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Introduction to ML strategy

Why ML Strategy?

Motivating example

     

90%

Ideas:

- Collect more data ←
- Collect more diverse training set
- Train algorithm longer with gradient descent
- Try Adam instead of gradient descent
- Try bigger network
- Try smaller network
- Try dropout
- Add L_2 regularization
- Network architecture
  - Activation functions
  - # hidden units
  - …

Introduction to ML strategy

Orthogonalization

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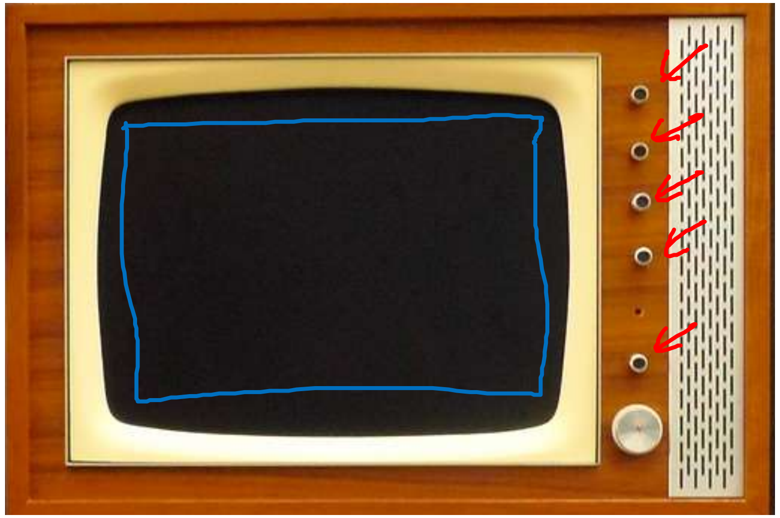
TV tuning example



Orthogonalization

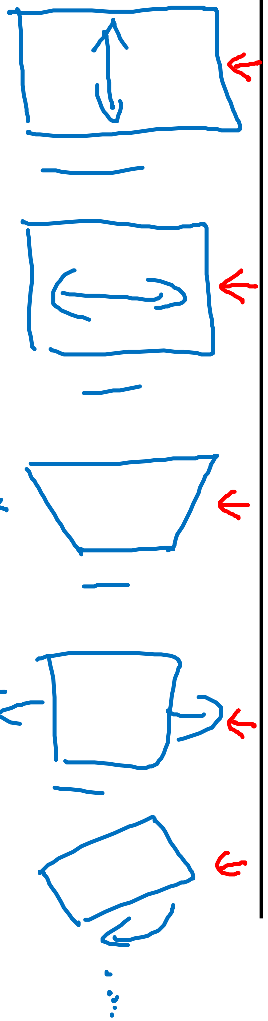
$0.1 \times$

$+0.3 \times$

$-1.7 \times$

$+0.8 \times$

$+ \ldots$



Car

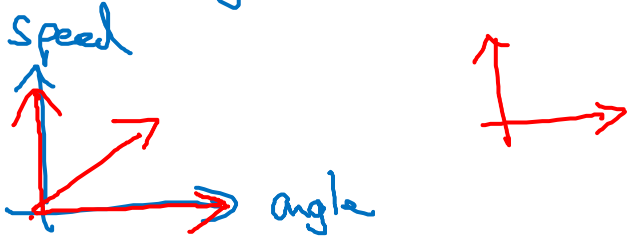
→ Steering

→ Acceleration

Braking

→ $0.3 \times \text{angle} - 0.8\ \text{speed}$

→ $2 \times \text{angle} + 0.9\ \text{speed}$.



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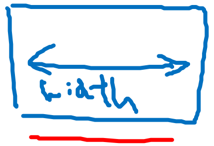
Chain of assumptions in ML

→ Fit training set well on cost function

(≈ human-level performance)

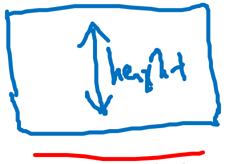
bigger network
Adam
...



early stopping

→ Fit dev set well on cost function

Regularization
Bigger train set



→ Fit test set well on cost function

Bigger dev set

→ Performs well in real world

(Happy cat pic app users.)

Change dev set or cost function

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Setting up your goal

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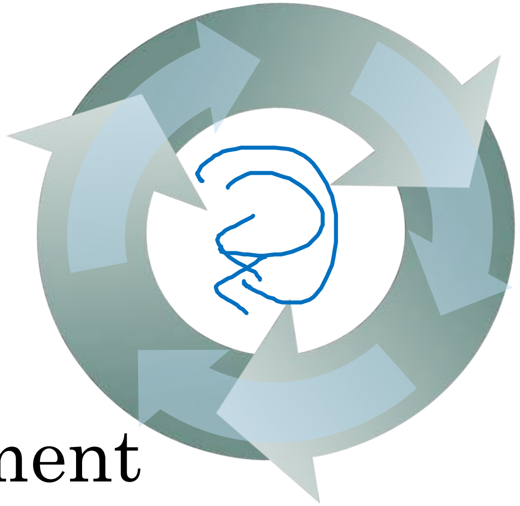
Single number evaluation metric

Using a single number evaluation metric



Of examples recognized as cat, what % actually are cats?

what % of actual cats are correctly recognized

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

F_1 score = "Average" of P and R.

$\left(\frac{2}{\frac{1}{P}+\frac{1}{R}} . \text{ "Harmonic mean"} \right)$

Dev set + Single number evaluation metric

real

Speed up iterating

Andrew Ng

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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Setting up your goal

Satisficing and optimizing metrics

Another cat classification example

optimizing Satisficing

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

cost = accuracy − 0.5 × running time

maximize accuracy

subject to running time ≤ 100 ms.

