, y^{(i)}\right)$$

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1. Define metrics
2. Optimize on this matrix.

Another example

Algorithm A: 3% error
Algorithm B: 5% error ←

→ Dev/test

→ User images

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.

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WRONG Target.
or. correct target, ill-defined in the evaluation metrics

Even you can't decide: set up quickly some evaluation matrix. try => adjust the metrics, => train model again

compare

Comparing to human-level performance

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Why human-level performance?

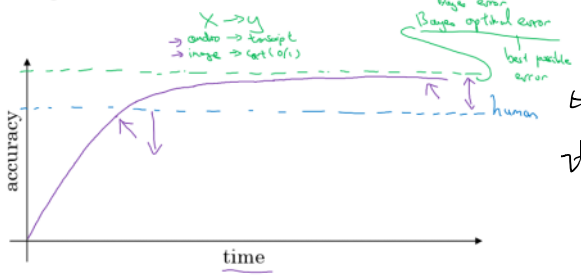
Comparing to human-level performance

$X \to y$
audio → transcript
image → cat (0/1)

Bayes error
Bayes optimal error

Bayes Optimal error: the Best possible error
e.g. Some audio is just too noisy; Some images are too blurry
progresses slow down after surpasses human performance

Comparing to human-level performance



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Why compare to human-level performance

Humans are quite good at a lot of tasks. So long as ML is worse than humans, you can:

- Get labeled data from humans.
- Gain insight from manual error analysis: Why did a person get this right?
- Better analysis of bias/variance.

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avoidablebias

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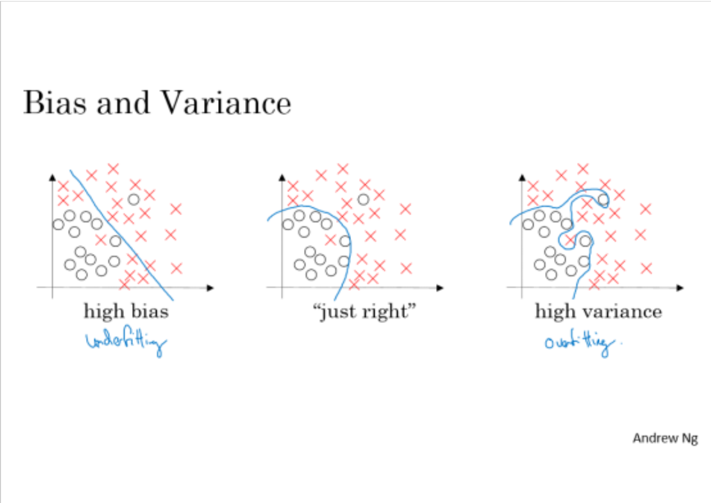
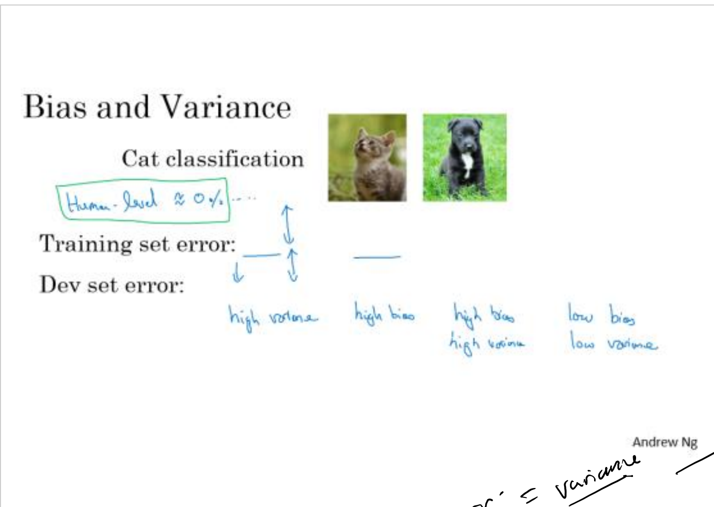
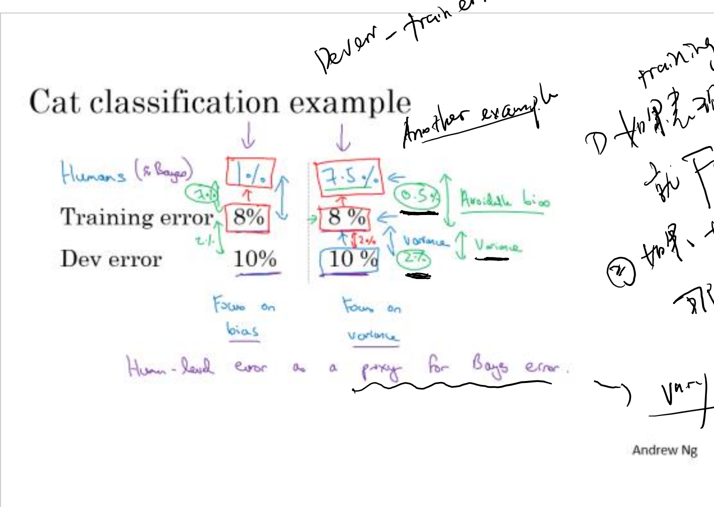
Comparing to human-level performance

