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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%

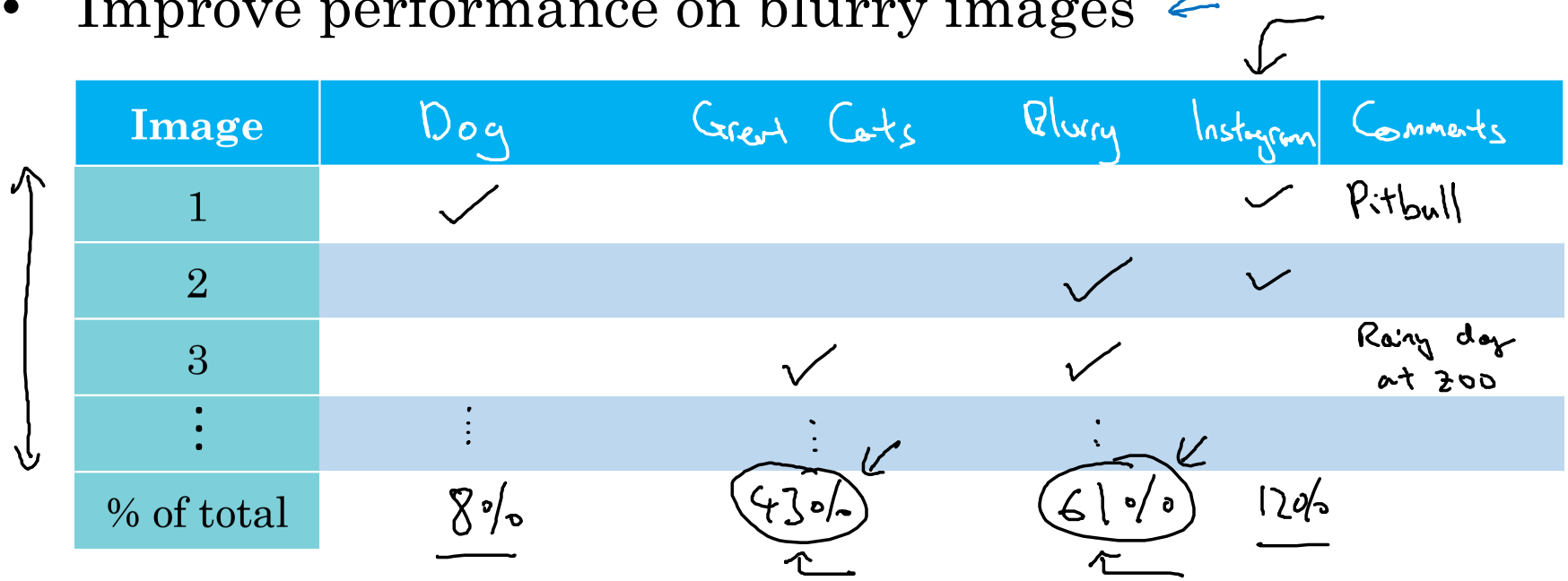
→ 50% → 50/100

10% → 5%

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



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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

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 right as well as ones it got wrong.
- 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 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

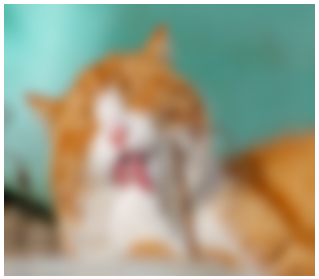
Cat app example

Data from webpages



Data from mobile app



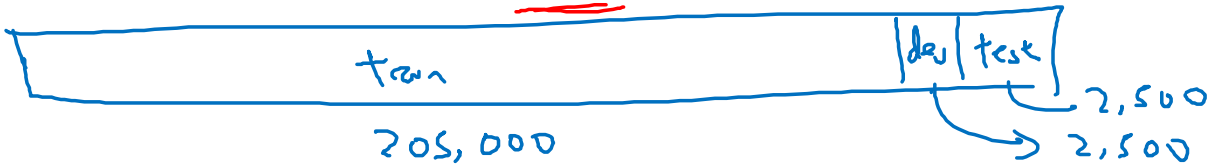


care about this

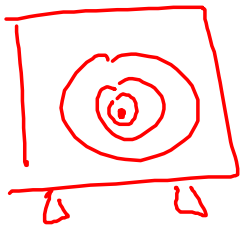
→ ≈200,000 → 210,000 ← → ≈10,000

(shuffle

Option 1:



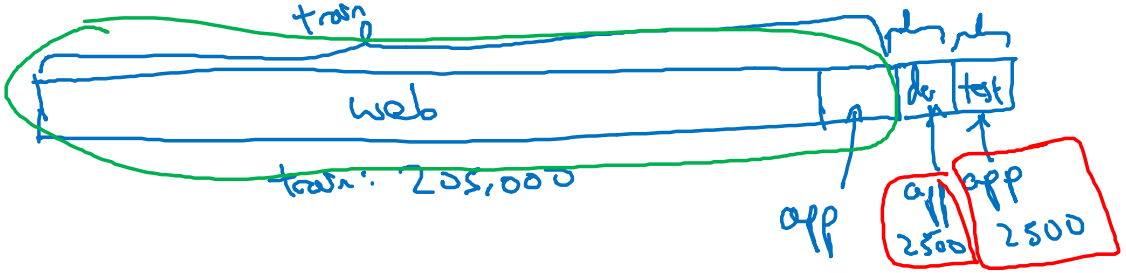
200K / 210K

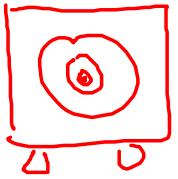


2381 - web

119 - mobile app

Option 2:





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Speech recognition example

Speech activated rearview mirror

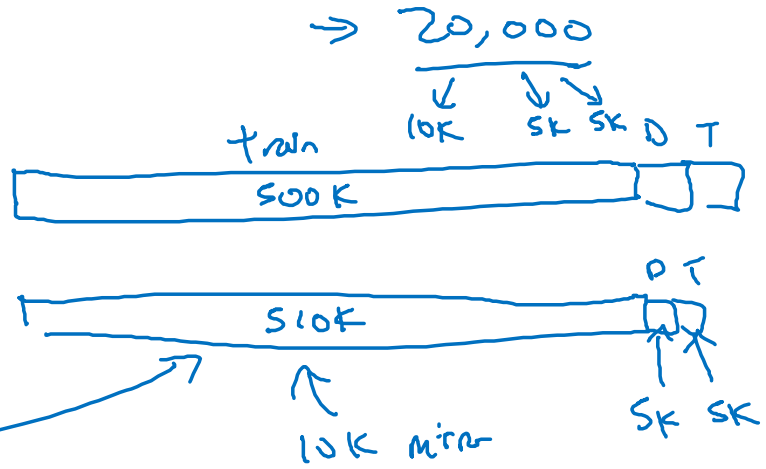
Training

- Purchased data
- Smart speaker control
- Voice keyboard
- …

500,000 utterances

Dev/test

Speech activated rearview mirror



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Mismatched training and dev/test data

Bias and Variance with mismatched data distributions

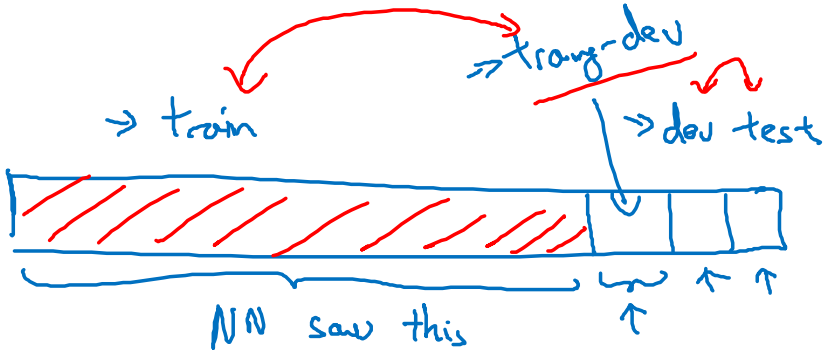
Cat classifier example

Assume humans get ≈ 0% error.

Training error 1%
Dev error 10%

9%

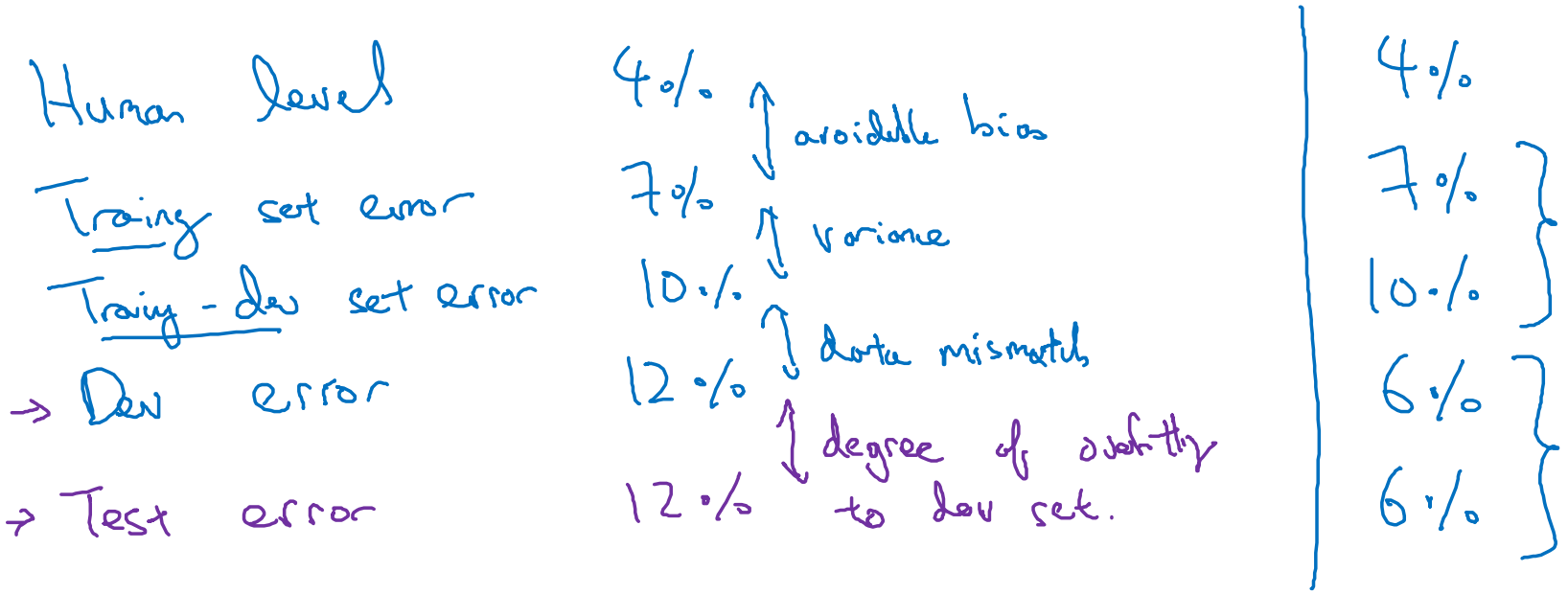
Training-dev set: Same distribution as training set, but not used for training