N metrics : 1 optimizing

N-1 satisficing

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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Setting up your goal

Train/dev/test distributions

Cat classification dev/test sets

development set, hold out cross validation set

Regions:

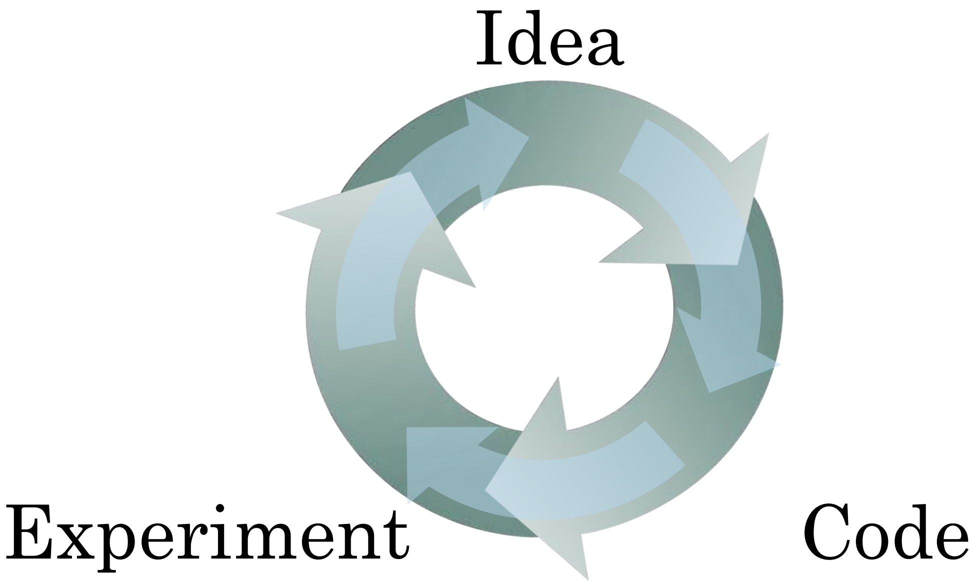
- US
- UK
- Other Europe
- South America
- India
- China
- Other Asia
- Australia

Dev

Test

Randomly shuffle into dev/test

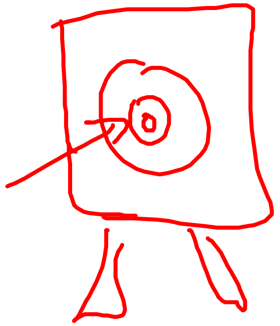
dev set + metric



True story (details changed)

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

$x \longrightarrow y$ (repay loan?)



Tested on low income zip codes

~ 3 month

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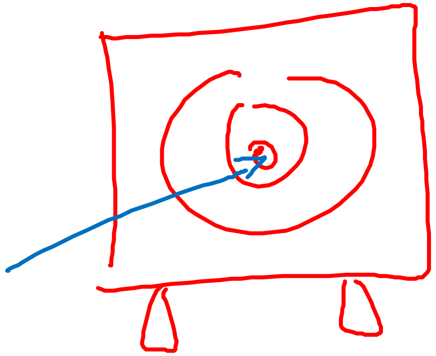
Guideline

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.

training



dev metric

test

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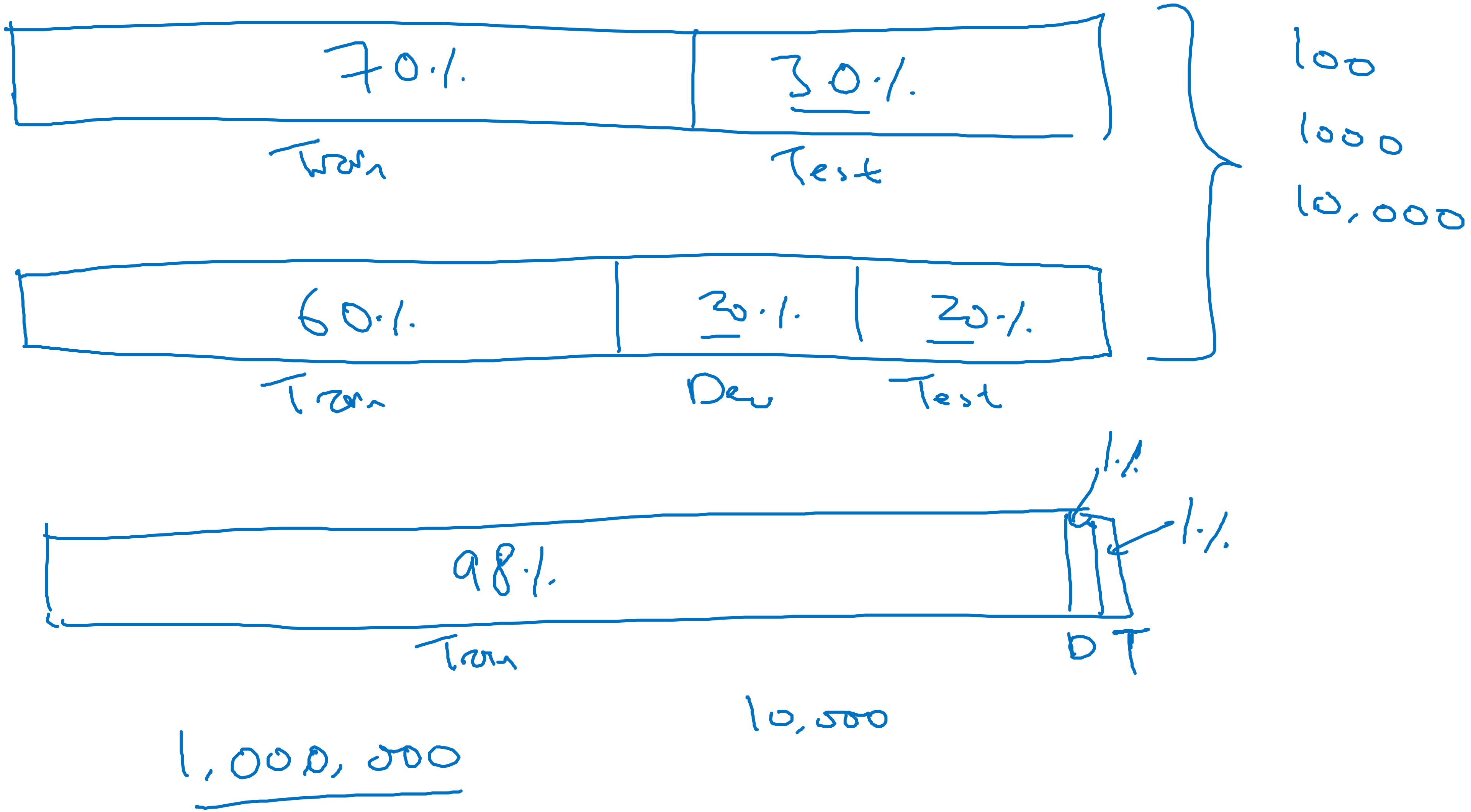
Setting up your goal

