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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%

# 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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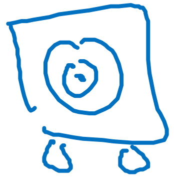
# Error Analysis

## 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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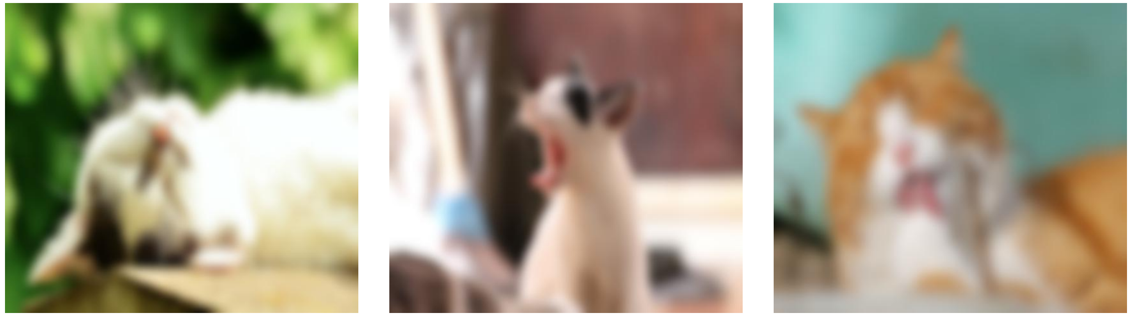
# Mismatched training and dev/test data

## 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

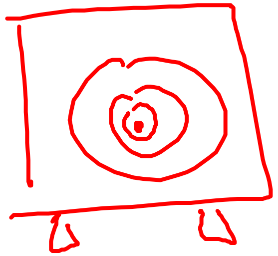
shuffle

X Option 1: train | dev | test

205,000

2,500

2,500



200K / 210K

2381 - web

119 - mobile app

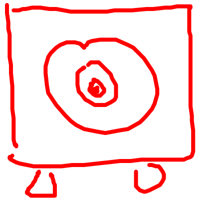
Option 2: train | web | dev | test

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

10K mirror 5K 5K

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# Mismatched training and dev/test data

## Bias and Variance with mismatched data distributions

# Cat classifier example

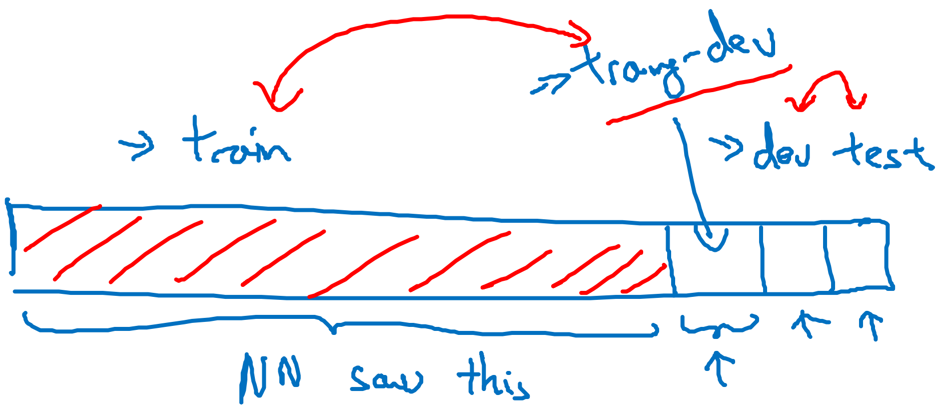
Assume humans get ≈ 0% error.