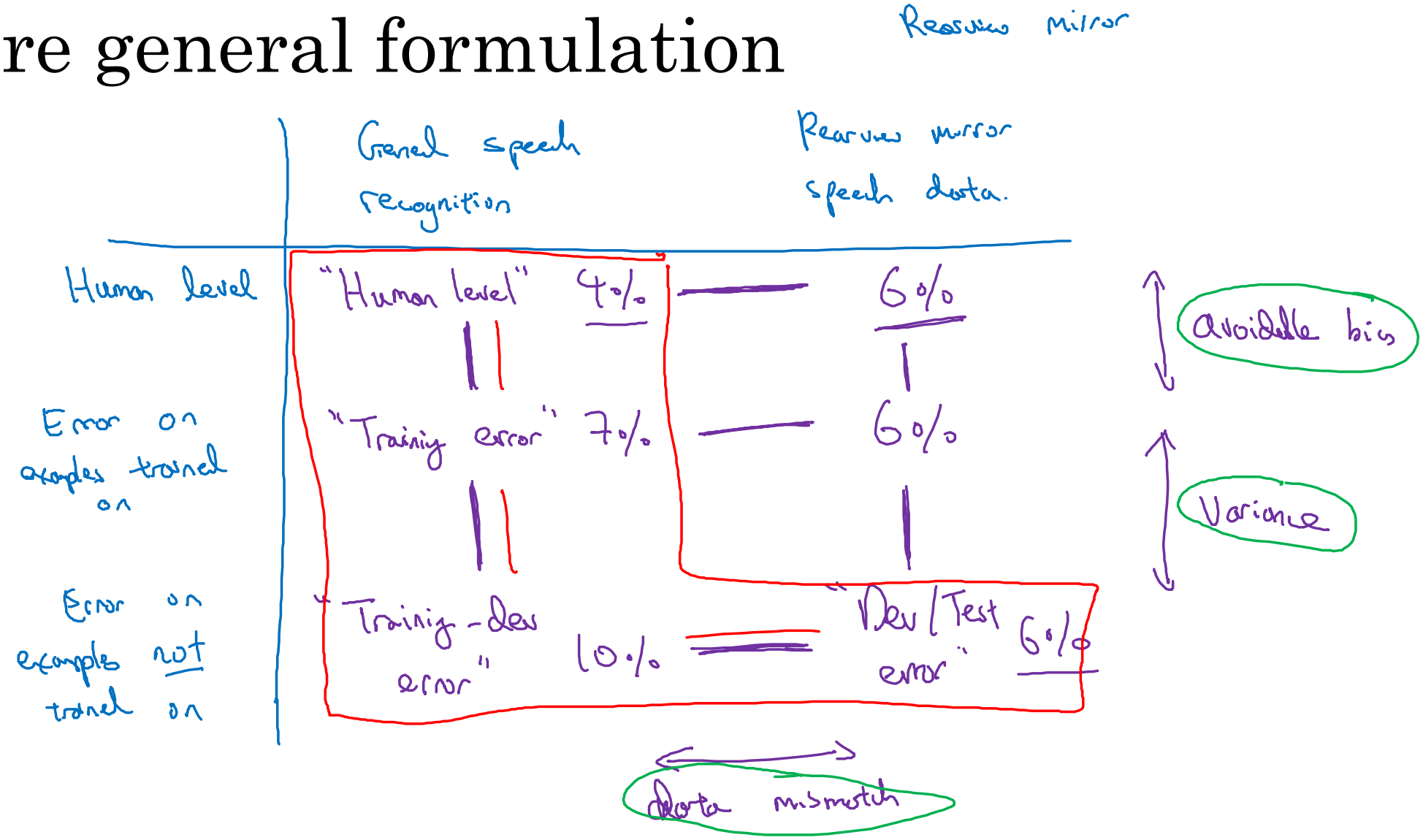
Training error 1% — variance — 1%
Training-dev error 9% — 1.5% — data mismatch
Dev error 10% — 10%