Avoidable bias





Dev err - train err = variance → 这里的 variance 最好说明了...



training error
① 如果和 human 差距过大，
就 Focus on reducing bias.
② 如果 training error 接近 human error 了，
那就要 focus on ↓ variance (dev test error ↓
regularization, ...

→ vary across tasks

humanlevelperfom

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Comparing to human-level performance

Understanding human-level performance

Human-level error as a proxy for Bayes error

Medical image classification example:

Suppose:

(a) Typical human ..... 3 % error

(b) Typical doctor ..... 1 % error

(c) Experienced doctor ..... 0.7 % error

(d) Team of experienced doctors .. 0.5 % error

What is "human-level" error?

How to define

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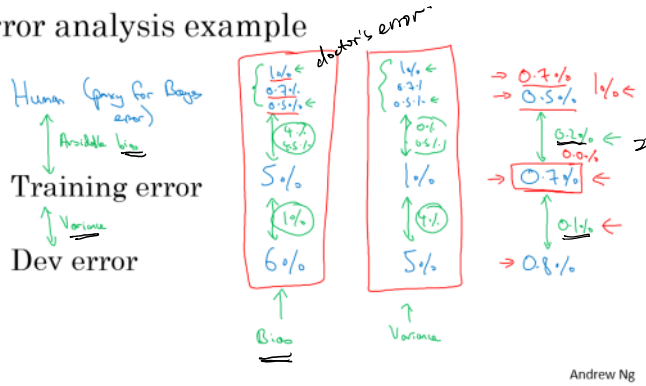
It is a matter of what you choose as the benchmark.

define human-level error as a proxy for Bayes error.

Error analysis example



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What if all bad?

i.e. can't improve training error any more

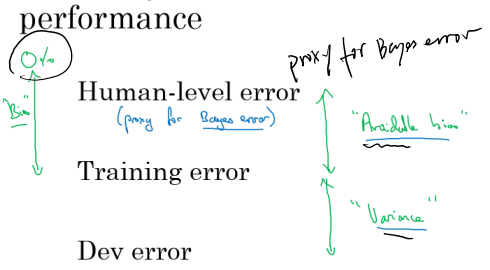
≠ variance ⇒ avoidable bias is a bigger problem

比較 training set performance 和 human level performance

test set performance

可能決定 Focus 在 bias 還是 variance reduction.

Summary of bias/variance with human-level performance



Instead of comparing { with 0% — bias
with human-performance — avoidable bias.

Human-level performance ⇒ Bayes Error ⇒
Decide whether to focus on { bias reduction / variance reduction

Noisy data: Having a better estimate of Bayes error helps knowing what the "avoidable error" is

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surpass human

Comparing to human-level performance

Surpassing human-level performance

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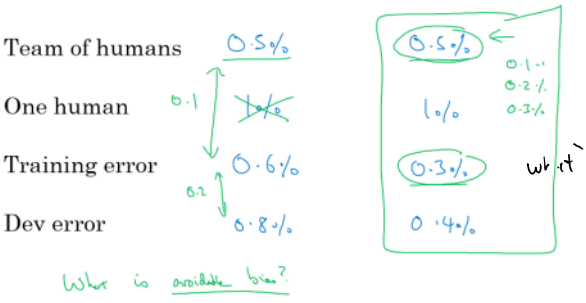
Surpassing human-level performance



What is avoidable bias?

what it means? ① over-fitting
② the Bayes error is actually lower.

