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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

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

"ceiling"

→ 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%

example 1
should not correct labels

example 2
should correct labels

Errors due incorrect labels 0.6% | 0.6%

Errors due to other causes 9.4% | 1.4%

2.1% 1.9%

this 0.6% heavily influences
the selection in this case

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%

for accurate model is hard to do this

- Train and $\boxed{\text{dev/test}}$ data may now come from slightly different distributions.

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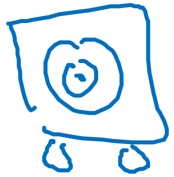
Error Analysis

Build your first system quickly, then iterate

Speech recognition example



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

3

Guideline: there are too many directions that can improve the model !

1

Build your first system quickly, then iterate

- Set up dev/test set and metric

2

- 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

Data from webpages

Data from mobile app

care about this

→ ≈ 200,000 → 210,000 ← → ≈ 10,000

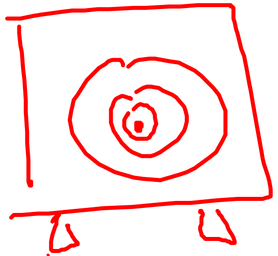
210,000

shuffle

better!

Option 1: train | dev | test

205,000 2,500 2,500



200K / 210K

we don't care the performance on web images

2381 - web

119 - mobile app

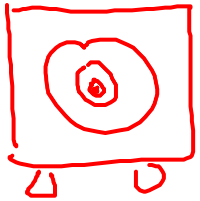
Option 2: web | dev | test

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

train D T
500K
10k 10k

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%

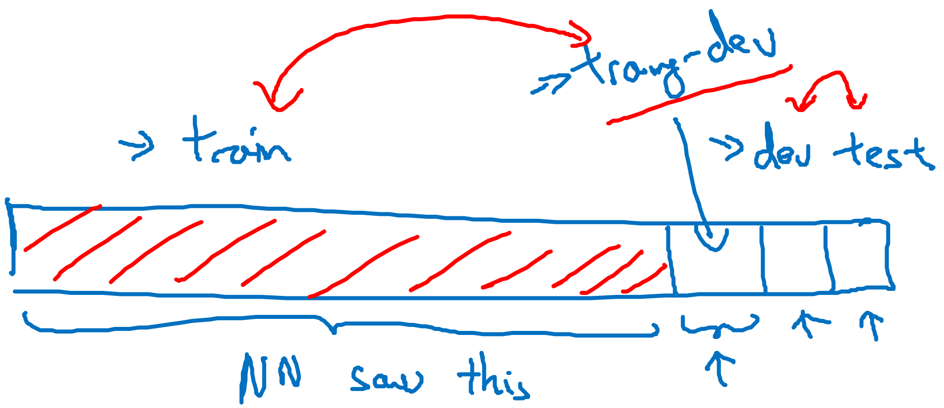
9%

maybe caused by other reasons like:

different distributions between training and dev set

-> data mismatch

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



Training error	1%	1%
Training-dev error	9%	1.5%
Dev error	10%	10%
	Variance	data mismatch

variance

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

Avoidable bias

Data mismatch

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Bias/variance on mismatched training and dev/test sets

Human level	4%	avoidable bias	4%
Training set error	7%	variance	7%
Training-dev set error	10%	data mismatch	10%
→ Dev error	12%	degree of overfitting to dev set.	6%
→ Test error	12%		6%

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

Mismatched training and dev/test data

Addressing data mismatch

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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

Synthesize

Set of all audio in car

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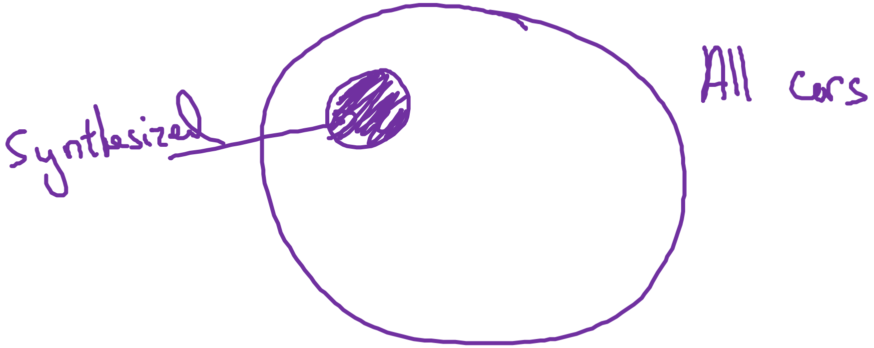
Artificial data synthesis