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

Bias/variance on mismatched training and dev/test sets



More general formulation



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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

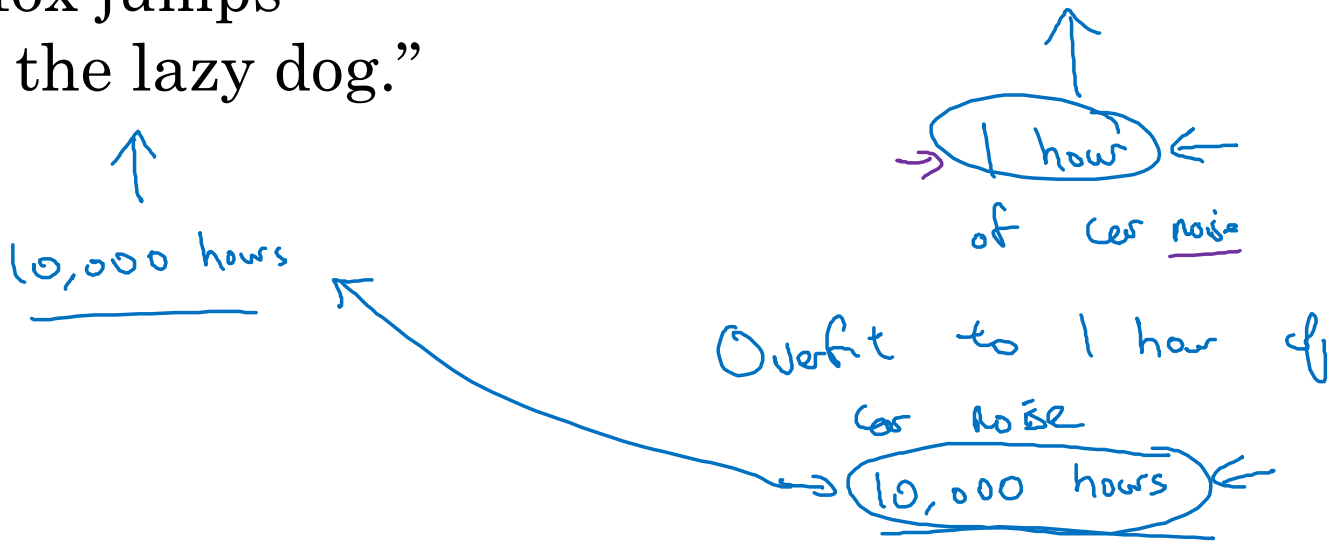
+

=

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

Car noise

Synthesized in-car audio



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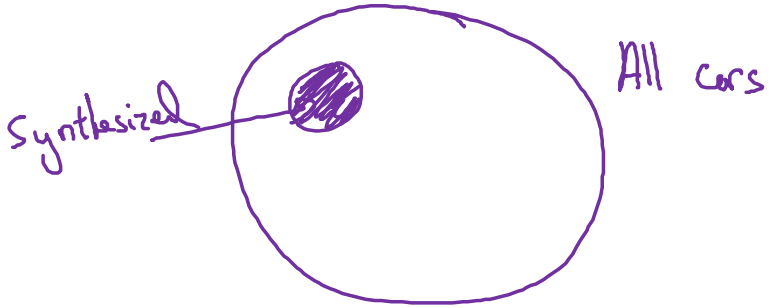
Artificial data synthesis

Car recognition:

~20 cars



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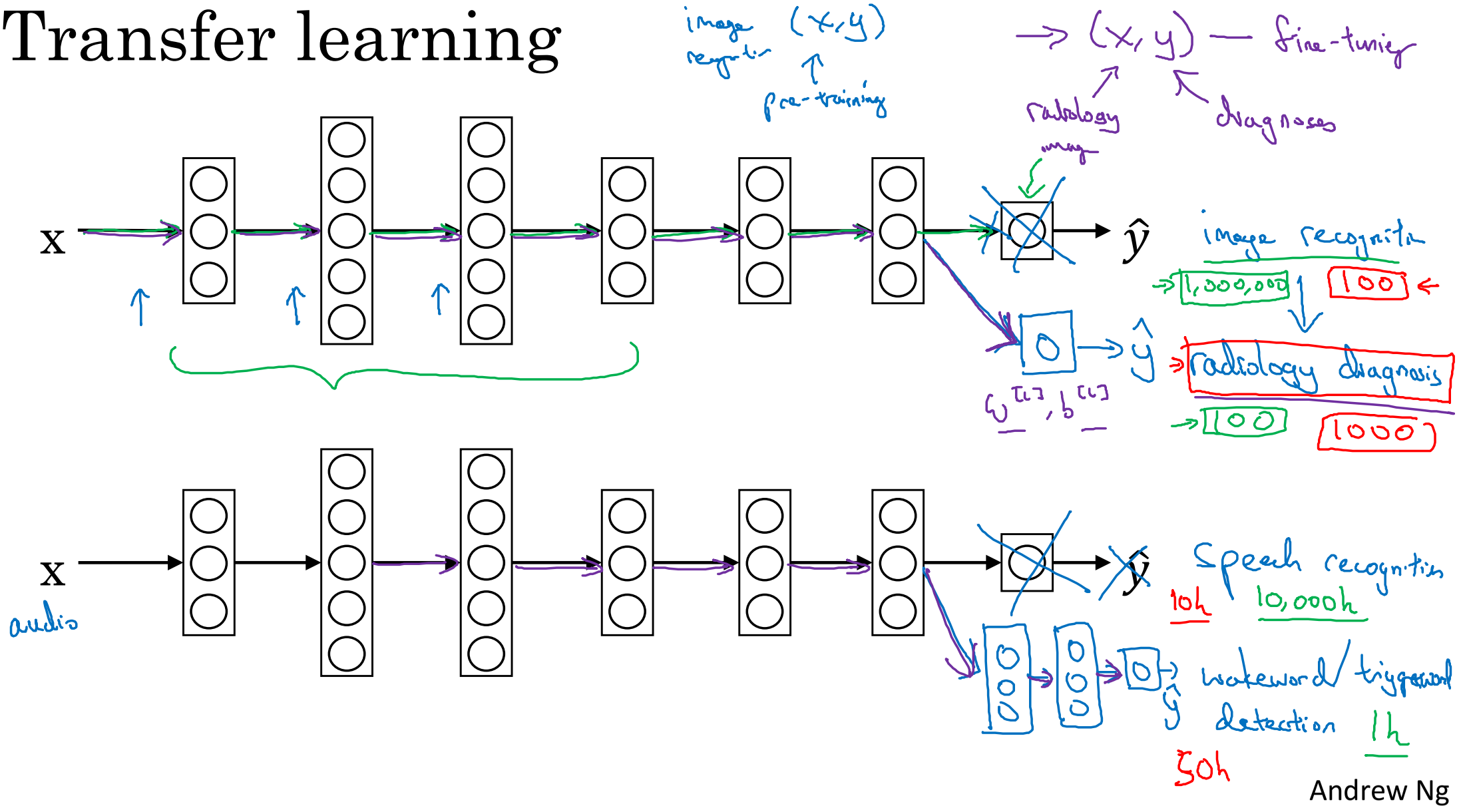
Learning from multiple tasks

Transfer learning

Transfer learning



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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

$x^{(i)}$

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

Pedestrians 0
Cars 1
Stop signs 1
Traffic lights 0
⋮ ⋮

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

$(4, m)$

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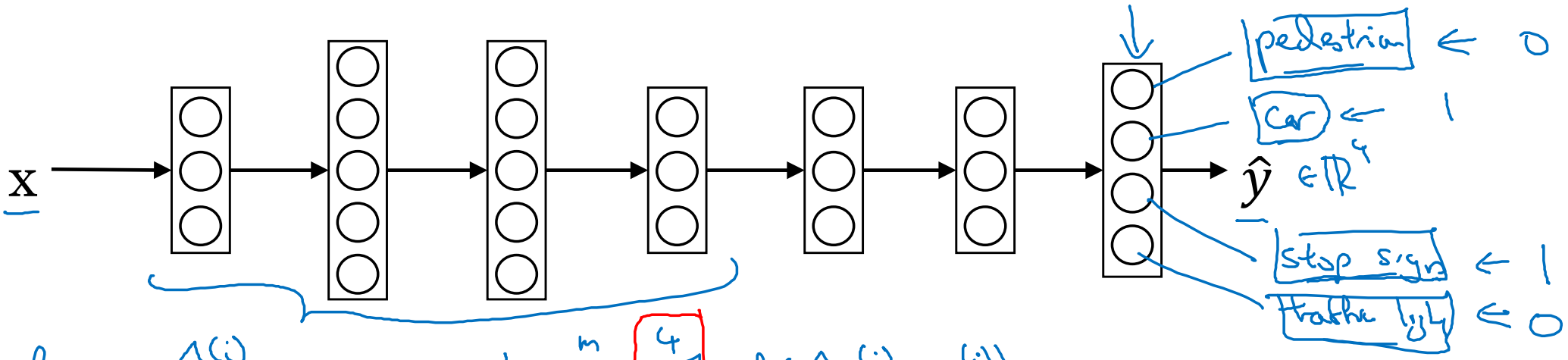
Neural network architecture



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

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

Sum over values of j with 0/1 label.