⇓
That slows down the speed to make progress

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Problems where ML significantly surpasses human-level performance

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

Structured data
Not natural perception
lots of data

- Speech recognition
- Some image recognition
- Medical
  - ECG, Skin cancer, ...

↓

in some cases, can surpass human-level performance

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ML 比 human 更好的 2 种情况

what these share in common

Structured data

e.g. what you bought.
your loan record.

不是 natural perception problems (?)

improve model

Comparing to human-level performance

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Improving your model performance

The two fundamental assumptions of supervised learning

low avoidable bias

1. You can fit the training set pretty well.
   ≈ Avoidable bias
2. The training set performance generalizes pretty well to the dev/test set.
   ≈ Variance not bad

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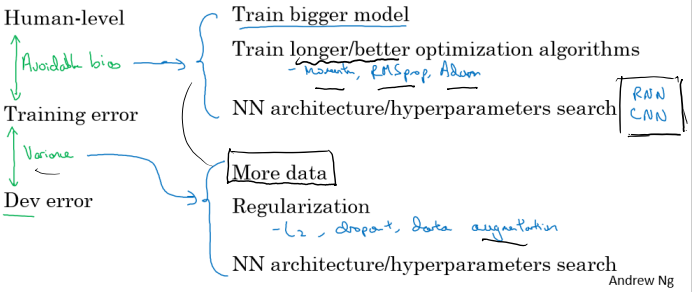
Reducing (avoidable) bias and variance



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error analysis

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Error Analysis

Carrying out error analysis

Look at dev examples to evaluate ideas

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.

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手工看数据.

example: cat classifier 把狗认成猫.

Focus on "dog pictures".

Q: 值得 worth doing it — focusing on dogs

What to do? Examine if dogs account for a large proportion of mislabeled pictures.

Ceiling: how much improvement can focusing on the dog problem help?

This won't take long

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

猫科动物.

OK.. 所以手工检验花时间是重要的

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

filtering

Image	Dog	Great Cats	Blurry	Instagram	Comments
1	✓			✓	Pitbull
2			✓	✓	
3		✓	✓		Rainy day at zoo
⋮	⋮	⋮	⋮		
% of total	8%	43%	61%	12%	

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work on them seperately

Create a table for this

cleagning up

Error Analysis

Cleaning up Incorrectly labeled data

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Incorrectly labeled examples

mislabeled

x							
y	1	0	1	1	0	1	1

Training set

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

less robust to Systematic errors

eg. label all white dogs as cats

need not worry much

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How about incorrectly labeled data in dev or test sets.

Error analysis

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%	

Overall dev set error	10%	2%
Errors due incorrect labels	0.6%	0.6%
Errors due to other causes	9.4%	1.4%

not a large problem for now.

model 的 error 相对还是大于 mislable %.

Overall dev set error	10%	2%
Errors due incorrect labels	0.6%	0.6%
Errors due to other causes	9.4%	1.4%
		2.1% 1.9%

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

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can fix this 9.4%

not a large problem for now.
model 的 error 目前还远大于 mislable %.
所以主要精力还是model. 不是 correct labeling

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. (98.1) (2%)
- Train and dev/test data may now come from slightly different distributions.

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if only fix those getting wrong - overconfidence on performance.

this is ok — there are tricks to deal with this

Training set is too large.
→ Sometimes you don't want to manually correct advice

Advice: Manual data analysis is important in ML practice
Sit down and look at the data.
good use of time — help to decide what direction to prioritize

build

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Error Analysis

Build your first system quickly, then iterate

lots of things to do...