Car recognition:

≈ 20 cars



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Learning from multiple tasks

Transfer learning

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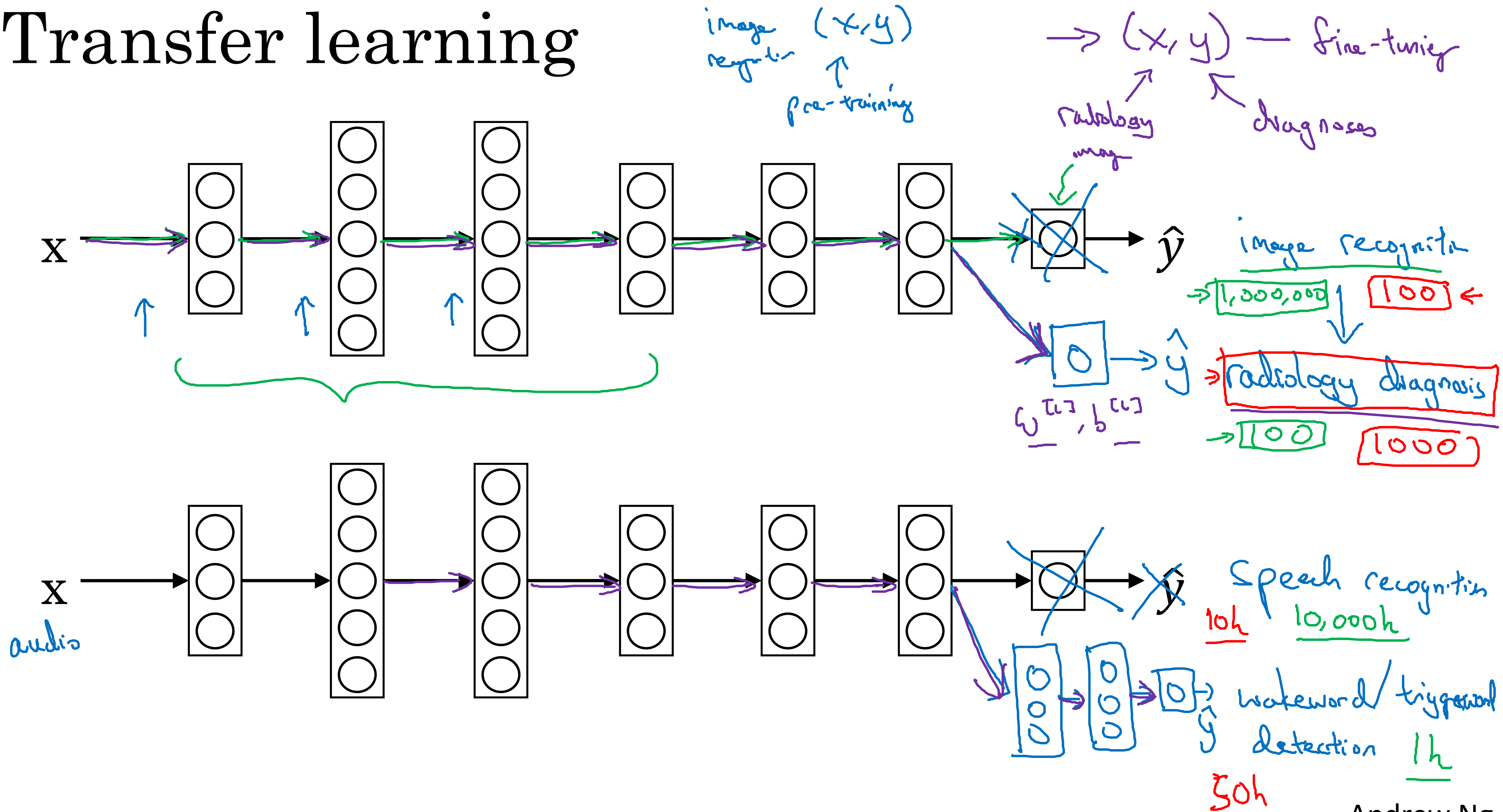
Transfer learning