$\mathcal{L}(\hat{y}_j^{(i)}, y_j^{(i)})$ → 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 ←

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

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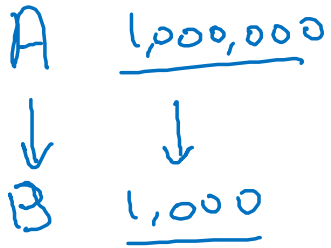
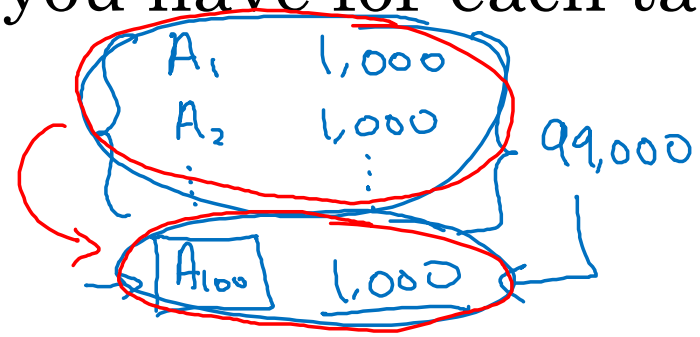
When multi-task learning makes sense

- 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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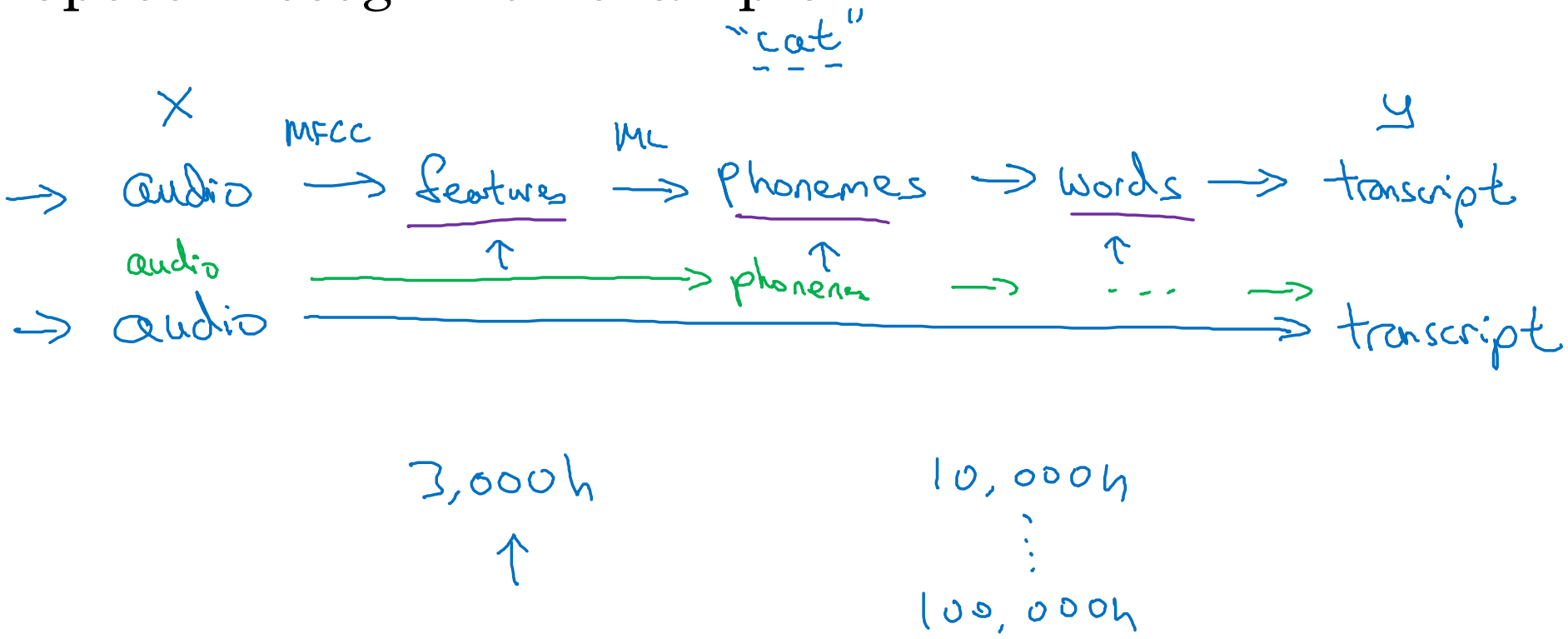
End-to-end deep learning

