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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:

- Get ~100 mislabeled dev set examples. → 5-10 min
- Count up how many are dogs.

→ 5%
5/100

10%
↓
9.5%

"ceiling"

→ 50%
50/100

10%
↓
5%

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	<u>8%</u>	<u>43%</u>	<u>61%</u>	<u>12%</u>	










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Error Analysis

Cleaning up
Incorrectly labeled
data

Incorrectly labeled examples

x							
y	<u>1</u>	<u>0</u>	<u>1</u>	<u>1</u>	<u>0</u>	<u>1</u>	1

Training Set.

The image shows a sequence of eight examples (x) with their corresponding labels (y). The first six examples are part of the Training Set. The seventh example, a white puppy, is highlighted with a blue box and an arrow pointing to its label '1', indicating it is an incorrectly labeled example (a cat).

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

Systematic errors

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	<u>8%</u>	<u>43%</u>	<u>61%</u>	<u>6%</u>	

↕

↙

↙

Overall dev set error

Errors due incorrect labels

Errors due to other causes

..... 100%

..... 0.6% ←

..... 9.4% ←

↑

20%

0.6%

1.4%

2.1%

1.9%

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. 20%
- Train and dev/test data may now come from slightly different distributions.

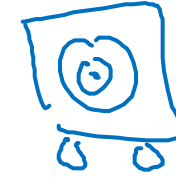


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Error Analysis

Build your first system
quickly, then iterate

Speech recognition example



- • Noisy background
 - • Café noise
 - • Car noise

- • Accent
- • Far from
- • 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

Data from webpages



core about this
Data from mobile app

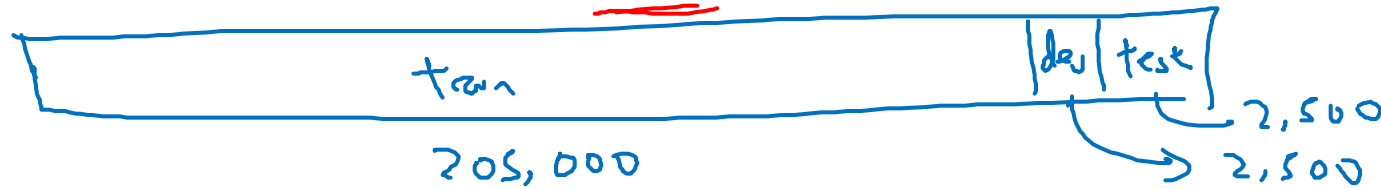


→ ≈ 200,000

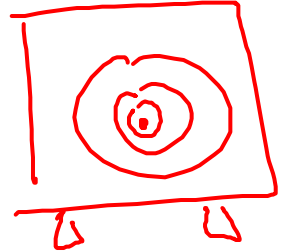
→ 210,000
↓ shuffle

→ ≈ 10,000

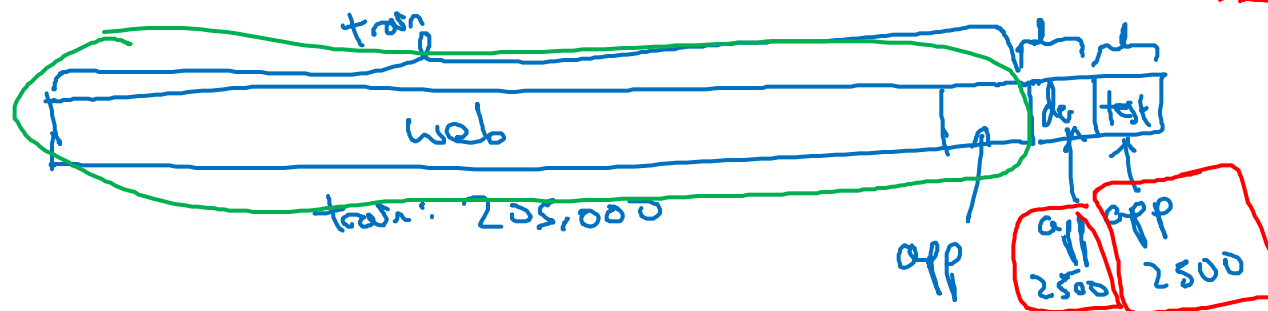
~~Option 1:~~



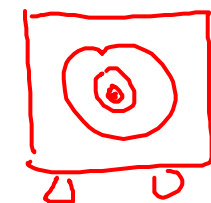
$\frac{200K}{210K}$



Option 2:



2381 - web
119 - mobile app



Speech recognition example

Speech activated rearview mirror



Training

Purchased data

$\downarrow \downarrow$
 X, y

Smart speaker control

Voice keyboard

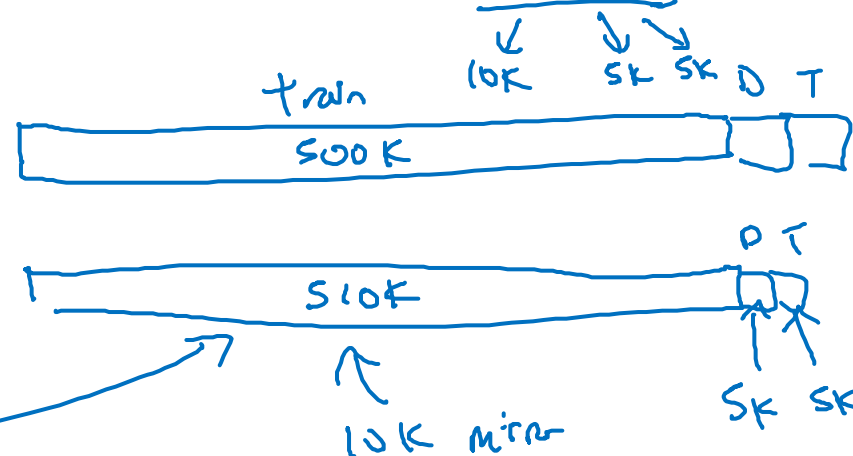
...

500,000 utterances

Dev/test

Speech activated
rearview mirror

→ 20,000





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Mismatched training and dev/test data

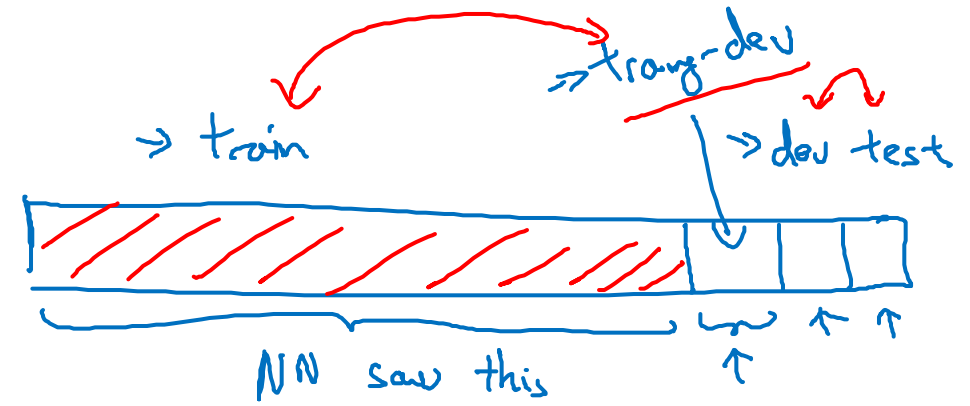
Bias and Variance with mismatched data distributions

Cat classifier example

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

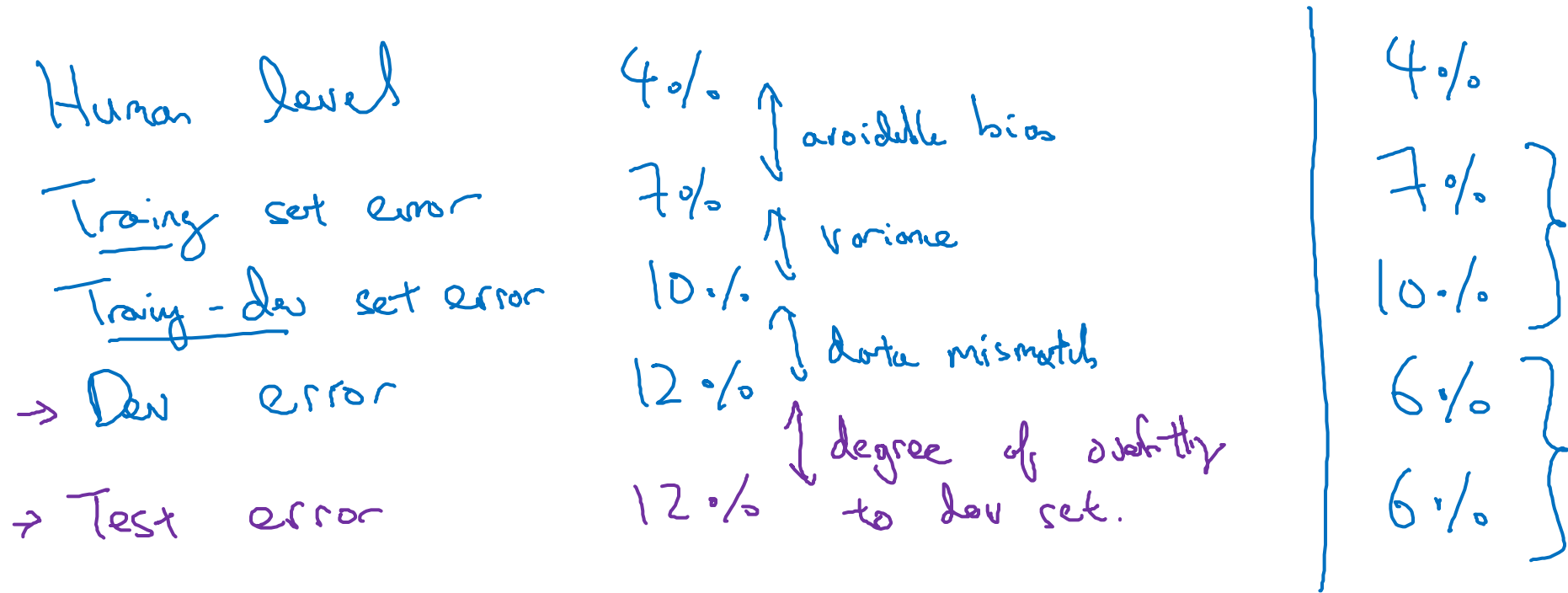
Training error 1%
Dev error 10% $\downarrow 9\%$