Size of dev and test sets

Old way of splitting data



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Size of dev set

A B

Set your dev set to be big enough to detect differences in algorithm/models you're trying out.

100 : small

1%

1,000

10,000

100,000

A B

97% → 97.1 %

0.1%

0.01%

0.001%

Online advertising

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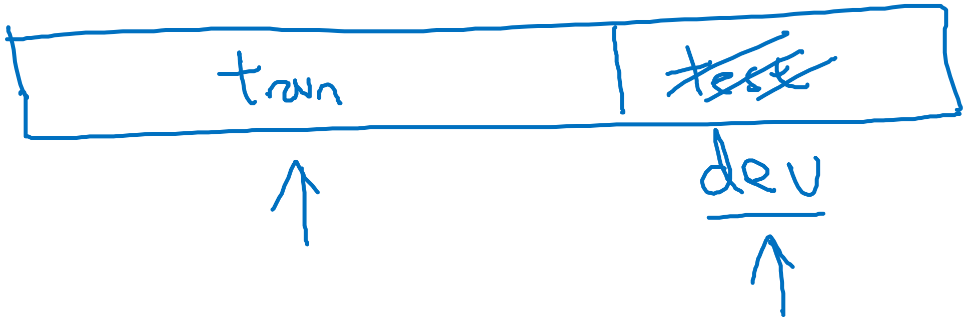
Size of test set

- 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.



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Setting up your goal

When to change dev/test sets and metrics

Cat dataset examples

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

→ Metric: classification error

Algorithm A: 3% error → pornographic

✓ Algorithm B: 5% error

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

predicted value (0/1)

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

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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

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

$\Sigma w^{(i)}$

Andrew Ng

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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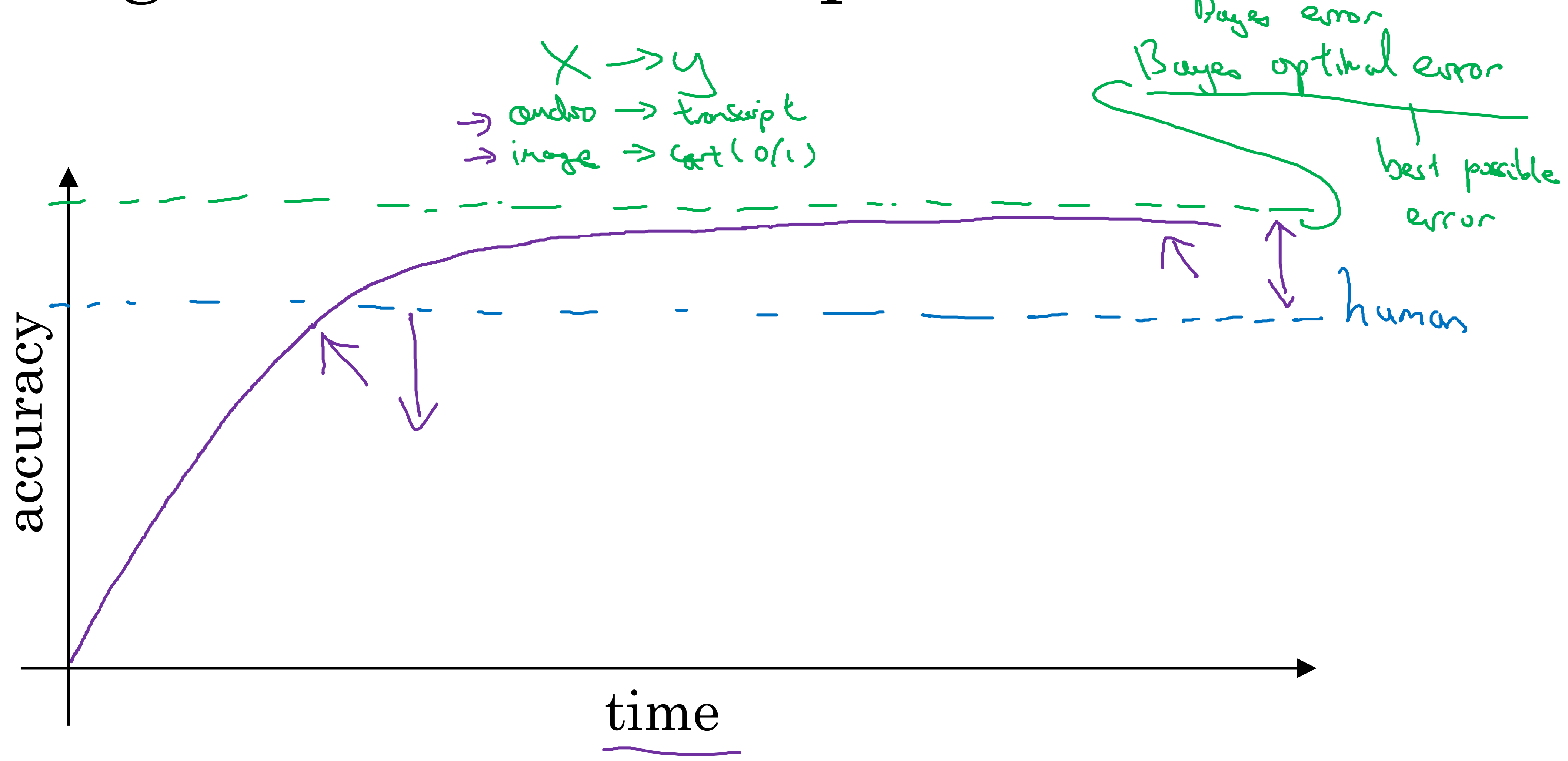
Comparing to human-level performance