What is end-to-end deep learning

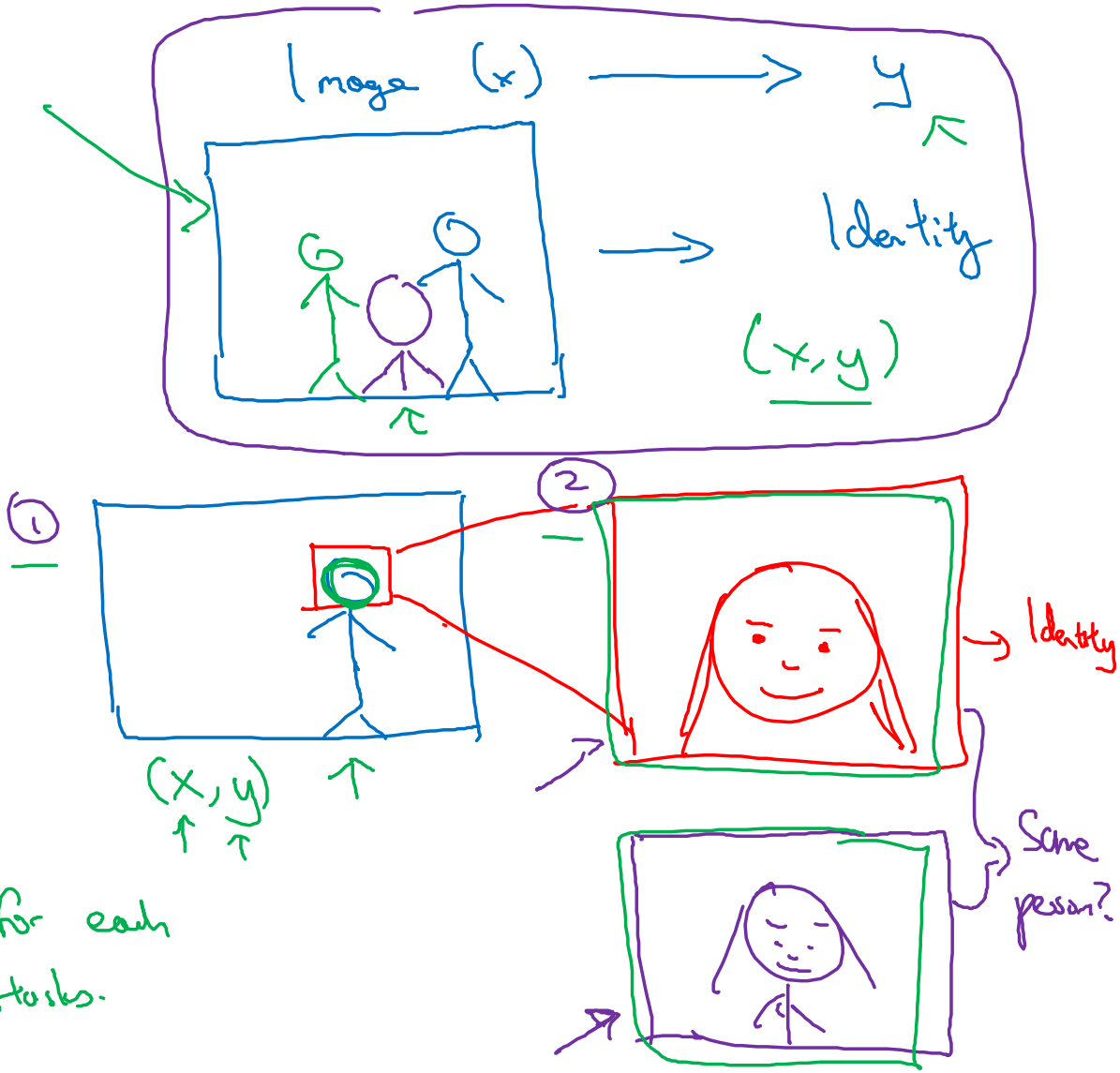
What is end-to-end learning?

Speech recognition example



Face recognition

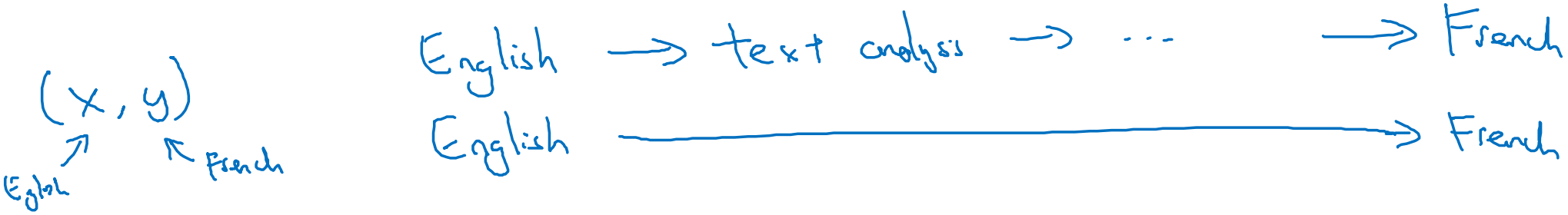
[Image courtesy of Baidu]



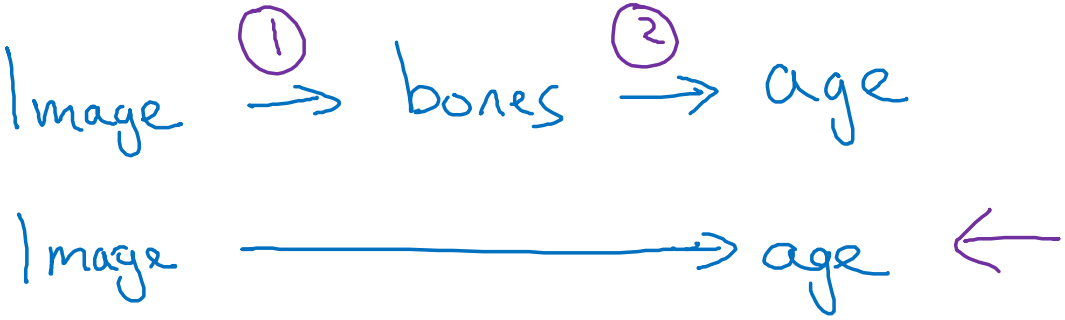
Have data for each of 2 subtasks.