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



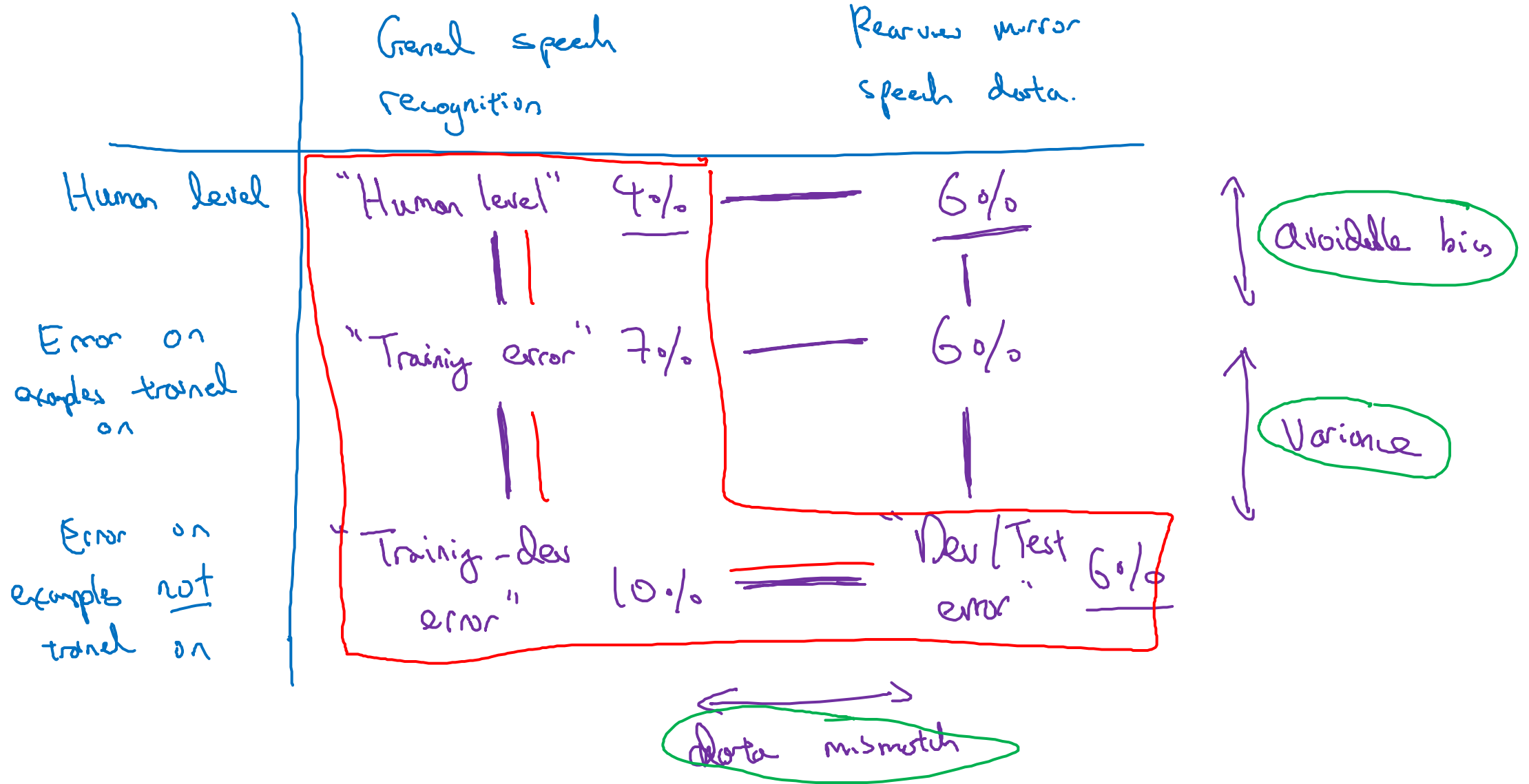
Training error	1%		1%	
→ Training-dev error	9%	↑ Variance	1.5%	↑ Data mismatch
→ Dev error	10%		10%	
		Variance		
Human error 0%	↑ Avoidable bias		↑ Avoidable bias
Training error	10%	↓	10%	↓
Training-dev error	11%		11%	↑ Variance
Dev error	12%		20%	↑ Data mismatch
	Bias		Bias + Data mismatch	

Bias/variance on mismatched training and dev/test sets



More general formulation

Recurrent mirror





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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