Why human-level performance?

Comparing to human-level performance



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. (x, y)
- Gain insight from manual error analysis: Why did a person get this right?
- Better analysis of bias/variance.

Comparing to human-level performance

Avoidable bias

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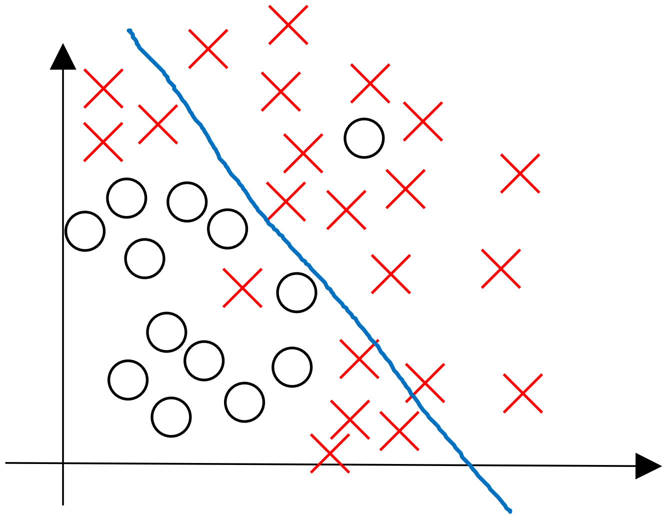
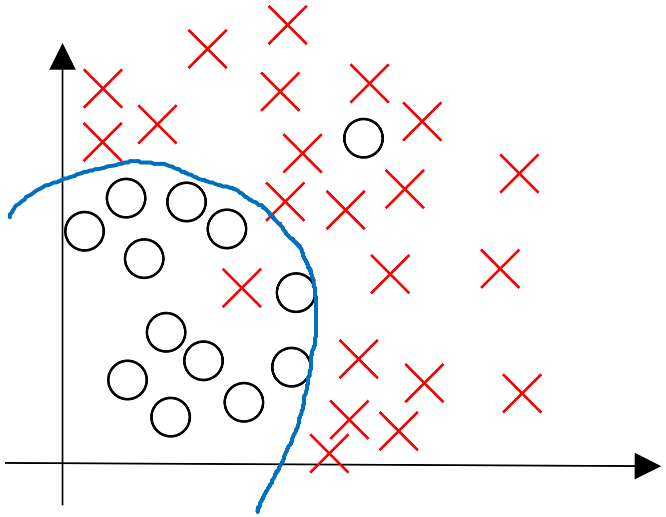
Bias and Variance

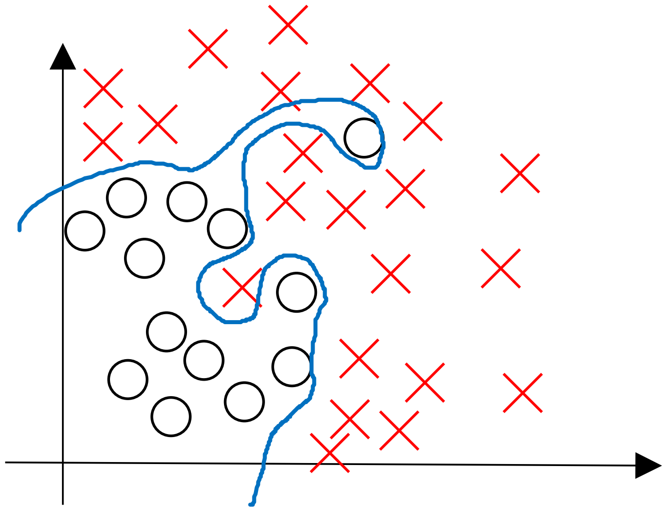


high bias

underfitting



"just right"



high variance

overfitting.

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Bias and Variance

Cat classification

Human-level ≈ 0% ....