More examples

Machine translation



Estimating child's age:



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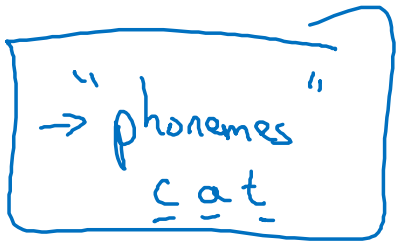
End-to-end deep learning

Whether to use end-to-end learning

Pros and cons of end-to-end deep learning

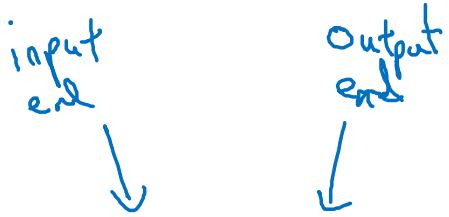
Pros:

- Let the data speak



- Less hand-designing of components needed

Cons:



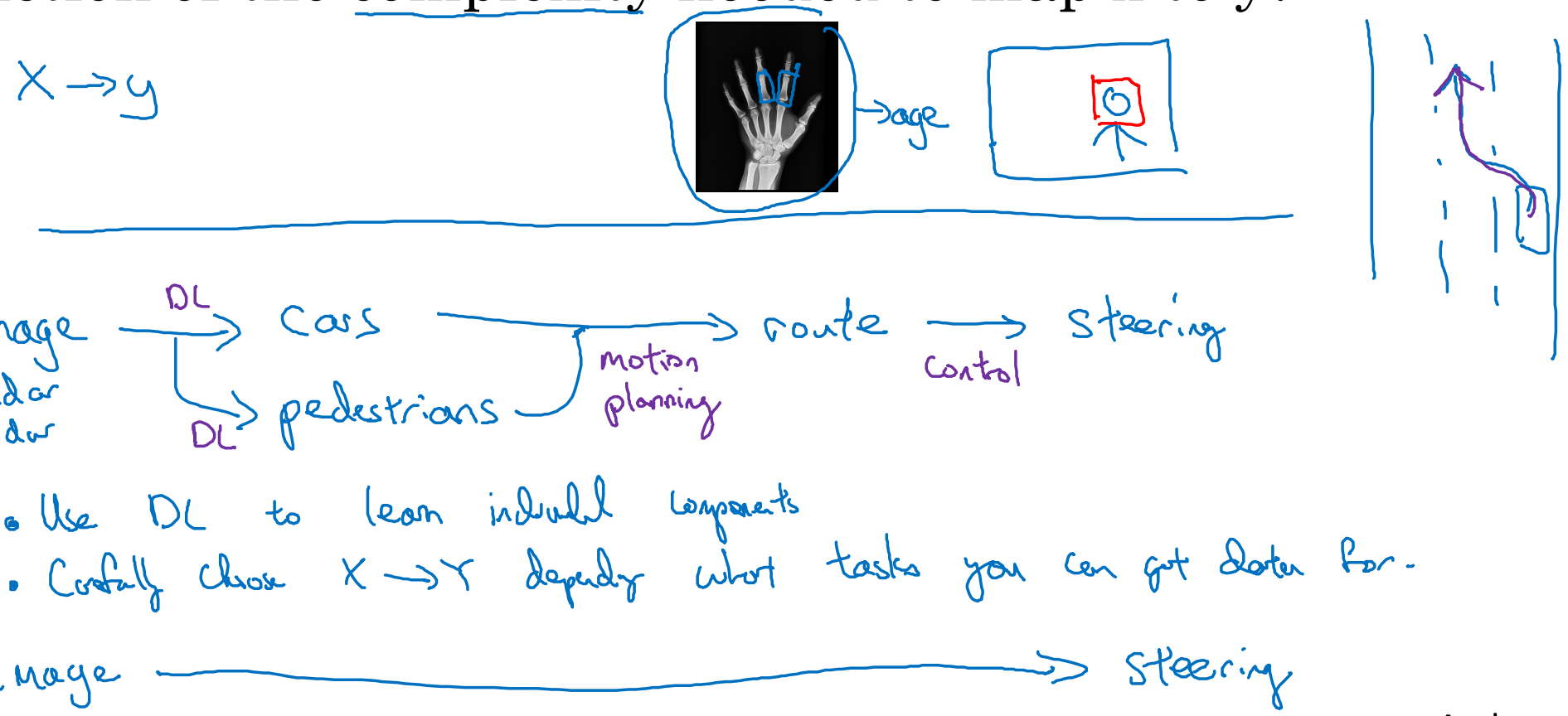
- May need large amount of data
- Excludes potentially useful hand-designed components

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?



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