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

$x^{(i)}$

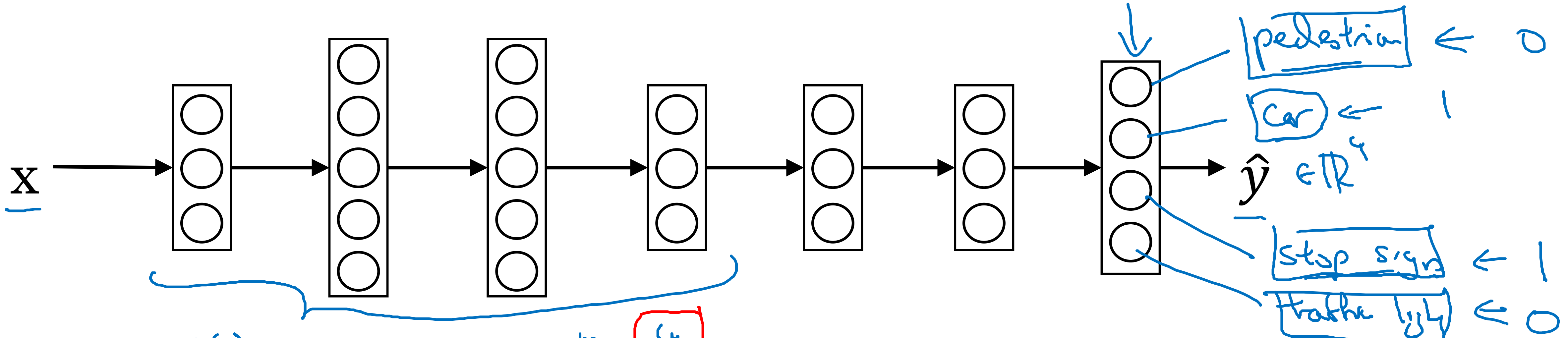
$y^{(i)}$ $(4,1)$

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

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

$(4, m)$

Neural network architecture



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

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 ←

$$Y = \begin{bmatrix} 1 & \boxed{1} & \cdots & \boxed{0} & \cdots & ? & \cdots \\ 0 & \boxed{1} & \cdots & \boxed{1} & \cdots & 1 & \cdots \\ \boxed{?} & ? & \cdots & \boxed{1} & \cdots & ? & \cdots \\ ? & ? & \cdots & \boxed{0} & \cdots & ? & \cdots \end{bmatrix}$$ ← allow to skip ? terms

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
  ↓
  B 1,000

  A_1 1,000
  A_2 1,000
  ⋮
  A_{100} 1,000

  99,000

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

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End-to-end deep learning

What is end-to-end deep learning

What is end-to-end learning?

Speech recognition example

"cat"

x $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ 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