Speech recognition example

- Noisy background
  - Café noise
  - Car noise
- Accent
- Far fro

Guideline:
Build your first

- Set up dev/test set and metric
- Build initial system quickly
- Use Bias/Variance

analysis helps to examine

- Car noise
- Accent
- Far fro
- Young
- Stutter
- …

Guideline:
Build your first system quickly, then iterate

- Build initial system quickly
- Use Bias/Variance analysis & Error analysis to prioritize next steps.

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error analysis helps to examine where you got wrong

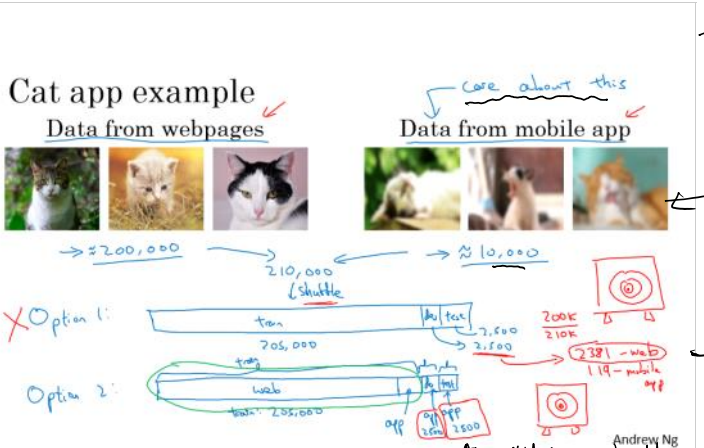
But if there's a literature telling you where to start, it helps to start with complex systems.

- Don't OVERTHINK when starting
- Build something that works (quick & dirty), then fix it using Bias/variance analysis & error analysis

diff distribution

Mismatched training and dev/test data

Training and testing on different distributions

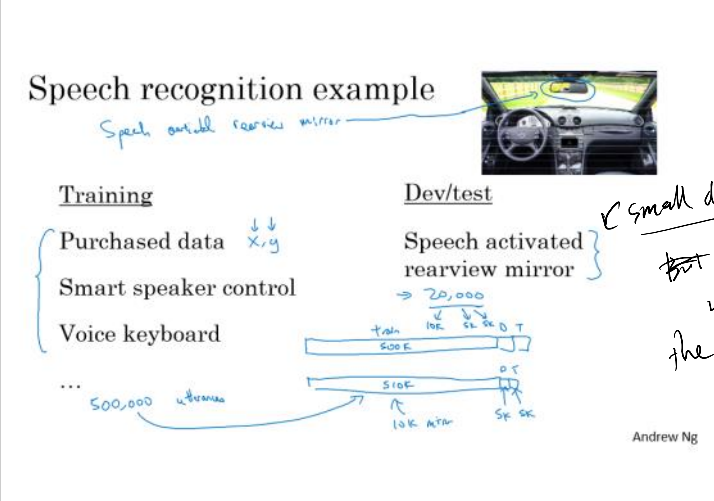


train model and test it on data from a different distribution.

← if use this only — small dataset.

— WRONG TARGET. optimize for a different dist of data from what you care about

☆ All test should be from the app (what you ultimately care about)



< small dataset

~~But~~ since this is what you want, the dev/test should consist of this only.

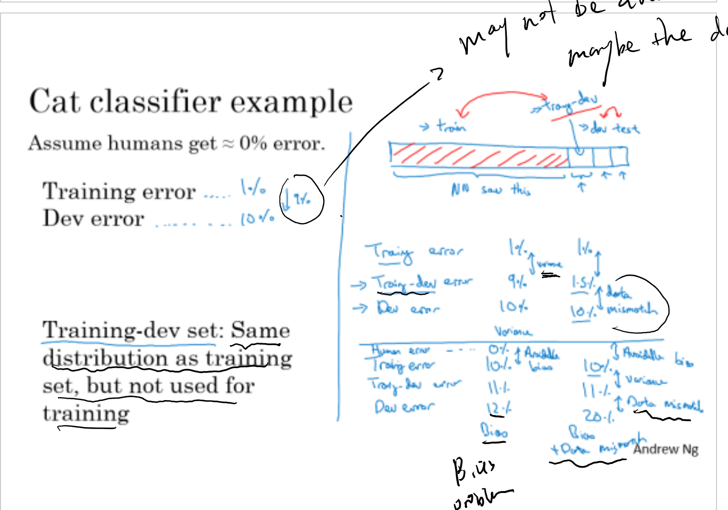
Q: should you always use all the data you have? Not really