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% | 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

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# Mismatched training and dev/test data

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## 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

Synthesize

Set of all audio in car

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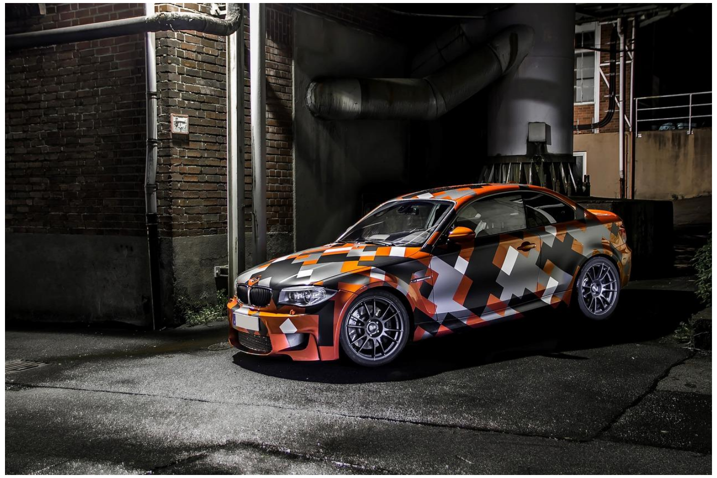
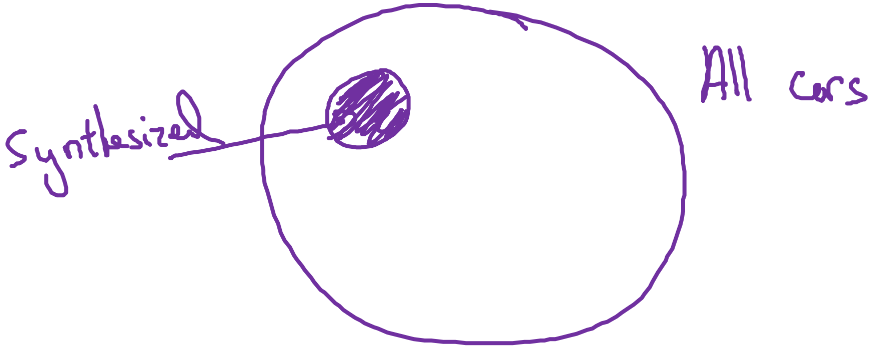
# Artificial data synthesis

Car recognition:



≈ 20 cars



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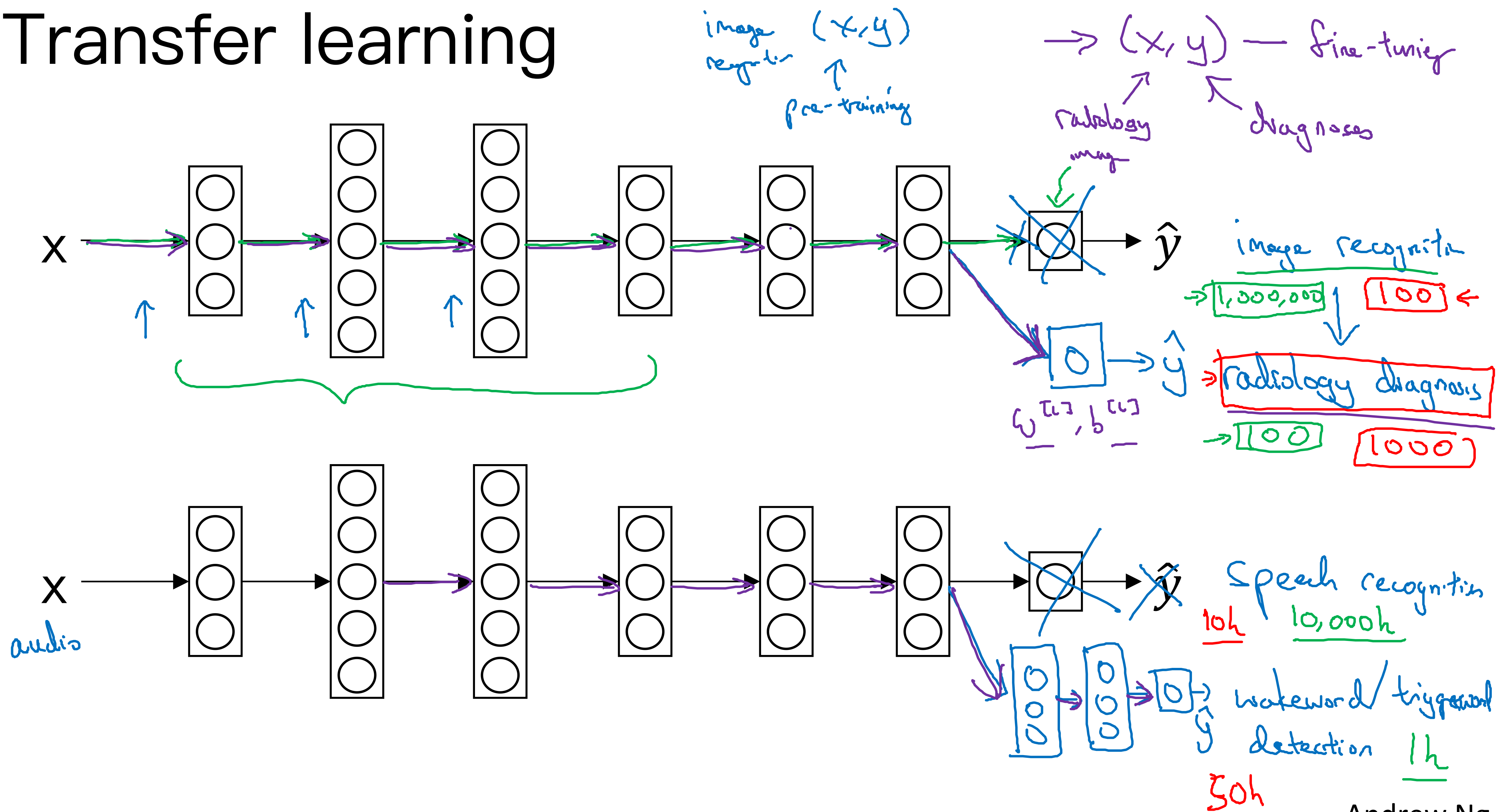
# Learning from multiple tasks