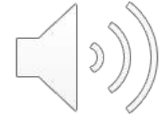
Artificial data synthesis



+



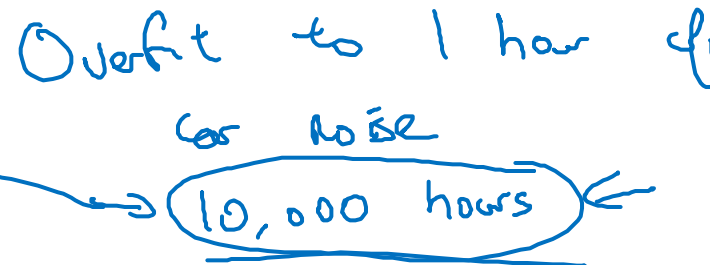
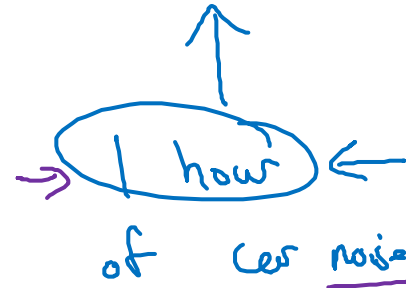
=



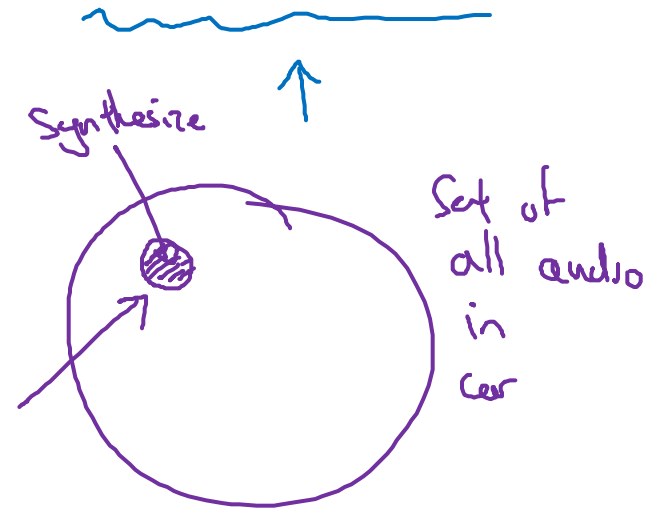
“The quick brown
fox jumps
over the lazy dog.”

↑
10,000 hours

Car noise



Synthesized
in-car audio

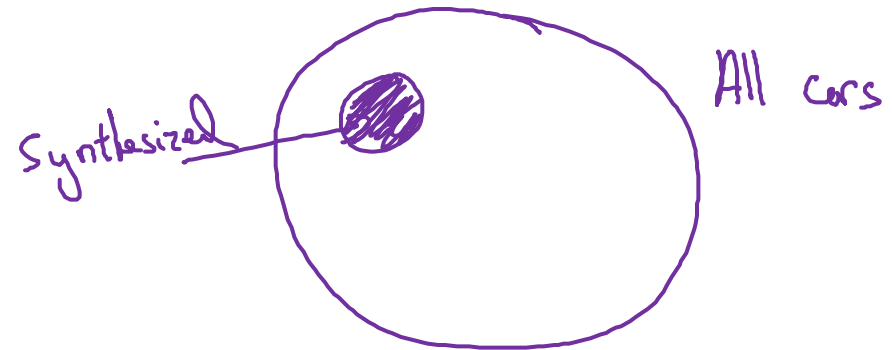


Artificial data synthesis

Car recognition:



≈ 20 cars



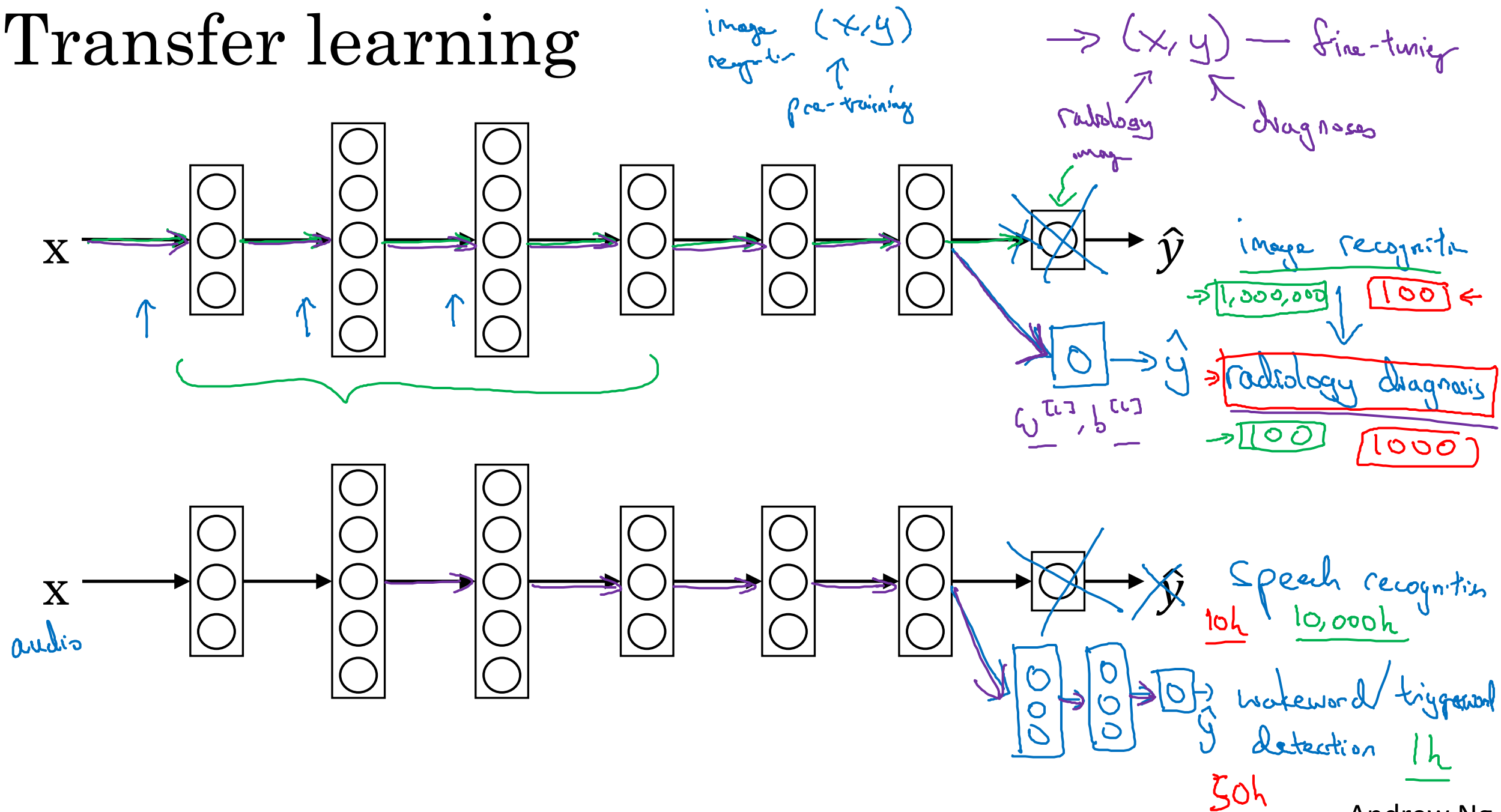


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Learning from
multiple tasks


Transfer learning

Transfer learning



When transfer learning makes sense

Transfer from A \rightarrow 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