Training set error: ____ ____

Dev set error:

high variance

high bias

high bias
high variance

low bias
low variance

Cat classification example

Humans (≈ Bayes)	$\boxed{1\%}$	$\boxed{7.5\%}$
Training error	$\boxed{8\%}$	$\boxed{8\ \%}$
Dev error	10%	$\boxed{10\ \%}$

7% 2% 2% 0.5% variance 2%

Avoidable bias

Variance

Focus on bias

Focus on variance

Human-level error as a proxy for Bayes error.

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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

Baye error $\leq$ 0.5%

What is "human-level" error?

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Error analysis example

Human (proxy for Bayes error)	1% 0.7% 0.5%	1% 0.7% 0.5%	0.7% 0.5% 1%
Avoidable bias	4% 4.5%	0% 0.5%	0.2% 0.0%
Training error	5%	1%	$\boxed{0.7\%}$
Variance	1%	4%	0.1%
Dev error	6%	5%	0.8%
	Bias	Variance	

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Summary of bias/variance with human-level performance

0%

"Bias"

Human-level error

(proxy for Bayes error)

"Avoidable bias"

Training error

"Variance"

Dev error

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Comparing to human-level performance

Surpassing human-level performance

Surpassing human-level performance

Team of humans	0.5%		0.5%
One human	~~1%~~		1%
Training error	0.6%		0.3%
Dev error	0.8%		0.4%

0.1

0.2

0.1%

0.2%

0.3%

What is avoidable bias?

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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, ...

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Comparing to human-level performance

Improving your model performance

The two fundamental assumptions of supervised learning

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

Reducing (avoidable) bias and variance

Human-level

Avoidable bias

Training error

Variance

Dev error

Train bigger model

Train longer/better optimization algorithms

- momentum, RMSprop, Adam

NN architecture/hyperparameters search

RNN

CNN

More data

Regularization

- L_2, dropout, data augmentation

NN architecture/hyperparameters search

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Error Analysis

Carrying out error analysis

Look at dev examples to evaluate ideas

90% accuracy
→ 10% error

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

Error analysis: → 5-10 min

"ceiling"

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

→ 5%

5/100

10%

9.5%

→ 50%

50/100

10%

5%

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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
- Improve performance on blurry images

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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Error Analysis

Cleaning up Incorrectly labeled data

Incorrectly labeled examples

x

y 1 0 1 1 0 1 1

Training set.

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

Systematic errors

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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%

2.1% 1.9%

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

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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 98% right as well as ones it got wrong. 2%
- Train and $\boxed{\text{dev/test}}$ data may now come from slightly different distributions.

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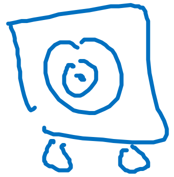
Error Analysis

Build your first system quickly, then iterate

Speech recognition example



- Noisy background
  - Café noise
  - Car noise
- Accent
- Far fro
- Young
- Stutter
- …

Guideline:

Build your first 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.

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Mismatched training and dev/test data

Training and testing on different distributions

Cat app example

care about this

Data from webpages	Data from mobile app
	
→ ≈ 200,000	→ ≈ 10,000

210,000

shuffle

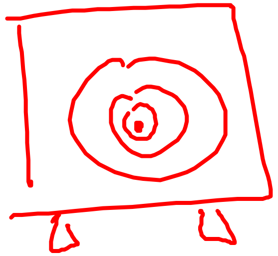
Option 1: train | dev | test

205,000 | 2,500 | 2,500

200K / 210K

2381 – web

119 – mobile app



Option 2: web | dev | test

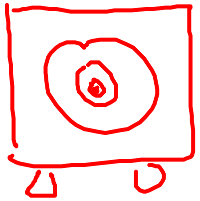
train

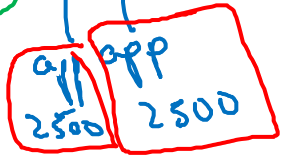
train: 205,000

app

app 2500

app 2500





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Speech recognition example

Speech activated rearview mirror

Training

Purchased data x, y

Smart speaker control

Voice keyboard

...

500,000 utterances

Dev/test

Speech activated rearview mirror

→ 20,000

10K 5K 5K

train D T

500K

D T

510K

5K 5K

10K mirror

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Mismatched training and dev/test data

Bias and Variance with mismatched data distributions

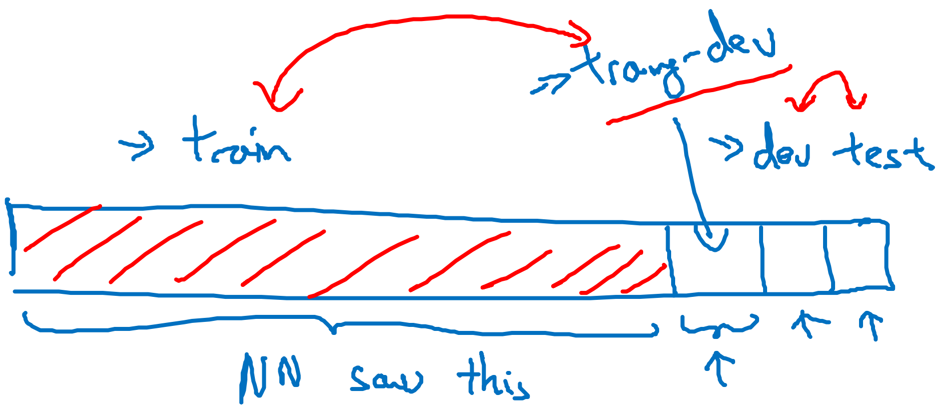
Cat classifier example

Assume humans get ≈ 0% error.