mismatch

may not be a variance problem

maybe the dev set is just larger

Data mismatch

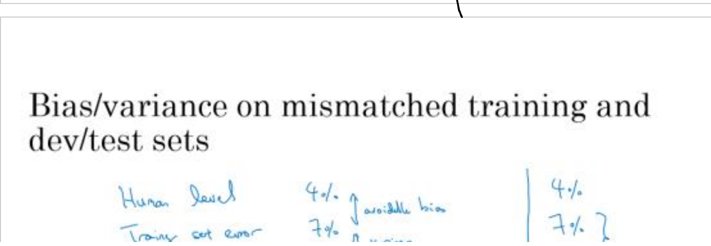


Bias problem

这像是个不错的打表办法.

利用一些和本任务弱相关的数据

检验模型的表现.



Bias/variance on mismatched training and dev/test sets

Human level	4%	4%
Training set error	7%	7%
Training-dev set error	10%	10%
→ Dev error	12%	6%
→ Test error	12%	6%

avoidable bias; variance; data mismatch; degree of overfitting to dev set.

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More general formulation

	General speech recognition	Rearview mirror speech data
Human level	"Human level" 4%	6%
Error on examples trained on	"Training error" 7%	6%
Error on examples not trained on	"Training-dev error" 10%	"Dev/Test error" 6%

avoidable bias; variance; data mismatch

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Avoidable Bias: Human-level performance ↕ training set performance

Variance: training set performance ↕ train-dev set performance

Data mismatch: train-dev set performance ↕ dev set performance

degree of overfitting to the dev set: dev set performance ↕ test set

if overfit ⇒ find a larger dev set.

What if you do better in dev/test set than on training set? e.g.

one possibility: dev/test set is easier (clearer photo)

More general formulation

General speech recognition

Human level 4%

Training error 7%

Training-dev set error 10%

Dev/test set error 6%

data mismatch

Rearview mirror speech recognition.

6%

6%

avoidable bias

variance

1. Human level.
2. Errors of examples trained on
3. Errors of example not trained on

How to deal with data mismatch? up next. — not much

addressmismatch

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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

  E.g. noisy – car noise street numbers

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

  E.g. Simulate noisy in-car data

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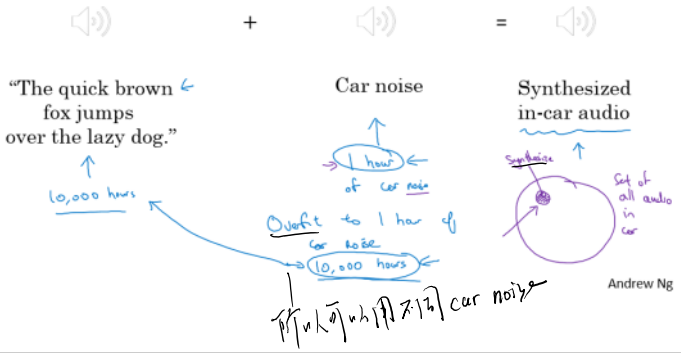
Key: manual error analysis

"How your dev/test sets are different from your training set?"

eg ~~too~~ too noisy

Artificial data synthesis

SYNTHESIS



加入同一种 car noise

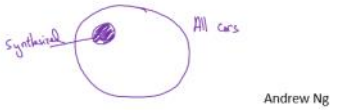
会导致 overfit to certain car noise.

Artificial data synthesis

Car recognition:



≈20 cars



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recognize car

用 car video game 的截图.