$x^{(i)}$

Pedestrians

Cars

Stop signs

Traffic lights

⋮

$y^{(i)}$

0

1

1

0

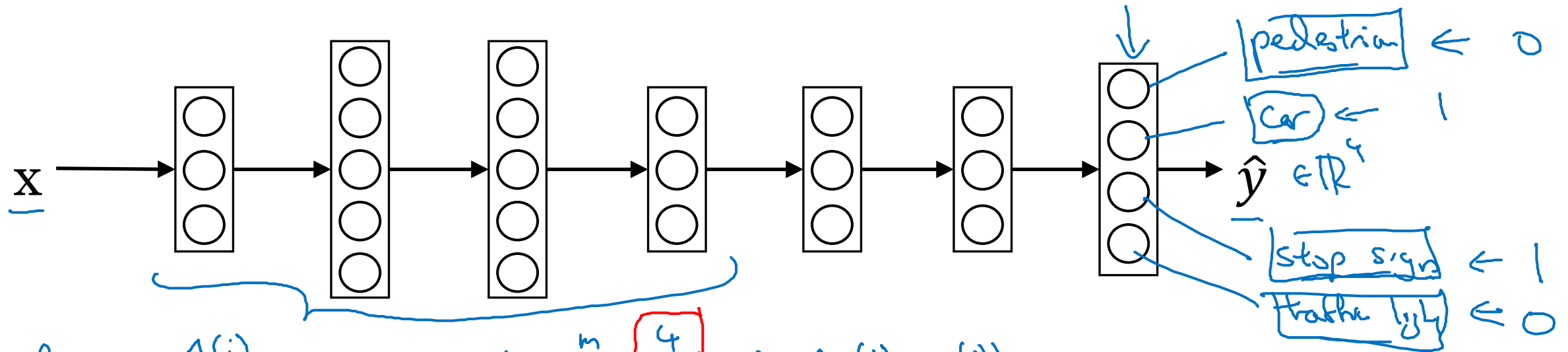
⋮

$(4, 1)$

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

$(4, m)$

Neural network architecture



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

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

Unlike softmax regression:
One image can have multiple labels

Usual logistic loss

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

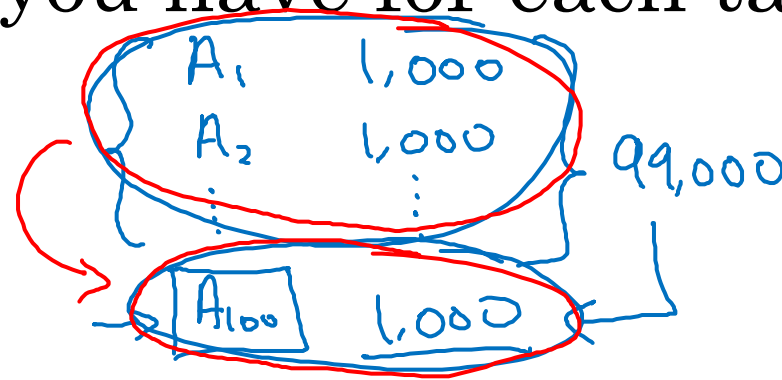
Multi-task learning \leftarrow

$$Y = \begin{bmatrix} 1 & 1 & \dots & 1 & ? & \dots \\ 0 & 1 & \dots & 1 & 1 & \dots \\ ? & ? & \dots & ? & ? & \dots \\ ? & ? & \dots & ? & ? & \dots \end{bmatrix}$$

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



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



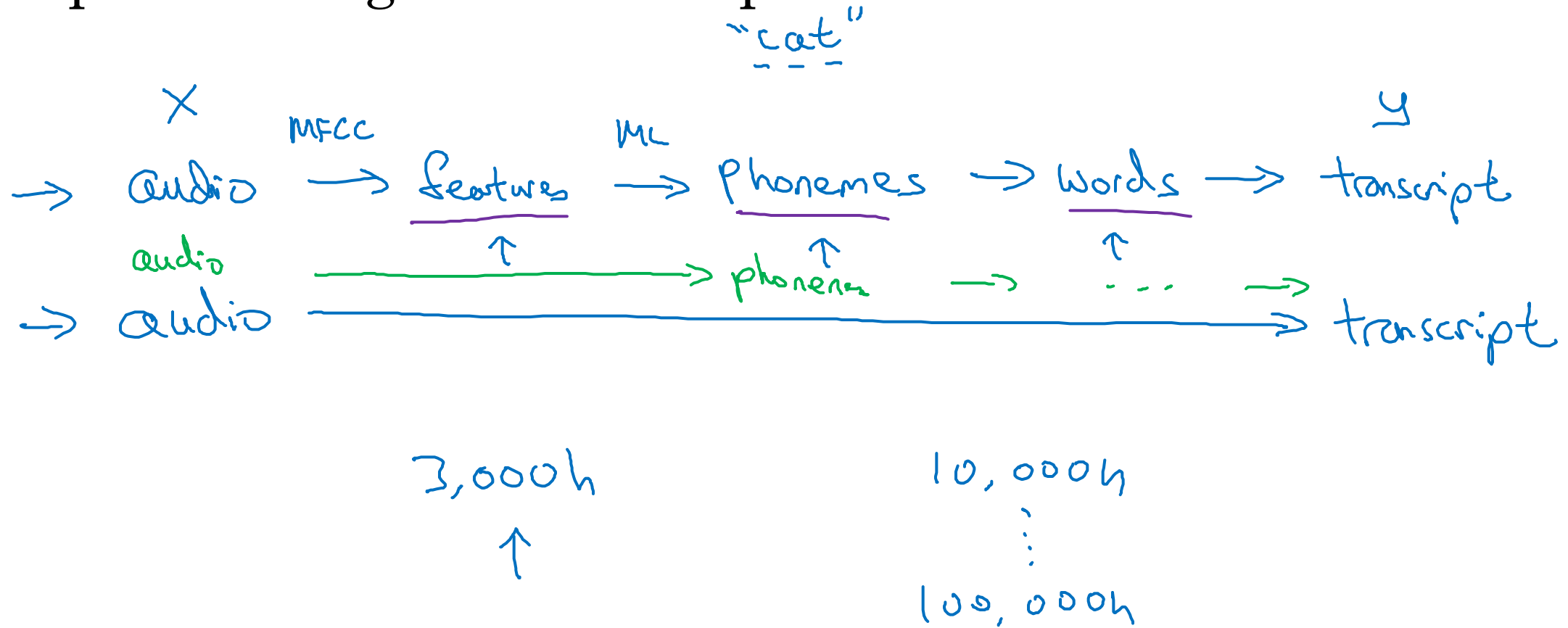
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End-to-end deep learning

What is end-to-end deep learning

What is end-to-end learning?