## Transfer learning

# 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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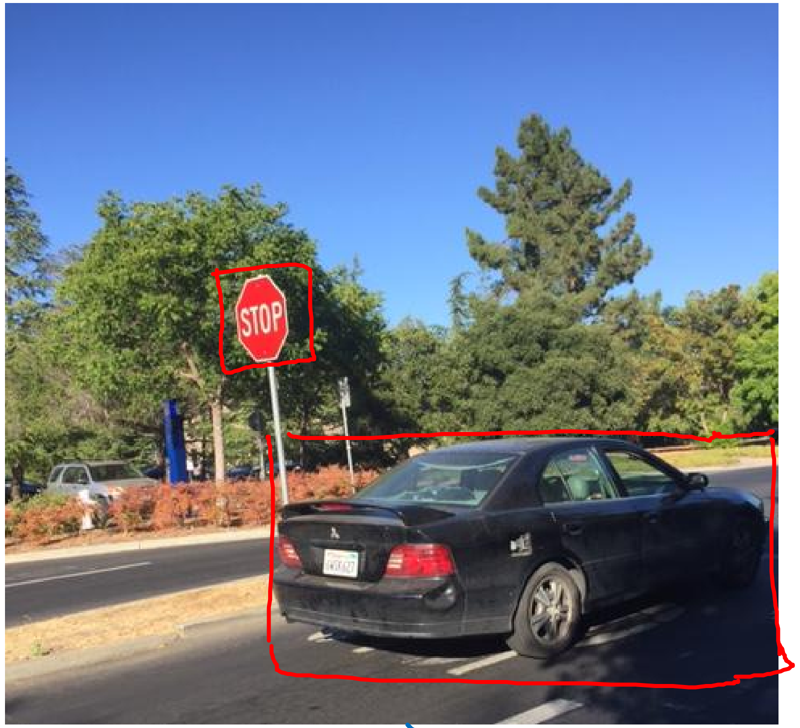
# Learning from multiple tasks

## Multi-task learning

# Simplified autonomous driving example




$x^{(i)}$

| | $y^{(i)}$ |
|---|---|
| Pedestrians | 0 |
| Cars | 1 |
| Stop signs | 1 |
| Traffic lights | 0 |
| $\vdots$ | $\vdots$ |