门槛：竞赛 game 里面车的种类有限

Take away: ① Error analysis

② Artificial synthesis. — caution: overfit.

transfer learning

Learning from multiple tasks

Transfer learning

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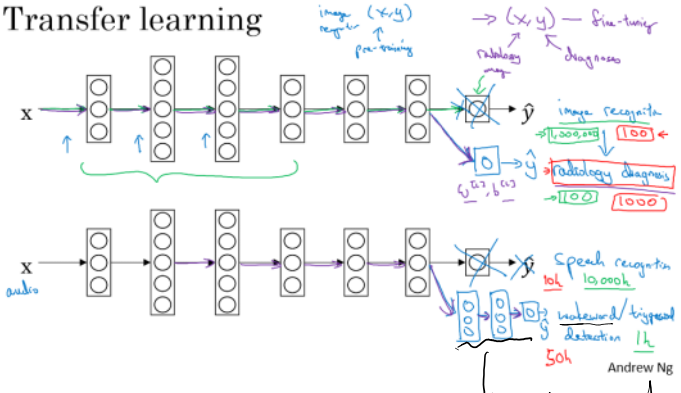
Transfer learning



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create several new layers.

transfer learned model to other task.

把最后一层重新 train

pre-training：用步们很多 data train 出来的部分

fine-tuning.

If you want to collect more data.

When transfer learning makes sense

Trade from A → B

- Task A and B have the same input x.
- You have a lot more data for Task A than Task B.
- Low level features from A could be helpful for learning B.

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learn lower-level features

If you want to collect more data. Data of the task of interest B more important.

multitask

Learning from multiple tasks

Multi-task learning

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Simplified autonomous driving example

Detect multiple objects

$x^{(i)}$

$y^{(i)}$ (4,1)

Pedestrians 0
Cars 1
Stop signs 1
Traffic lights 0

Outcome $= \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ y^{(1)} & y^{(2)} & y^{(3)} & \cdots & y^{(m)} \\ 1 & 1 & 1 & & 1 \end{bmatrix}$ (4, m)

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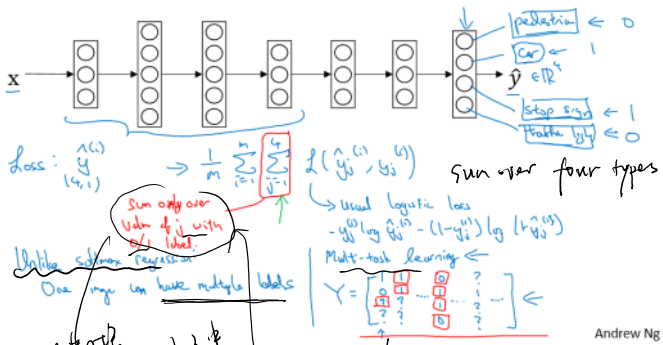
Neural network architecture

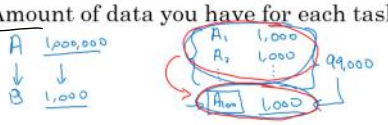


Sum over four types of object wanted

Building an NN that solves 4 problems could have done it by training 4 networks. But if some common lower-level features for 4 task, it will be helpful to train a multi-task learning

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 similar.



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

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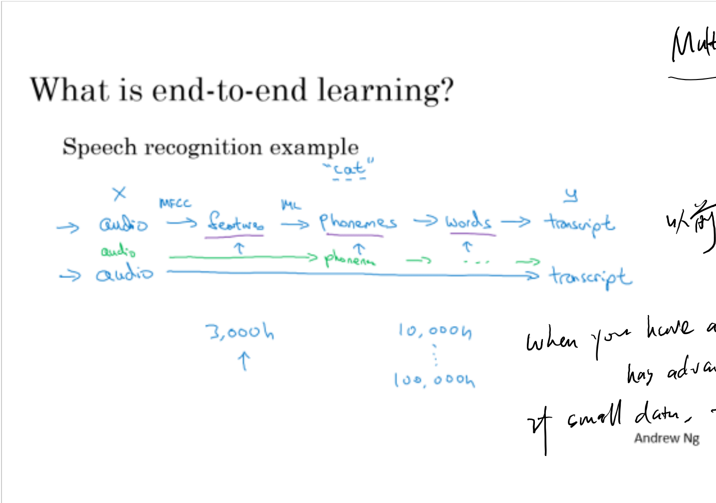
endtoend