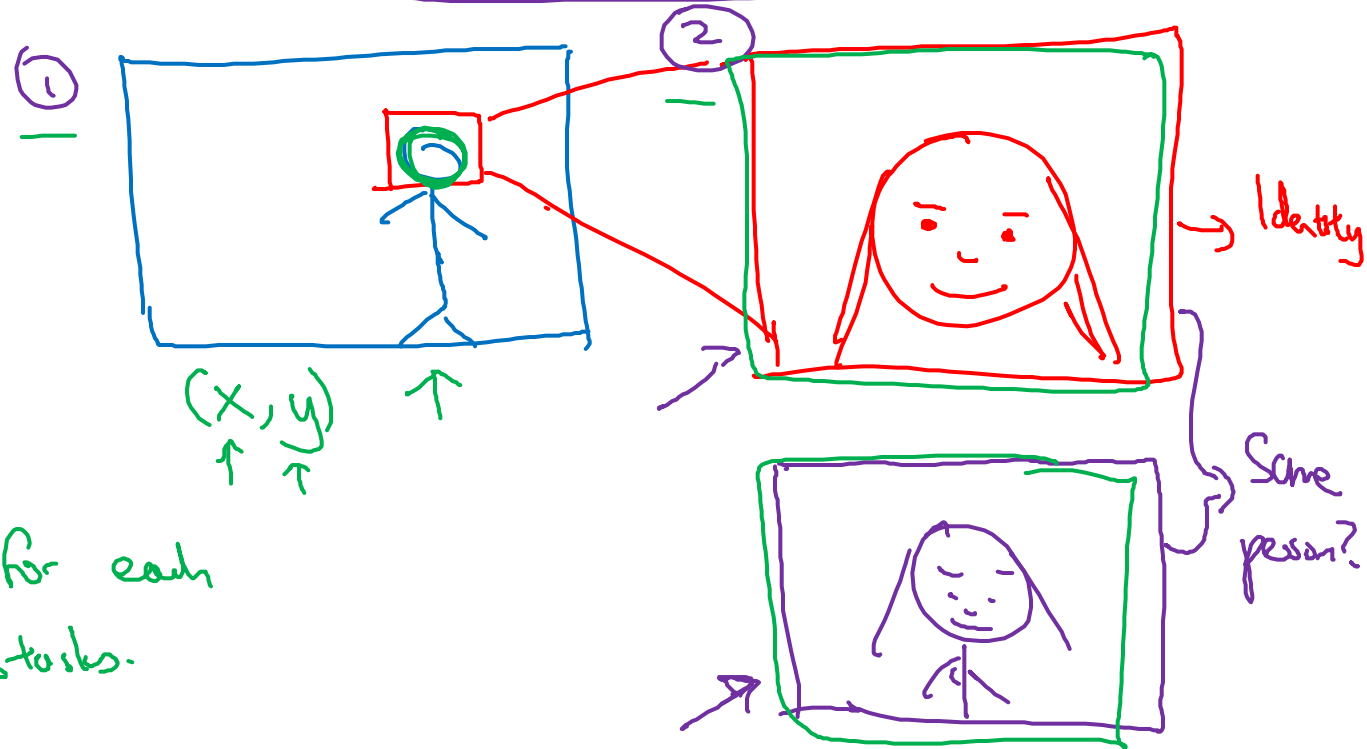
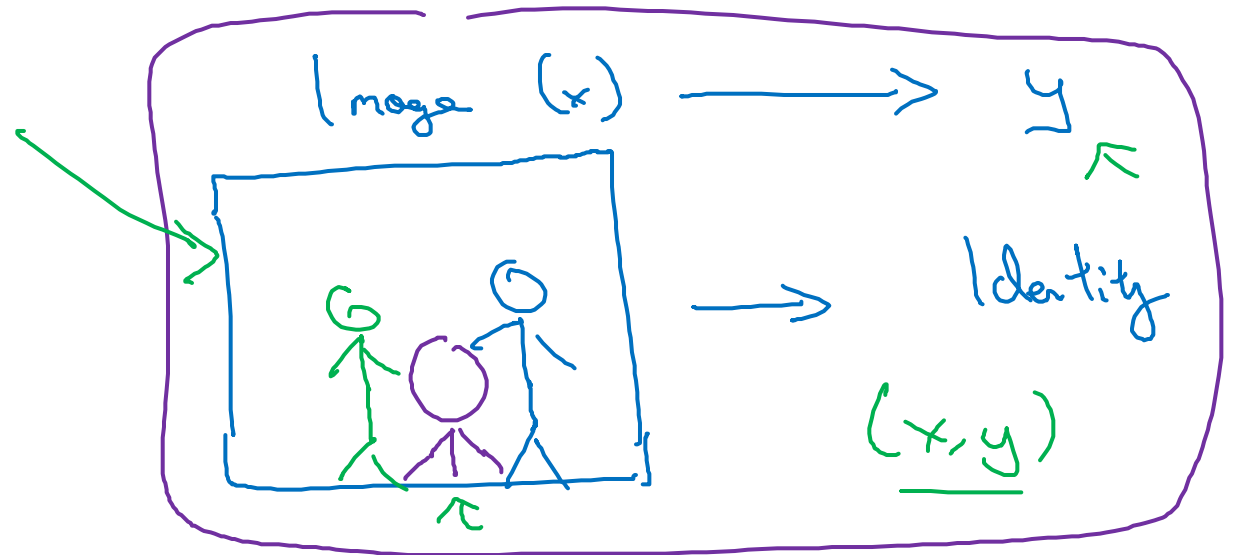
Speech recognition example