Training error 1%
Dev error 10%

9%

Training-dev set: Same distribution as training set, but not used for training



Training error	1%	1%
→ Train-dev error	9%	1.5%
→ Dev error	10%	10%
	variance	data mismatch

Variance

Human error	0%	
Training error	10%	10%
Train-dev error	11%	11%
Dev error	12%	20%
	Bias	Bias + Data mismatch

Avoidable bias
Avoidable bias
variance
Data mismatch

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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.

More general formulation

Rearview mirror

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

avoidable bias

variance

data mismatch

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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

Artificial data synthesis

+ =

"The quick brown fox jumps over the lazy dog."

10,000 hours

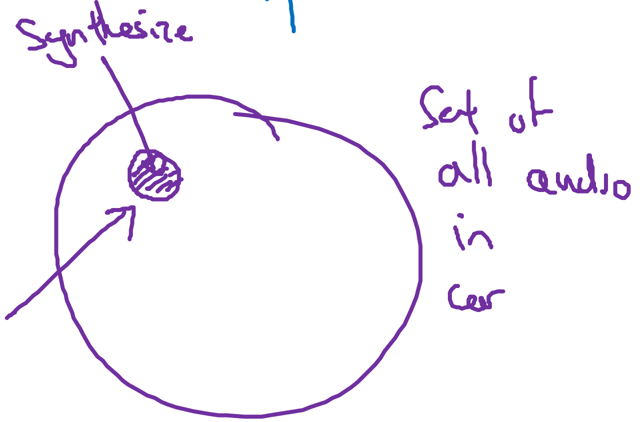
Car noise

1 hour of car noise

Overfit to 1 hour of car noise

10,000 hours

Synthesized in-car audio



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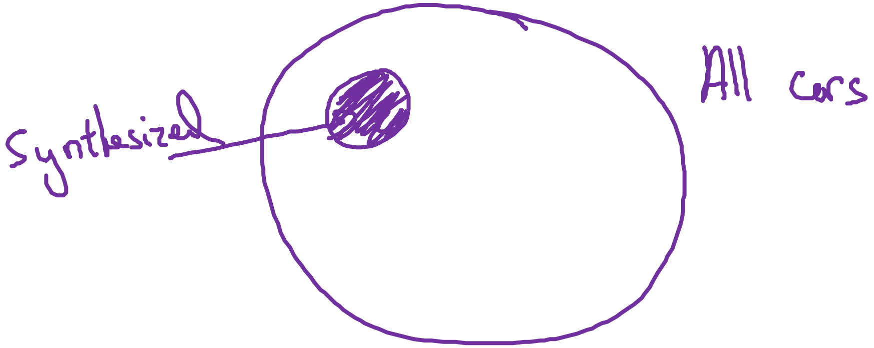
Artificial data synthesis

Car recognition:

≈ 20 cars



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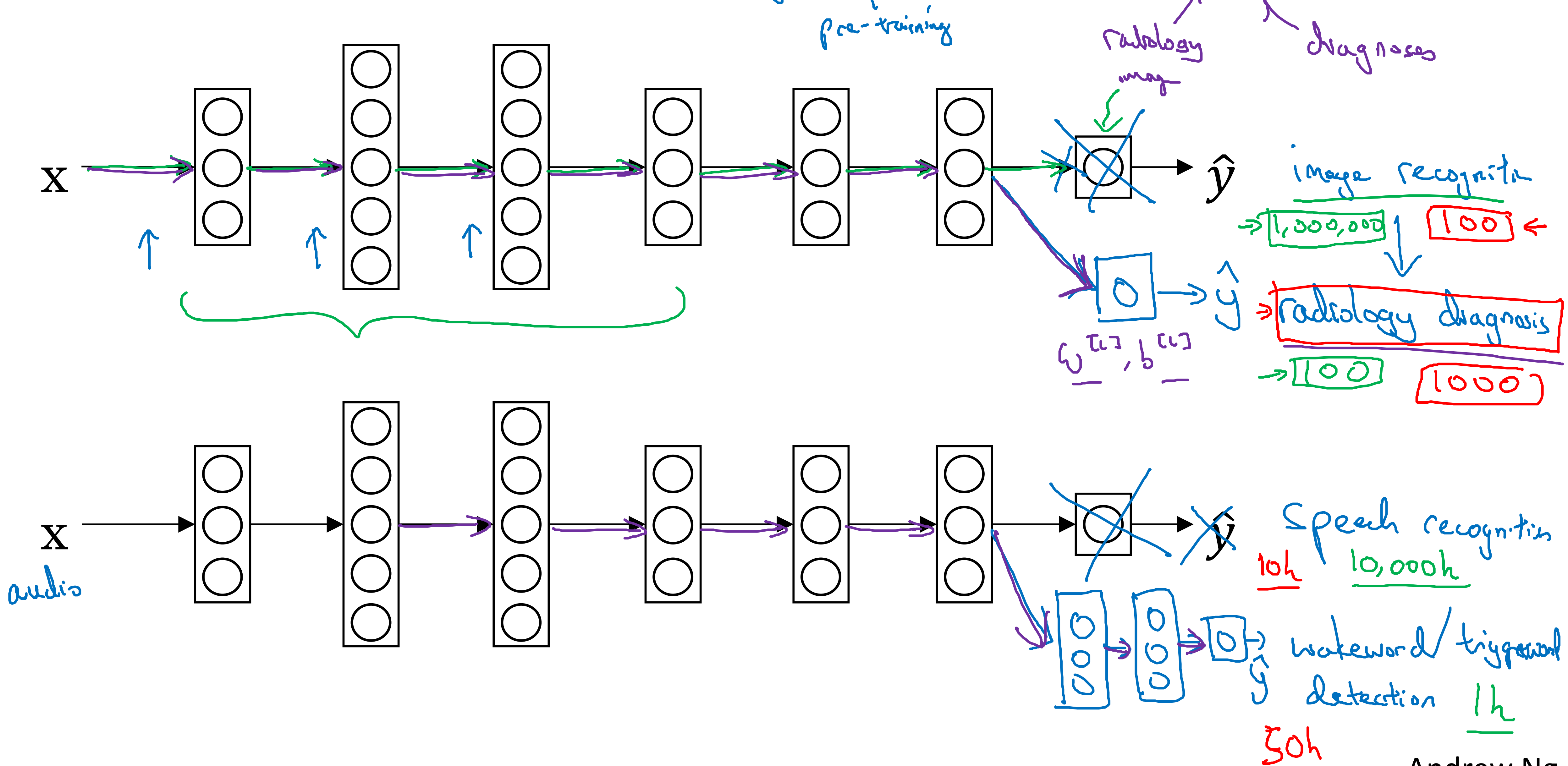
Learning from multiple tasks