$(4, 1)$

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

$(4, m)$

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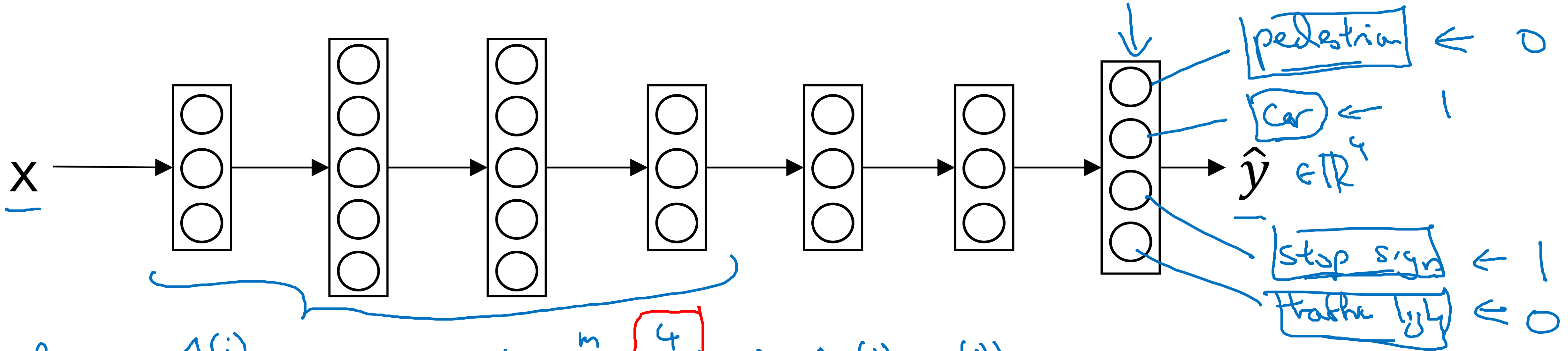
# Neural network architecture




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 ←

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

# 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

$B$ 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.

# 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"

$\rightarrow$ audio ($x$) $\xrightarrow{\text{MFCC}}$ features $\xrightarrow{\text{ML}}$ Phonemes $\rightarrow$ words $\rightarrow$ transcript ($y$)