Face recognition



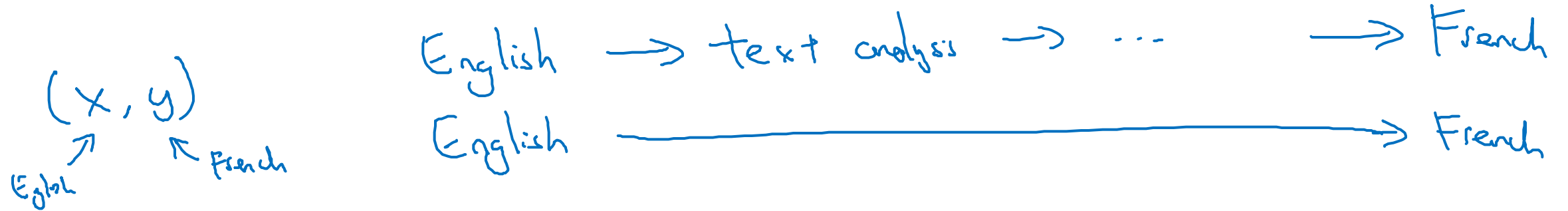
[Image courtesy of Baidu]



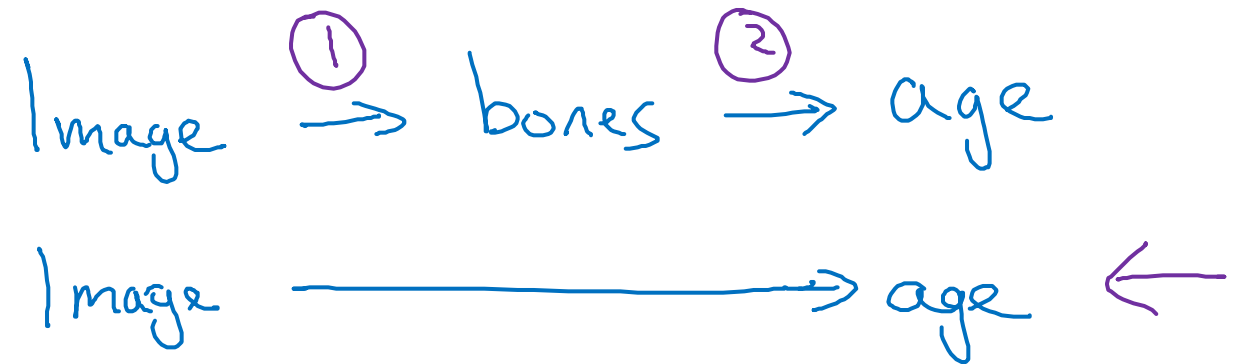
Have data for each
of 2 sub-tasks.

More examples

Machine translation



Estimating child's 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
- Less hand-designing of components needed

$x \rightarrow y$

→ "phonemes"
c a t

Cons:

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

$x - - - - - \rightarrow y$

input
end
↓
 $x \rightarrow y$
output
end
↓

(x, y)

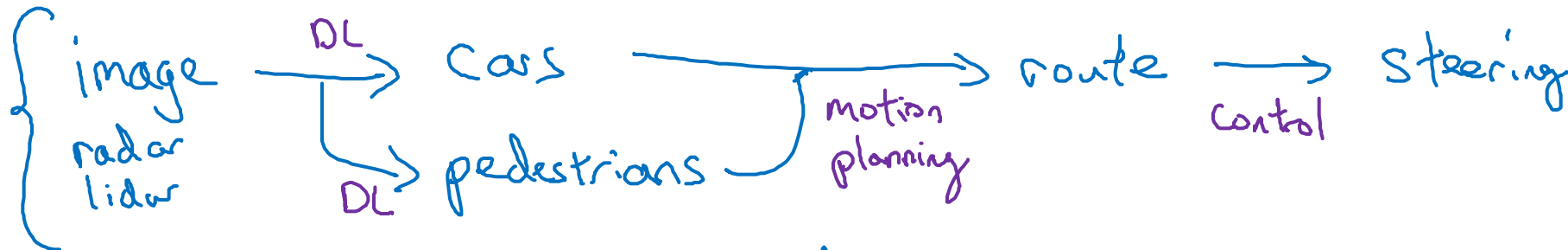
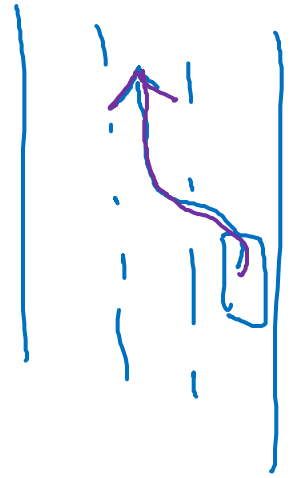
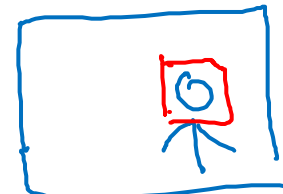
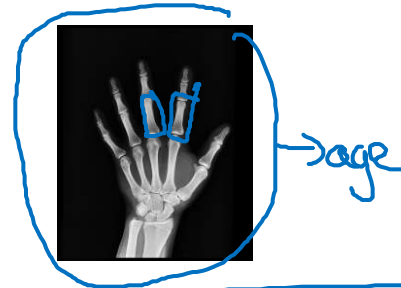
Data.
- - -

Hand-design.
- - -

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 ?

$x \rightarrow y$



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

\rightarrow image \rightarrow steering