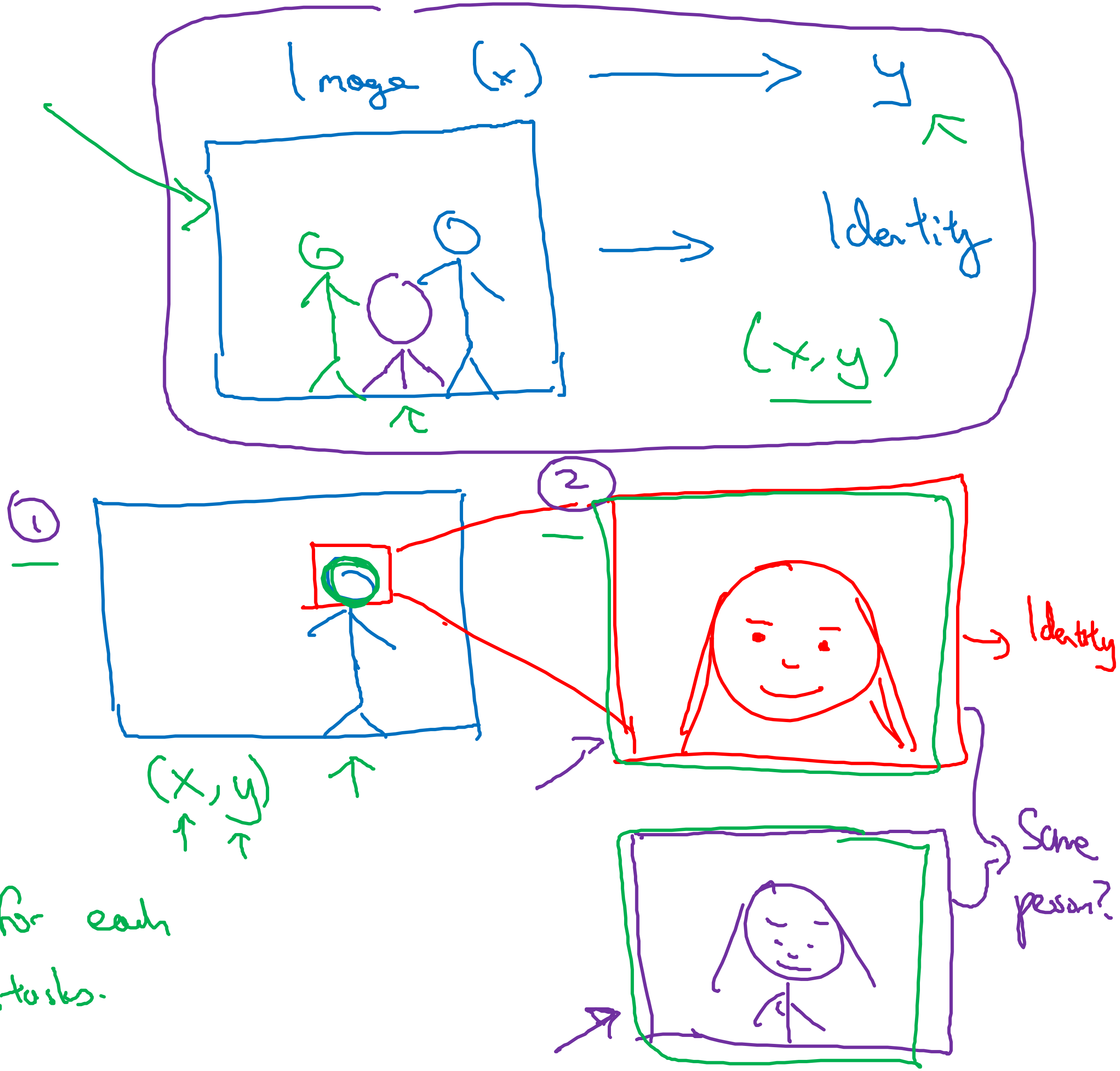
10,000h

⋮

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

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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 $x \rightarrow y$

→ "phonemes"

c a t

- Less hand-designing of components needed

$x - - - - - \rightarrow y$

input end

output end

Cons:

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

Data. Hand-design.

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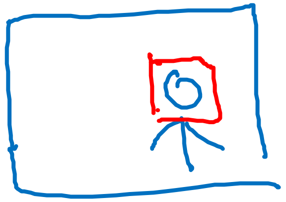
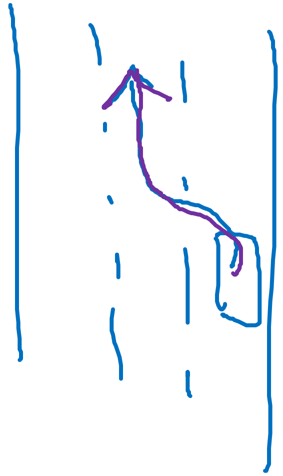
Applying end-to-end deep learning

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

$X \rightarrow y$

→ age





image, radar, lidar $\xrightarrow{DL}$ cars, $\xrightarrow{DL}$ pedestrians $\xrightarrow{\text{motion planning}}$ route $\xrightarrow{\text{control}}$ steering

- 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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