Transfer learning

Transfer learning

image recognition (x, y) → (x, y) — fine-tuning

pre-training



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When transfer learning makes sense

Transfer 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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Learning from multiple tasks

Multi-task learning

Simplified autonomous driving example

$x^{(i)}$

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

$$\begin{array}{lc} \text{Pedestrians} & 0 \\ \text{Cars} & 1 \\ \text{Stop signs} & 1 \\ \text{Traffic lights} & 0 \\ \vdots & \vdots \end{array}$$

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

$(4, m)$

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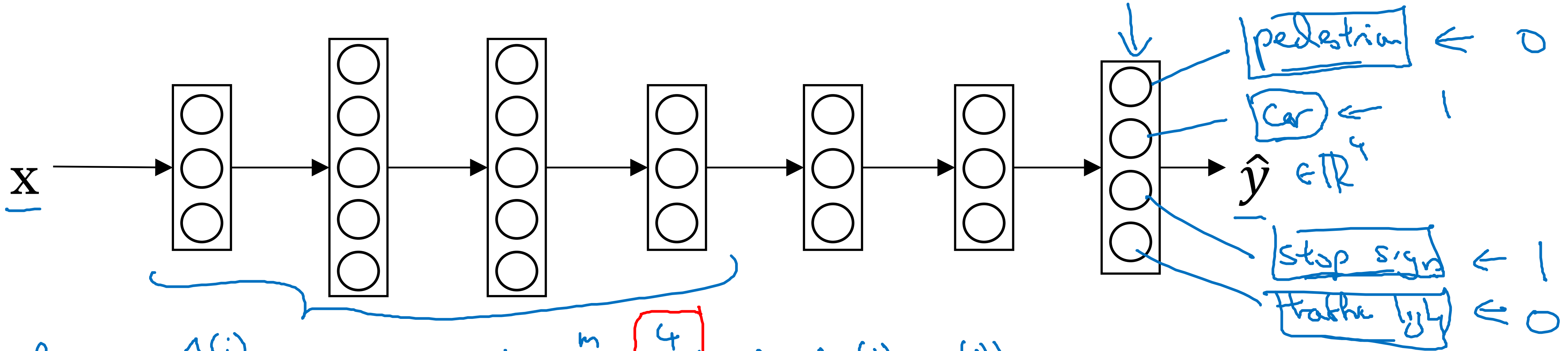
Neural network architecture



Loss: $\underset{(4,1)}{\hat{y}^{(i)}}$ $\rightarrow \frac{1}{m}\sum_{i=1}^{m}\boxed{\sum_{j=1}^{4}}\mathcal{L}(\hat{y}_j^{(i)}, y_j^{(i)})$

Sum only over value of j with 0/1 label.

↳ Usual logistic loss

$-y_j^{(i)}\log\hat{y}_j^{(i)} - (1-y_j^{(i)})\log(1-\hat{y}_j^{(i)})$

Unlike softmax regression:

One image can have multiple labels

Multi-task learning ⟵

$$Y = \begin{bmatrix} 1 & \boxed{1} & & \boxed{0} & & ? & \\ 0 & \boxed{1} & \cdots & \boxed{1} & \cdots & 1 & \cdots \\ \boxed{?} & ? & & \boxed{1} & & ? & \\ ? & ? & & \boxed{0} & & ? & \end{bmatrix} \leftarrow$$

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.

A 1,000,000 $\to$ B 1,000

A_1 1,000
A_2 1,000
⋮ ⋮
99,000
$\boxed{A_{100}}$ 1,000

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

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End-to-end deep learning

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What is end-to-end deep learning

What is end-to-end learning?