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

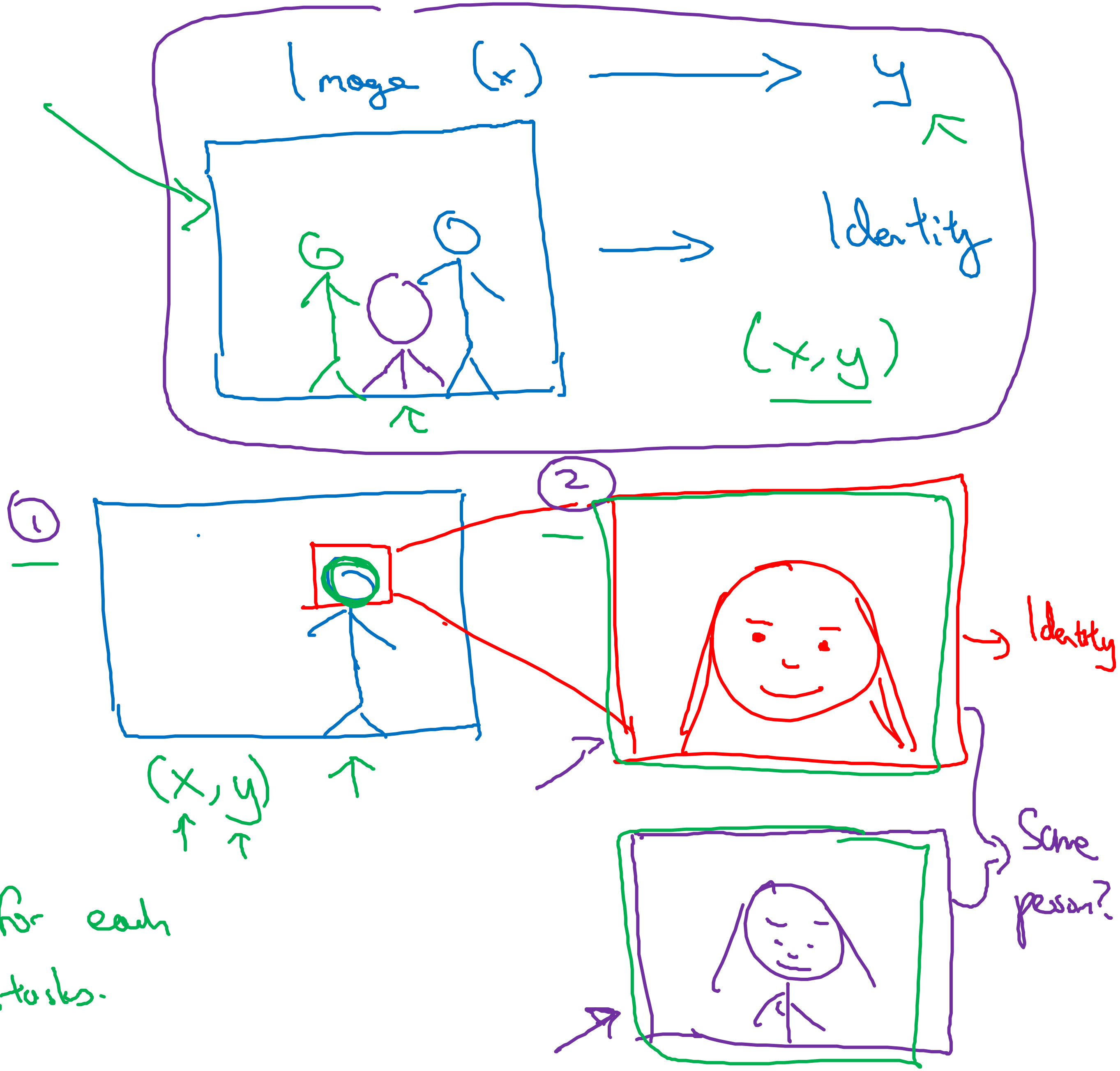
$\rightarrow$ audio $\longrightarrow$ transcript

3,000h

10,000h
⋮
100,000h

# Face recognition

[Image courtesy of Baidu]




Have data for each of 2 subtasks.

# More examples

## Machine translation

$(x, y)$

Eglish   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 $x \longrightarrow y$ → "phonemes" c a t
- Less hand-designing of components needed

$x - - - - \rightarrow y$

Cons:

- May need large amount of data

  input end, output end

  $x \longrightarrow y$ $(x, y)$
- Excludes potentially useful hand-designed components

  Data Hand-design

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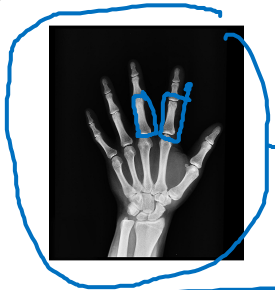
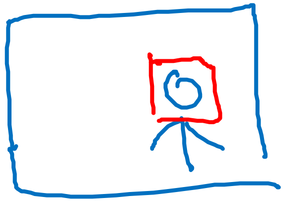
# Applying end-to-end deep learning

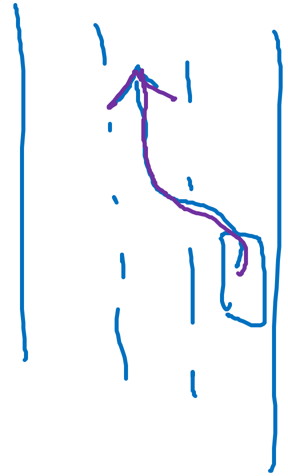
Key question: Do you have sufficient data to learn a function of the complexity needed to map x to y?

x → y



→ age





image, radar, lidar $\xrightarrow{DL}$ cars ⟶ route $\xrightarrow[\text{control}]{}$ steering

image, radar, lidar $\xrightarrow{DL}$ pedestrians ⟶ motion planning ⟶ route

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

→ image ⟶ steering

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