End-to-end deep learning

What is end-to-end deep learning

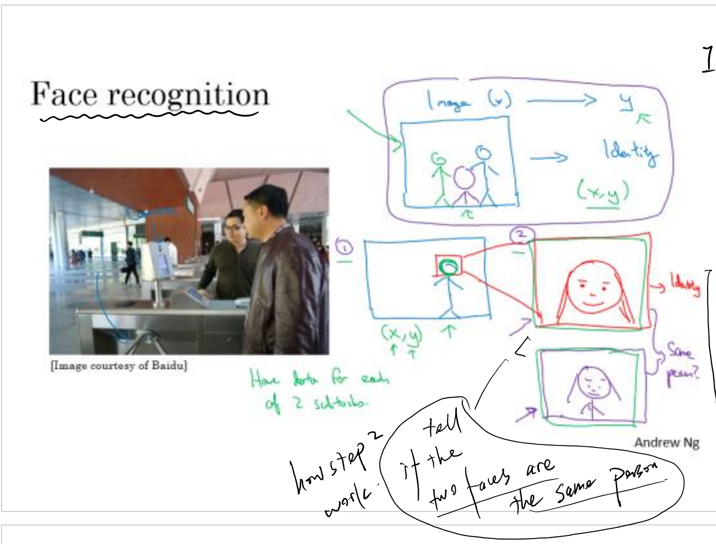


Multiple stages => one stage

以前break成不同stages的任务, 用DL一步完成

When you have a large dataset, the end-to-end approach has advantage.

If small data, traditional approach is better.



In this example, the two step approach works better?

① Two tasks are both simpler (much simpler). (更简单)

② lots of data for each ~~step~~ of the steps respectively (数据)

But much for the end-to-end tasks

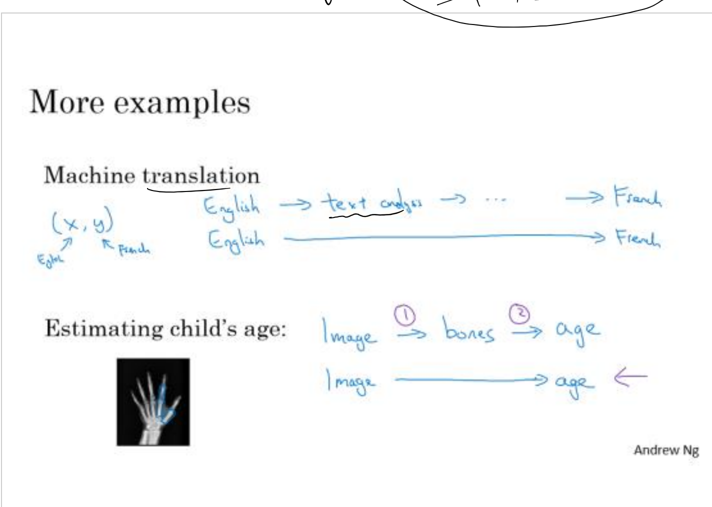
multi step

① Detect where the person's face is

② Crop image, center the person's face

③ Recognize the face

Two tasks — this



End-to-end DL.

works, but not a panacea.

endtoend2

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End-to-end deep learning

Whether to use end-to-end learning

End to end learning

Just let the data speak.

Pros and cons of end-to-end deep learning

Pros:

- Let the data speak $x \rightarrow y$ → "phonemes" c a t
- Less hand-designing of components needed

no need to reflect human pre-conception.
Some of these pre conception may be ~~err~~ wrong.

Cons:

- May need large amount of data $x \rightarrow y$ (x, y)
- Excludes potentially useful hand-designed components

Need LOTS of data

Data. Hand-design.

An algorithm has two sources of knowledge
[data → when small human knowledge is more important.
human design.

inject hand-designed knowledge

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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?

$x \rightarrow y$

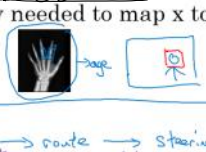

image → cars → route → steering
radar, lidar → pedestrians → (motion planning) → (control)

- Use DL to learn individual components
- Carefully choose $x \rightarrow y$ depending what tasks you can get data for.

image → steering

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for simple task → easily using end-to-end DL with small datasets

Example: Autonomous driving

for this task, end-to-end DL does not work well.