Speech recognition example

"cat"

x $\qquad$ y

$\rightarrow$ audio $\xrightarrow{\text{MFCC}}$ features $\xrightarrow{\text{ML}}$ Phonemes $\rightarrow$ words $\rightarrow$ transcript

audio $\longrightarrow$ phonemes $\rightarrow$ ... $\rightarrow$

$\rightarrow$ audio $\longrightarrow$ transcript

3,000h

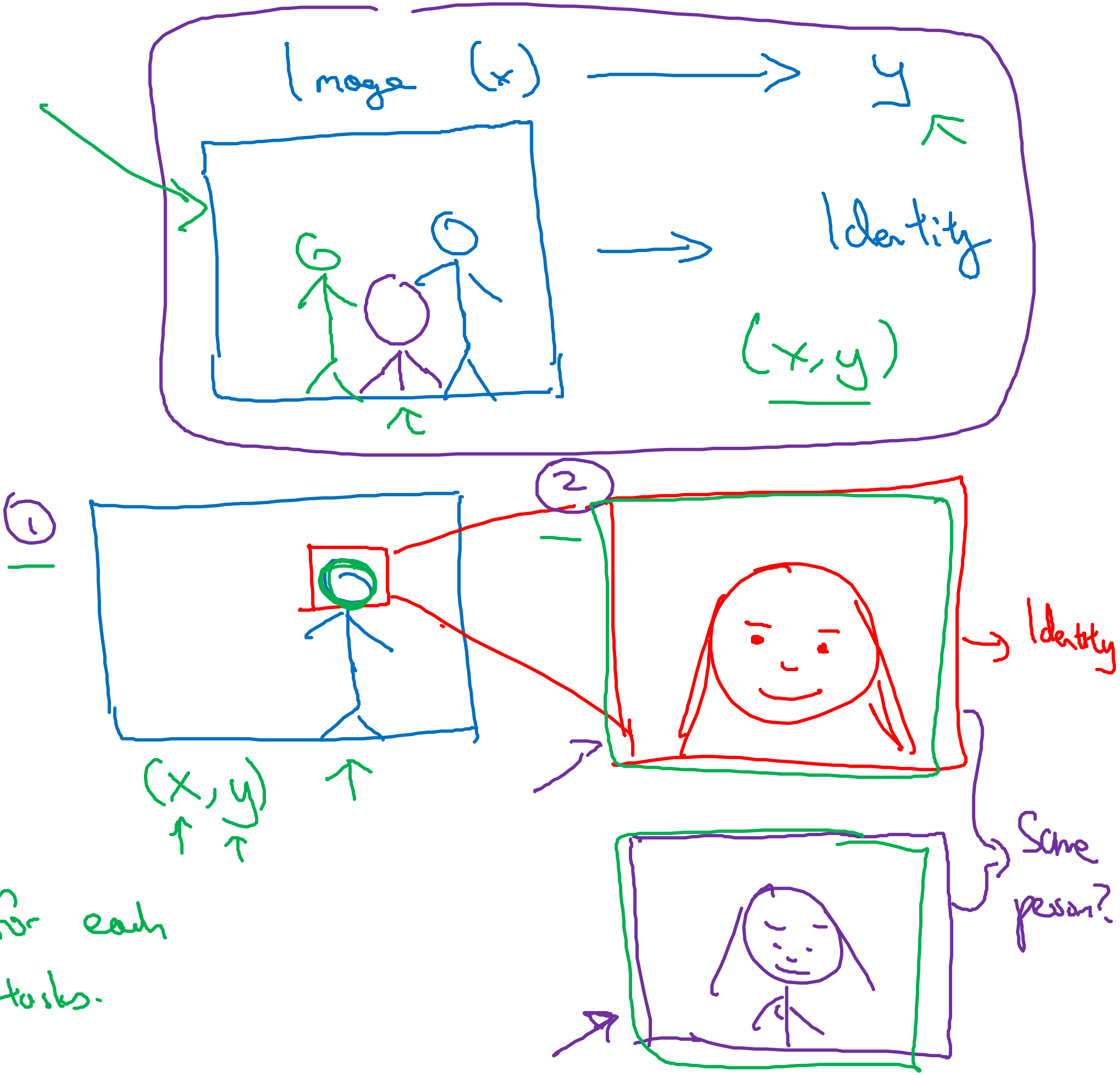
10,000h

⋮

100,000h

Face recognition

[Image courtesy of Baidu]



Have data for each of 2 subtasks.

More examples

Machine translation

(x, y)

English ↗   ↖ French

English → text analysis → ... → French

English → French

Estimating child's age:

Image $\xrightarrow{1}$ bones $\xrightarrow{2}$ age

Image → age ←

End-to-end deep learning

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Whether to use end-to-end learning

Pros and cons of end-to-end deep learning

Pros:

- Let the data speak

$x \longrightarrow y$

"phonemes"

c a t

- Less hand-designing of components needed

$x - - - - - \rightarrow y$

input end

output end

$x \longrightarrow y$ (x, y)

Cons:

- May need large amount of data
- Excludes potentially useful hand-designed components

Data

Hand-design.

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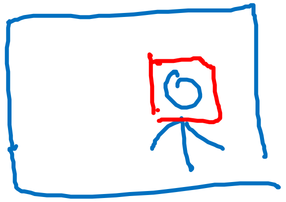
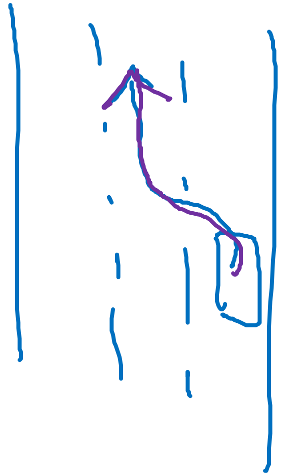
Applying end-to-end deep learning

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

X → y

→ age





image, radar, lidar $\xrightarrow{DL}$ cars → route $\xrightarrow{\text{control}}$ steering

$\xrightarrow{DL}$ pedestrians

motion planning

- Use DL to learn individual components
- Carefully choose X → Y depending on what tasks you can get data for.

→ image ——→ steering